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Essays in Market Microstructure

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Introduction

Main purpose of the present study is the examination of the investors' behavior round bubble episodes. Two aspects of this behavior are empirically examined. The first is related with investors' rationality (1st and 2nd Chapter) while the second is related with the implementation of specific market mechanisms (3rd Chapter) like price limits.

As bubble we define the market condition in which each investor buys an asset (for example stocks or real estate) not for the return it offers but because she expects that she will resell the asset to someone else at a higher price (Kindleberger & Aliber [71]).

The basic characteristic of a bubble is the dramatic price increase that is followed by a – probably more – dramatic downfall. It is obvious that the period of dramatic price increase - the upwards deviation of the price from the fundamental value of the asset - is a result of the excess demand caused by agents' behavior similar to the one just described on

Κύριος σκοπός της συγκεκριμένης εργασίας είναι η μελέτη της συμπεριφοράς των επενδυτών σε συνθήκες κερδοσκοπικής φούσκας. Η συγκεκριμένη συμπεριφορά εξετάζεται εμπειρικά ως προς δύο παραμέτρους. Πρώτον την ορθολογικότητα των επενδυτών (1ο και 2ο Κεφάλαιο) και δεύτερον, συγκεκριμένους μηχανισμούς της αγοράς (3ο Κεφάλαιο), όπως τα ανώτατα και κατώτατα όρια διαπραγμάτευσης τιμών.

Ως κερδοσκοπική φούσκα τώρα ορίζουμε την κατάσταση που επικρατεί στην αγορά όταν οι επενδυτές αγοράζουν περιουσιακά στοιχεία (π.χ. μετοχικούς τίτλους ή ακίνητα) όχι για να επωφεληθούν από τις αποδόσεις που αυτά προσφέρουν αλλά επειδή αναμένουν ότι θα μπορέσουν να τα μεταπωλήσουν σε υψηλότερη τιμή σε κάποιον άλλο επενδυτή (Kindleberger & Aliber [71]).

Σε γενικές γραμμές οι χρηματιστηριακές φούσκες χαρακτηρίζονται από δραματικές αυξήσεις τιμών που μετά από κάποια περίοδο ακολουθούνται από επίσης δραματικές μειώσεις των τιμών. Προφανώς, η περίοδος της δραματικής αύξησης των τιμών - της απόκλισης της τρέχουσας χρηματιστηριακής τιμής από την θεμελιώδη αξία του the definition of the bubble above. The downfall now is due to the false expectations of the future asset returns or to the reduction of liquidity in the market. This reduction in liquidity may come from factors that are directly to the asset's price or for exogenous reasons.

We can distinguish bubbles in two broad categories which are closely related with the participant investors' behavior. In the first broad category, all investors are rational while in the second two types of investors exist in the market, rational and irrational (or "noise") ones.

For models with rational investors only, it is easy to prove that in the case of finite time it is not possible to have a bubble. The argument is via backwards induction. In the case of infinite time, the existence of a bubble can be avoided only with the implementation of a transversality condition. Under asymmetric information, a bubble cannot occur only under specific assumptions.

The critical question is what happens when rational and irrational traders coexist in the market. Following Friedman [40], such a coexistence is only temporary. Soon the rational investors will push the irrational ones out of the market. But this is not always the case. DeLong et al [35] showed that risk averse rational investors might not want to place

περιουσιακού στοιχείου - είναι αποτέλεσμα της αυξημένης ζήτησης εξαιτίας του ορισμού της κερδοσκοπικής φούσκας που δόθηκε παραπάνω. Η κατάρρευση της τιμής οφείλεται είτε στη διάψευση των προσδοκιών για τις μελλοντικές αποδόσεις του περιουσιακού στοιχείου, είτε στον περιορισμό της ρευστότητας στην αγορά. Ο περιορισμός της ρευστότητας μπορεί να οφείλεται, είτε στην ίδια την τιμή του περιουσιακού στοιχείου, είτε και σε εξωγενείς παράγοντες.

Πέρα από αυτές τις γενικές παρατηρήσεις όμως, οι κερδοσκοπικές φούσκες μπορούν να διακριθούν σε δύο μεγάλες κατηγορίες που είναι άμεσα συνδεδεμένες με την συμπεριφορά των επενδυτών. Στην πρώτη κατηγορία όλοι οι επενδυτές είναι ορθολογικοί ενώ στη δεύτερη κατηγορία δύο τύποι επενδυτών συνυπάρχουν στην αγορά, ορθολογικοί και μη ορθολογικοί επενδυτές.

Για υποδείγματα που περιέχουν μόνο ορθολογικούς επενδυτές μπορεί εύκολα να αποδειχθεί ότι στην περίπτωση πεπερασμένου επενδυτικού χρόνου δεν είναι δυνατόν να υπάρξουν κερδοσκοπικές φούσκες. Για τον μη πεπερασμένο χρόνο, η ύπαρξη φούσκας μπορεί να αποφευχθεί μόνο με την εφαρμογή της συνθήκης μεταθετικότητας (transversality condition). Σε συνθήκες ασύμμετρης πληροφόρησης η μη ύπαρξη φούσκας - υπό κάποιες προϋποθέσεις - δεν είναι πλέον δεδομένη.

Το κρίσιμο ερώτημα που προκύπτει εδώ όμως, είναι τι συμβαίνει όταν στην αγορά συνυπάρχουν οι ορθολογικοί με τους μη ορθολογικούς επενδυτές. Σύμφωνα με τον Friedman [40], αυτή η συνύπαρξη themselves against the irrationals (and the bubble).

Even in the case were rational investors are risk neutral, it might not be possible to trade against the bubble. Abreu & Brunnermeier [1] build a model where the rational investors, due to their small size and their sequential entry into the market, cannot agree in a strategy against the bubble and ride it.

With all the above given, the 1st Chapter below examines the role of rational investors in the bubble – environment of the Real Estate Investment Trusts (REITs) sector of the New York Stock Exchange (NYSE).The rational investors are a sample of hedge funds that invested in the REITs stocks for the period 2002-2007. The study is based in the use of the 13f database provided by Thomson Financial. Our results show that our hedge fund managers behaved accordingly with the Abreu & Brunnermeier [1] approach. In the 2nd Chapter we examine the behavior of all the institutional investors in the REITs sector of the NYSE using the 13f database for the 1998-2008 period. Our analysis is based on the theory work of Nirei [90] which states that the optimal strategy for an investor – given that heterogeneity exists among investors – is to mimic the rest. In this case also our results support Nirei's [90] approach.

δε θα ήταν μόνιμη. Πολύ γρήγορα, οι ορθολογικοί επενδυτές θα έσπρωχναν τους μη ορθολογικούς έξω από την αγορά. Αυτό όμως δεν συμβαίνει πάντα. Οι DeLong et al [35] έδειξαν ότι κάτι τέτοιο μπορεί να μην είναι πάντα δυνατό, αφού ορθολογικοί επενδυτές που εμφανίζουν συμπεριφορά αποστροφής κινδύνου μπορεί να μην είναι διατεθειμένοι να αναλάβουν να τοποθετηθούν ενάντια στη κερδοσκοπική φούσκα.

Ακόμη και όταν όμως οι ορθολογικοί επενδυτές εμφανίζουν συμπεριφορά ουδετερότητας απέναντι στον κίνδυνο είναι πιθανό να μην μπορούν και πάλι να τοποθετηθούν ενάντια στη κερδοσκοπική φούσκα, αλλά αντίθετα να κινηθούν προς την ίδια κατεύθυνση με τους μη ορθολογικούς επενδυτές. Οι Abreu & Brunnermeier [1] παρουσιάζουν ένα υπόδειγμα, όπου οι ορθολογικοί επενδυτές εξαιτίας του μικρού τους μεγέθους και του ότι εισέρχονται στην αγορά διαδοχικά δεν μπορούν να συμφωνήσουν σε μια στρατηγική ενάντια στη κερδοσκοπική φούσκα, αλλά αντίθετα κινούνται στην ίδια κατεύθυνση με αυτή.

Με δεδομένο το παραπάνω πλαίσιο στο 1ο Κεφάλαιο εξετάζεται ο ρόλος των ορθολογικών επενδυτών σε μια κερδοσκοπική φούσκα όπως αυτή που σχηματίστηκε στον κλάδο Εταιρειών Διαχείρισης Περιουσιακών Στοιχείων (REITS) του Χρηματιστηρίου της Νέας Υόρκης. Ως ορθολογικούς επενδυτές θεωρούμε ένα δείγμα hedge funds που επένδυαν στις μετοχές των συγκεκριμένων εταιρειών για την περίοδο 2002-2007. Η εξέταση στηρίζεται στη χρήση της Βάσης Δεδομένων 13f που παρέχεται από την

The 3rd Chapter is focused on the study of the efficiency of price limits on the Athens Stock Exchange (ASE) for the period 1998-2001. At a first glance this study seems to be unrelated with the previous two. Nevertheless there is a connection. The basic argument for the price limits implementation is that they give time to investors to "digest" new information and to reassess their decisions. Brunnermeier & Pedersen [23] argue that price limits are an important tool against rational informed investors that push the price downwards (upwards), together with investors that are in need for selling (buying) the asset, in order to cause a bigger price decline (uprise) than it would otherwise be. Then, in a later round, the rational investors will enter the market and buy (sell) the asset. Their gains come from the difference between the price they sell (bought) the asset at the first round and the price they bought (sell) it at the second round. Price limit do not permit the liquidity decrease in the market and so they break up the informed investors "predatory" game. The basic result from the study of price limits for the ASE showed that their ineffectiveness cannot be rejected. A previous version of the 3rd Chapter has been published in a collective volume (Stamatiou [109]).

Thomson Financial. Τα αποτελέσματα δείχνουν πως τα hedge funds συμπεριφέρθηκαν σύμφωνα με την προσέγγιση των Abreu & Brunnermeier [1].

Στο 2ο κεφάλαιο, εξετάζουμε τη συμπεριφορά του συνόλου των θεσμικών επενδυτών στον κλάδο των Εταιρειών Διαχείρισης Περιουσιακών Στοιχείων (REITS) του Χρηματιστηρίου της Νέας Υόρκης με τη χρήση της βάσης δεδομένων 13f για την περίοδο 1998-2008. Η ανάλυση βασίζεται στην θεωρητική προσέγγιση του Nirei [90] σύμφωνα με την οποία η βέλτιστη στρατηγική ενός επενδυτή - με δεδομένη την ανομοιογένεια μεταξύ των επενδυτών σε μια αγορά - είναι να μιμηθεί τους υπολοίπους. Και σε αυτή την περίπτωση τα αποτελέσματα μας επιβεβαιώνουν το συγκεκριμένο θεωρητικό υπόδειγμα.

Το 3ο Κεφάλαιο ασχολείται με τη μελέτη της αποτελεσματικότητας των ανώτατων και κατώτατων ορίων διαπραγμάτευσης στο Χρηματιστήριο Αξιών Αθηνών (ΧΑΑ) για την περίοδο 1998-2001. Εκ πρώτης όψεως, η συγκεκριμένη εργασία φαίνεται να μην συνδέεται άμεσα με τις δύο προηγούμενες. Παρ' όλ' αυτά, υπάρχει άμεση σύνδεση. Βασικό επιχείρημα για την εφαρμογή των ορίων διαπραγμάτευσης είναι η εξασφάλιση χρόνου στους επενδυτές ώστε να επανεκτιμήσουν τις αποφάσεις τους και να διορθώσουν πιθανά σφάλματα. Παράλληλα, οι Brunnermeier & Pedersen [23] υποστηρίζουν ότι τα όρια διαπραγμάτευσης αποτελούν ένα σημαντικό εμπόδιο ενάντια σε ορθολογικούς επενδυτές που προσπαθούν να μειώσουν (αυξήσουν) την τιμή ενός περιουσιακού στοιχείου γνωρίζοντας ότι κάποιοι επενδυτές στην αγορά ήδη το πωλούν (αγοράζουν). Ο όγκος των πωλήσεων (αγορών) θα μειώσει (αυξήση) την τιμή περισσότερο από ότι αν δεν υπήρχαν οι πληροφορημένοι επενδυτές στην αγορά. Οι τελευταίοι, στη συνέχεια, θα επαναγοράσουν (πωλήσουν) το περιουσιακό στοιχεία και το κέρδος τους θα είναι η διαφορά ανάμεσα στην τιμή αγοράς και στην τιμή πώλησης. Η εφαρμογή των ορίων διαπραγμάτευσης, σε αυτή την περίπτωση, επιτρέπει την παροχή ρευστότητας στο σύστημα με αποτέλεσμα, η στρατηγική των πληροφορημένων επενδυτών να μην μπορεί να αποδόσει. Η εμπειρική εξέταση των ορίων διαπραγμάτευσης για το Χρηματιστήριο Αξιών Αθηνών για την περίοδο κερδοσκοπικής φούσκας 1998-2001 έδειξε ότι δεν είναι δυνατόν να απορριφθεί η μη-αποτελεσματικότητα των ορίων διαπραγμάτευσης. Προηγούμενη έκδοση του 3ου Κεφαλαίου έχει δημοσιευθεί σε συλλογικό τόμο (Stamatiou [109]).

Chapter 1

Hedge Funds and the US Real Estate Bubble: Evidence from NYSE Real Estate Companies

The recent US Real Estate Bubble had consequences not only for the real economy but for the stock market as well. Real Estate Investment Trusts' (REITs) prices reached levels which could not be supported by their fundamentals until mid-2007. Using this observation as a starting point we assume that hedge fund managers are rational investors and we examine their holdings behavior in the REITs sector of the NYSE. Our working assumption is based on the DeLong et al [35] and Abreu & Brunnermeier [1] argument that rational investors under certain conditions may not always short a bubble but instead ride it so as to gain from the price rise. Using data on hedge fund managers holdings from the 13f filing database provided by Thomson Financialwe find that hedge funds were overloaded with REITs stocks prior to the price peak of the sector but their positions were placed in such a way that they gained from this strategy. Moreover, non - specialized hedge fund managers outperformed specialized ones.

1.1 Introduction

The recent US Real Estate Bubble had consequences not only for the real economy but for the stock market as well. Real Estate Investment Trusts' (REITs) prices reached levels which could not be supported by their fundamentals until mid-2007. Using this observation as a starting point we assume that hedge fund managers are rational investors and we examine their holdings behavior in the REITs sector of the New York Stock Exchange (NYSE). Our working assumption is based on the DeLong et al [35] and Abreu & Brunnermeier [1] argument that rational investors under certain conditions may not always short a bubble but instead ride it so as to gain from the price rise.

We use a sample of 111 NYSE traded REITs and analyze the behavior of the hedge fund managers holdings. The REITs' PE ratios - for the 2002-2007 sample period - reached levels that could not be supported by their fundamentals and thus strongly pointing to a bubble episode. We obtain hedge fund managers' holdings from the 13f filing database. In our empirical analysis, we examine if hedge fund managers were overloaded with REITs holdings for the sample period and if they were timing their REITs trades properly to profit from the peak of the bubble. Our purpose is not to draw any conclusion about the hedge fund industry in general. Our REITs sample and the sample hedge fund managers are too small for such a venture. Instead we consider that our approach is fruitful because it adds another piece to the puzzle of the behavior of rational investors in bubble environments. Moreover it is interesting by itself to examine if such a behavior can happen again after a similar event in the REITs market that took place back in 70s and after the Abreu & Brunnermeier [1] and Brunnermeier & Nagel [22] papers that highlighted the behavior of rational investors in bubble episodes. Nevertheless, our results are supportive of the case that hedge funds were acting as rational investors in the DeLong et al [35] and Abreu & Brunnermeier [1] sense. They ride the bubble as long as it was rising and this behavior was profitable.

In the reminder of the paper, Section 2 provides a review of the literature, Section 3 gives a short description of the real estate bubble and identify the segment of real estate stocks to be examined. Section 4 presents the sample more formally and gives details on the use of the 13f holdings data and the construction of the hedge funds' sample that will be used in what follows. Moreover it gives a summary statistics for the stock holdings of these hedge funds and presents the hypotheses to be tested. Section 5 and Section 6 provide the empirical analysis of the paper. A brief conclusion ends the paper.

1.2 Literature Review

It is interesting that back in the '70s the REITs sector was again in the center of a bubble episode. Institutional investors played a significant role in creating the bubble and also made profits from it as it is pointed out by Soros [100]. This event does not necessary preclude a bubble from happening again and in addition places the REITs market in a series of markets that experienced bubble episodes in the last centuries. Kindleberger & Aliber [71] analyze such a series of bubbles. The first bubble episode occurred in the 17th century Netherlands (the Tulip Bulb Bubble, 1636), the second and third occurred in France and England in the 18th century (the Mississippi and South Sea Bubbles respectively) and so on until the 1920s US stock Bubble and more recently the 2000 DotCom Bubble. Even though it is old, a quote from Adam Smith can describe the investors behavior during such an episode. *...the conduct of almost all the unfortunate...have arisen from their not knowing when they were well, when it was proper for them to sit still and be contended.*

Despite the evidence from the financial history the Efficient Markets Hypothesis does not cope well with the occurrence of bubbles. A fully rational[1] investor will anticipate a bubble and so she will play against it. In such a way under symmetric information and finite time a bubble cannot take place. Using the fact that after the end of the game the price will be zero and backwards induction we can prove that the price of the asset today is just the sum of the discounted dividends. Under infinite time the imposition of the transversality condition precludes a bubble from occurring. These two results are enough for the standard rational result on the non existence of bubbles. Nevertheless, this view contradicts with financial history and reality - the real estate bubble is still unfolding.

[1]Rationality here is perceived as choosing in accordance with a preference ordering that is complete and transitive subject to perfect and costless acquired information (Blaug [12]). Brunnermeier([17], [19]) provides an excellent review on bubbles.

The question that arises here is if there is an alternative approach in analyzing the behavior of investors around bubble episodes. An answer exists and has two main branches. Both are more or less related with behavioral finance. Under the first branch Adam Smith's *great unfortunate* can not anticipate where she is well enough so as to exit from the market. This is due mainly to behavioral biases and learning problems. But despite these problems, rational investors cannot profit from irrational ones and drive the latter out of the market [2]. It may be the case that certain aspects of rational investors behavior will prevent them from playing against the bubble. So irrational investors will ride the bubble, rationals will play along, the bubble will rise, burst and so on. Under DeLong et al [35] rational and irrational investors coexist in the market. The former are risk averse and this prevents them from playing against the bubble. So they push the price up as good news are announced so as to cause more buying from the irrational - feedback investors [3]. Rational investors risk aversion prevents them from playing against the bubble. The main result of such a behavior is profits for the rational traders that come from the expropriation of the feedback traders.

The second branch of the literature - even though strongly related with the first - gives more active role to rational investors. In Abreu & Brunnermeier [1] rational investors anticipate that a bubble exists exogenously in the market. The causes of the bubble are not central in the analysis anymore. It might be attributed to irrational investors, overconfidence, feedback investors, etc. The focus is on the behavior of rational investors. These are small in the competitive sense (i.e. each of them alone cannot play effectively against the bubble) and they enter the market sequentially. So at each moment only a fraction of them enters the market. Until this fraction become large enough so as to form the critical mass that will burst the bubble, rational investors will never play against it.

Abreu & Brunnermeier's [1] work is not based on risk aversion that prevents rational investors to short the bubble like in the DeLong et al [34] and DeLong et al [35] papers. Rational investors' risk neutrality permits them to short the bubble but they do not have enough power to be effective against it because they are competitive

[2] Milton Friedman [40] pointed out that rational investors will drive the irrational investors out of the market.

[3] Feedback investors are those that buy when prices rise and sell when prices fall (DeLong et al. [35])

and they face synchronization risk. As long as a mass of them is formed, everything goes back to a Friedman's [40] world. Rational investors stabilize prices by pushing the irrational ones out of the market. Both approaches above deviate from the standard rational approach. In the in between period - that starts from the point where rational investors anticipate the bubble and ends when the critical mass is formed to burst it - rational investors ride the bubble along with the irrational ones. This is due to their (rational) incentive to gain from the price rise that the bubble causes as long as they can not play against it. This causes the bubble to rise more. The behavior of the rational investors during the in between period will be the main objective of the paper.

Empirical work on the subject is scant. Brunnermeier & Nagel [22] using 13f filings holdings for the 1998-2000 period identify a list of hedge funds and closely examine their behavior as the 2000 DotCom Bubble unfolded. Their main result was that hedge funds managers placed their holdings in a way to profit from the bubble. The main drawback of their analysis was the absence of direct information in the short side of hedge funds managers holdings. As a result they view their approach not as the one that will give evidence against the rational approach to bubbles but rather as a clinical study of the behavior of a group of rational investors during the 2000 DotCom bubble.

The use of 13f filing database places our paper in a - short - line of papers that examine the behavior of institutional investors or sub categories of them. Gompers & Metrick [45] using 13f filing data to analyze institutional investors' demand for stocks find that the level of institutional ownership in a stock can help to forecast its future return. Sias [99] uses 13f filing data to examine herding among institutional investors. Herding is decomposed in two parts. The first consists of institutional investors that follow their own lagged trades while the second consists of institutional investors that follow each others trades. His results are in favor of the latter definition. More recently, Campbell et al [24] used 13f filing data to extrapolate institutional investors daily stock holdings. According to their analysis institutional investor trades generate short term losses but longer term profits.

1.3 The US Real Estate Bubble and the NYSE Sample Stocks

In recent years (after 2002) there was a sharp rise in US Real Estate asset prices that led to what is today identified as the "US Real Estate Bubble". Brunnermeier & Julliard [20] provide a review of the literature on housing bubbles and an interesting explanation for their existence. To make a long story short, the movement of investment funds from the stock market to the real estate sector of the economy started just after the 2000 DotCom Bubble. The main factors that led to the latter were the historical low interest rates, the aversion of the stock market due to the 2000 DotCom Bubble, the invention of new financial products that focused in real estate (for example mortgage backed loans, the creation of the Subprime market[4]).

But all these did not leave the stock market unaffected. From 2002 onwards funds were directed to firms that were directly or indirectly related with the real estate market. In order to observe the behavior of real estate stocks we use a sample of 111 Real Estate Investment Trusts[5] traded in the NYSE for the period 2001:Q1 to 2007:Q4[6]. The choice of the specific market segment was made not only in terms of their price behavior but also because these stocks are the closest substitute for real estate in the stock market[7]. Figure 1.1 below presents the total US market index and compares it with a weighted (by market value) index of the 111 REITs (RE stocks from now on) of our sample. Indexes data and stock prices data were obtained from Thomson's Financial DataStream.

Observe that from 2002 onwards there was an appreciation in REITs that accelerated by the end of 2005, reached a peak in 2007:Q1 and moved downwards thereafter.

Figure 1.2 shows the P/E ratio for real estate stocks form the first quarter of 2002 to the first quarter of 2008 and again compares it with the respective P/E ratio of an index that includes all the US traded stocks. P/E ratios for the real estate stocks

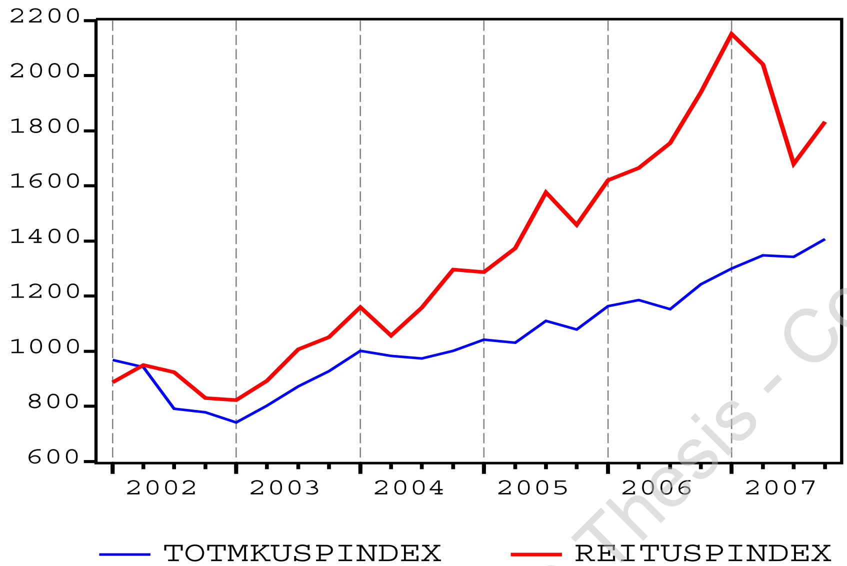
[4] Gorton [47] provides an excellent review of the Subprime markets and the respective panic etc.

[5] For more details on the sample selection process as well as the names of the REITs and their summary statistics refer to Appendix.

[6] The website `http://www.nareit.com/about/2007FAQ.pdf` provides a detailed description of the nature of a REIT, the size of the REITs industry etc.

[7] The analysis was performed using other real estate stocks (for example construction firms and firms related directly or indirectly with real estate). Nevertheless results were similar.

Figure 1.1: Total US Market Index versus REITs Index



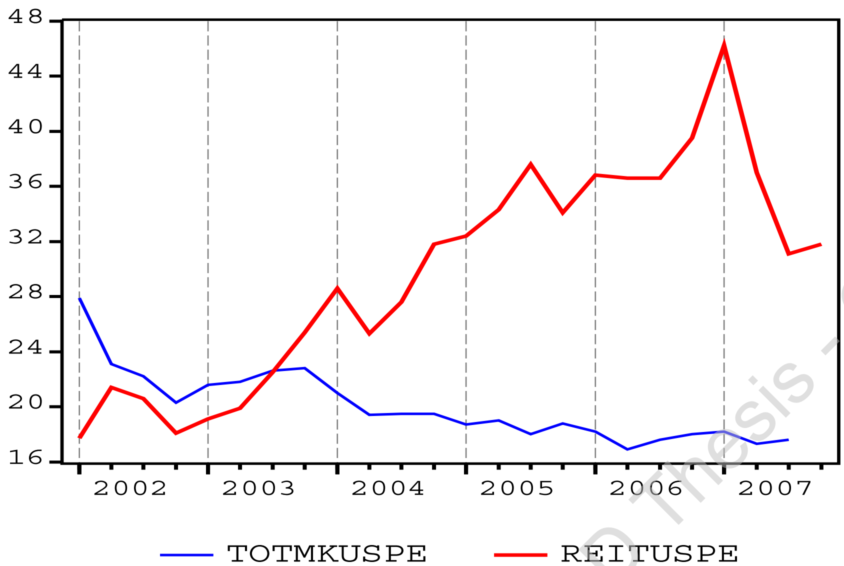
more than doubled from 2002 to the end of 2006 but all this gains vanished from from mid 2007. Clearly there is an argument here for an extreme mispricing in the real estate sector. This mispricing becomes more evident if we compare the P/E ratio of the real estate sector with the P/E ratio of the total US market. The latter almost lost half of its value during the specific period.

So as to have a better view on the mispricing we follow Ofek & Richardson [93] that build on Miller & Modigliani's [84] seminal paper. Their approach is based on the relation of the P/E ratio of a firm that has supernormal profits (r^*) for a number of T periods and for a fraction κ of earnings invested in the supernomal project and the P/E ratio of the firm for the period it reverts back to normal return and earnings. This relation is:

$$(\frac{P}{E})^{Super\ Normal} = (\frac{1+r^*}{1+r})^T (\frac{P}{E})^{Normal} \tag{1.1}$$

with $(\frac{P}{E})^{Super\ Normal}$,$(\frac{P}{E})^{Normal}$ being the P/E ratios for the supernormal and normal

Figure 1.2: Total US Market Index Price Earnings Ratio versus REITs Index Price Earnings Ratio



periods respectively[8]. Table 1.1 below presents the relative supernormal returns needed so as to equate the P/E ratios at the peak of the bubble with various levels of historical P/E ratios.

Even though the relative supernormal returns needed do not seem quite high one has to observe that one of the basic assumptions of equation (1) above is that all earnings are retained within the firm. But by definition REITs pay as dividends more than 95% of their earnings each year. This supports the argument that the supernormal returns from Table 1.1 above cannot exist for a long time - giving a clear warning for the existence of a mispricing in the real estate market.

Payne & Waters [95] examine the existence of rational bubbles in REITs market. Under a rational bubble environment an investor recognizes the overvaluation but rides the bubble because he is compensated with excess positive returns for the risk of a bubble collapsing. Their sample consists of the period 1972:Q1 - 2005:Q3. Their

[8] The derivation of the above formula is presented in the Appendix

Table 1.1: Required Supernormal Returns

Required Returns			
	Historical P/E Ratios		
Years	15	20	25
5	0.25	0.18	0.13
10	0.12	0.09	0.06
15	0.08	0.06	0.04

The table presents the required supernormal returns needed so as to equate the P/E ratios at the peak of the bubble with historical P/E ratios of 15, 20 and 25% respectively.
The supernormal returns are computed as a solution $\frac{1+r^*}{1+r}-1$ of equation (1.1) above ($i.e.$ $(\frac{P}{E})^{Super\ Normal}=(\frac{1+r^*}{1+r})^T(\frac{P}{E})^{Normal}$

results are mixed. Even though they cannot detect periodically collapsing bubbles for the sub-period 1975-1994 they detect evidence of such bubbles for specific REITs categories and for the period 1994-2005.

1.4 The Sample and the Conjectures to be Tested

We obtained hedge funds stock holdings using the 13f filing data provided by Thomson Financial. It is worth spending some time here explaining the details of the 13f filing data. Under Section 13f of the Securities Exchange Act of 1934 all institutional investment managers with more than $100 million under discretionary management are required to disclose their holdings in "Section 13(f) Securities". The latter include:

- Exchange traded quoted stocks (traded in NYSE, AMEX or NASDAQ)
- Equity options and warrants
- Shares of closed-end investment companies
- Certain convertible debt securities

Institutional investment managers now include banks, insurance companies, brokers/dealers, investment advisors who manage private accounts, mutual fund assets, pension plan assets and hedge fund assets. Only the long positions of a manager are included in his 13f filing and this is a drawback for the empirical analysis. There is no direct way for obtaining information on the short position of the manager.

The 13f filing data are crucial to our analysis of rational investors behavior because it is the sole source of information for the behavior of hedge funds. This is because the latter are not regulated by the Securities and Exchange Commission or any other similar institution. Beware that the 13f filings data are organized at the firm level. So a firm that operates more than one hedge funds will disclose the equity holdings of all the hedge funds it operates under its name. This is the reason we refer in hedge fund managers and not in hedge funds in what follows.

The process for selecting the hedge funds managers to be included in the analysis is as follows:

- We obtained the files with the 13f filings for each quarter of the sample period (2001:Q1-2007:Q4) for the sample 111 REITs. Each file contains the list of institutional investors (firm level) that hold the 111 REITs, their 13f categorization, the value of each investor's holdings in REITs, the number of REITs shares he owns, the number of securities held in his portfolio and the total value of his stock portfolio. For example in 2007:Q4, 1st Global Advisors Inc., an investment advisor with 15 securities in his portfolio which had total value of $ 141.51 million, owned $ 0.22 millions of the AMB Property Corp REIT (3,803 of AMB Property Group shares).

- From 2001:Q1 to 2001:Q4 we identified the Institutional investors categorized as "Hedge Funds" or "Hedge Funds / Investment Advisors" and filtered these results using information from the SEC (Form ADV) and Thomson Financial. These are the hedge funds managers investing in REITs prior to 2002:Q1. 283 hedge fund managers were identified in this way. This identification process is needed because we do not want our sample to be biased by "latecomers".

- Using the above list we examined which of them still invested (i.e. existed in the 13f filing file of the respective quarter) as the "bubble" unfolded (period 2002:Q1-2007:Q4). We obtained the value of their holdings in the 111 sample REITs, the number of REITs shares they owned, the number of securities they held in their portfolio and its total value for each quarter.

The hedge fund managers identified for each quarter as described above will consist our sample hedge fund managers from now on[9]. Table 1.2 below presents summary statistics for the sample hedge funds managers. Since this is the first summary statistics for real estate stocks - and the second in the hedge fund literature after the Brunnermeier & Nagel [22] one - we will give some details on it.

The first column presents the number of hedge funds managers that were investing in real estate stocks each quarter. Observe that the number is not constant over time. This is due to the fact that some of the hedge funds managers that were in the initial 2001 list had equity holdings that did not cross the $100 million threshold required by the 13f filing Form listing requirements.

The second set of columns shows the stock holdings per manager. Interestingly enough the mean value is $8,9 billion which is far away from the respective $1 billion of Brunnermeier & Nagel [22]. But again the mean, median and semi inter quantile range (s.i.q.r) indicate that the distribution of holdings is skewed with only a small number of hedge funs controlling the largest part of equity holdings.

The third set of columns shows the number of stocks held by hedge funds managers in our sample. The average number of stocks held by our sample hedge funds managers is around 10 with the median and the s.i.q.r. indicating that the distribution of the stocks held by the hedge fund managers is skewed. Such an observation is not strange for hedge funds managers which are focused on specialized strategies (and not diversification).

The next to the last column reports portfolio turnover. Following Chen, Jegadeesh, & Wermers [25] portfolio turnover is define as:

$$Portfolio\,Turnover_{i,t} = \frac{min(Buys_{i,t}, Sells_{i,t})}{Total\ Net\ Assets_{i,t}}$$

where $Buys_{i,t}(Sells_{i,t})$ is the minimum absolute total value of stock purchases (sales) during quarter t by fund i and $Total\ Net\ Assets_{i,t}$ is the value of total stock assets

[9] A more detailed description of the construction of the sample hedge fund managers list as well as the list can be found in the Appendix.

Table 1.2: Hedge Funds' Holdings Summary Statistics

		Summary Statistics								
		Number of Managers	Stock Holdings per Manager			Number of Stocks per Manager			Turnover	Aggregate Assets
			Mean	Med	s.i.q.r	Mean	Med	s.i.q.r		
2002	**Q1**	210	7719.6	610.6	1644.9	10	3	3.63	55.01	1621115.0
	Q2	212	7777.2	636.3	1713.7	10	3	3.88	58.11	1648757.0
	Q3	201	8121.6	704.0	1807.8	10	3	4.25	55.17	1632438.0
	Q4	200	8172.0	682.0	1815.4	10	3	4.25	59.79	1634407.0
2003	**Q1**	198	8248.5	743.4	1802.1	10	4	3.63	60.61	1633193.0
	Q2	186	8690.4	682.0	2005.4	11	4	4.50	62.16	1616412.0
	Q3	189	8553.7	660.0	1804.0	11	4	4.63	62.81	1616647.0
	Q4	187	8600.6	639.4	1796.2	11	4	4.88	65.21	1608314.0
2004	**Q1**	189	8650.5	660.0	1800.9	13	5	5.50	63.34	1634942.0
	Q2	188	8691.3	722.3	1794.2	14	5	6.50	65.57	1633971.0
	Q3	184	8879.5	746.8	1907.9	15	6	7.25	68.69	1633835.0
	Q4	188	8717.2	725.0	1880.8	15	5	8.25	64.08	1638839.0
2005	**Q1**	187	8759.6	746.1	1932.7	16	5	8.75	63.30	1638047.0
	Q2	186	8761.0	648.3	1799.4	16	6	9.50	63.09	1629552.0
	Q3	189	8645.6	657.1	1843.6	17	6	9.13	61.95	1634013.0
	Q4	193	8478.3	639.4	1795.3	17	6	9.00	60.56	1636317.0
2006	**Q1**	194	8514.3	648.3	1797.0	19	8	10.00	63.21	1651772.0
	Q2	191	8645.6	660.0	1802.0	19	7	10.88	62.20	1651302.0
	Q3	195	8509.8	660.0	1802.2	20	8	11.00	61.63	1659404.0
	Q4	195	8554.8	747.5	1812.6	20	8	11.00	64.69	1668190.0
2007	**Q1**	192	8577.3	733.6	1803.8	21	7	11.50	65.71	1646836.0
	Q2	193	8543.8	756.3	1795.2	18	6	10.00	61.72	1648944.0
	Q3	193	8539.8	747.5	1857.6	18	6	10.00	64.12	1648185.0
	Q4	194	8506.1	751.9	1824.0	18	6	9.63	63.37	1650177.0

Summary Statistics for the sample hedge fund managers are presented.
For Stock Holdings Per Manager and Number of Stocks Per Manager s.i.q.r. indicates the semi inter quantile range.
Turnover is defined as the minimum of buys or sells in a given quarter divided by total net assets ($i.e.\ Portfolio\,Turnover_{i,t} = \frac{min(Buys_{i,t},Sells_{i,t})}{Total\,Net\,Assets_{i,t}}$)

of fund i for quarter t. This measure is commonly used in the literature because it captures the funds trading that is unrelated to investor inflows or outflows. Here our quarterly data were used and the turnover is annualized. Turnover is used because it shows how quickly a hedge fund trades in stocks. If turnover is high then the hedge fund under question buys and sells stocks very quickly and our quarterly equity holdings cannot capture such a behavior. For our quarterly data to be of any use we need a low turnover which means that a large portion of equity holdings survives in the hedge fund portfolio from one quarter to the other. The average turnover for our sample hedge funds managers is well bellow 100% indicating that a large portion of our hedge funds holdings survive between successive quarters. Such a fact will permit us to draw credible conclusions below by observing the behavior of hedge fund holdings. In the opposite case - with average turnover more than 100% - the quarterly frequency and hence the 13f holdings are inadequate for making results about hedge funds behavior.

Finally - observe from the last column - that mean hedge fund managers' aggregate assets are around 1,494,526.6. This number compared with the total capitalization of the US market (15 $ trl for 2007[10]) shows that our hedge fund managers' holdings represent only 6% of the total capitalization. In other words, our sample hedge fund managers are price takers and cannot change the aggregate behavior in the REITs market on their own.

After examining the hedge fund managers sample, it is time to state explicitly the conjectures the validity of which we will test in the following analysis. The critical point of the analysis is the question if rational investors (hedge funds) ride the bubble or not. For our managers to ride the bubble we will expect them to be overweighted in the stocks of our sample (*Conjecture 1*) Moreover we will expect them to gain from the bubble i.e. place their trades in such a way they will make profits. So hedge fund managers anticipated the bubble and placed their holdings accordingly (*Conjecture 2*)

[10]Source: Thomson Financial DataStream

1.5 Hedge Fund Portfolio Weights

An answer to *Conjecture 1* first require an assessment on hedge fund managers holdings during the sample period. We use the 13f filing data on real estate holdings for the hedge funds managers identified above in order to calculate the following ratios:

$$HF\ Load = \frac{Market\,Value\,of\ Hedge\ Fund\ REITs\,Holdings}{Market\,Value\,of\,Total\,Hedge\,Fund\,Holdings}$$

So as to have a benchmark loading we calculate the following ratio also:

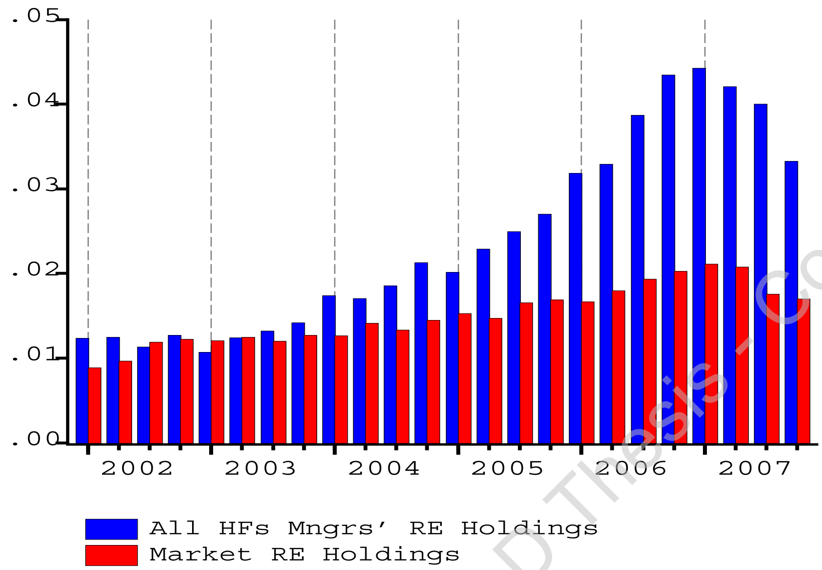
$$Market\ Load = \frac{Market\,Value\,of\ REITs\,Stocks}{Market\,Value\,of\ All\,Stocks\,in\,NYSE}$$

For the numerator of the first ratio, the hedge funds managers total REITs holdings for each quarter are used. For the denominator the hedge funds managers total stock holdings for each quarter are used. The numerator of the second ratio is the total market value of REITs stocks and the denominator is the total market value of all the NYSE stocks for each quarter. Note here that relative price movements change portfolio weights over time. So the hedge fund managers portfolio weights should be compared with the respective market REITs holdings within a quarter and not from quarter to quarter.

From Figure 1.3 observe that hedge fund managers were overloaded relative to the market benchmark for most of the period. The market REITs holdings vary around 1% for most of the period while the hedge fund managers holdings quadrupled reaching 4.3% for the quarters prior to the REITs sector peak in 2007:Q1. Observe that overweighting in REITs increases sharply after 2005:Q4 and decreased after the peak of 2007:Q1 relative to the respective market benchmarks. It has to be noted here that the loadings we observe are not biased upwards by IPOs during the end of our sample period because we selected our sample REITs in a way to avoid such a problem.

As a result we cannot reject *Conjecture 1*(*i.e.* that hedge funds managers were overweighted in REITs as the bubble was unfolding). One might argue here that at the same time hedge fund managers may had short positions in REITs. We will

Figure 1.3: All Hedge Fund Real Estate Holdings versus Market Real Estate Holdings



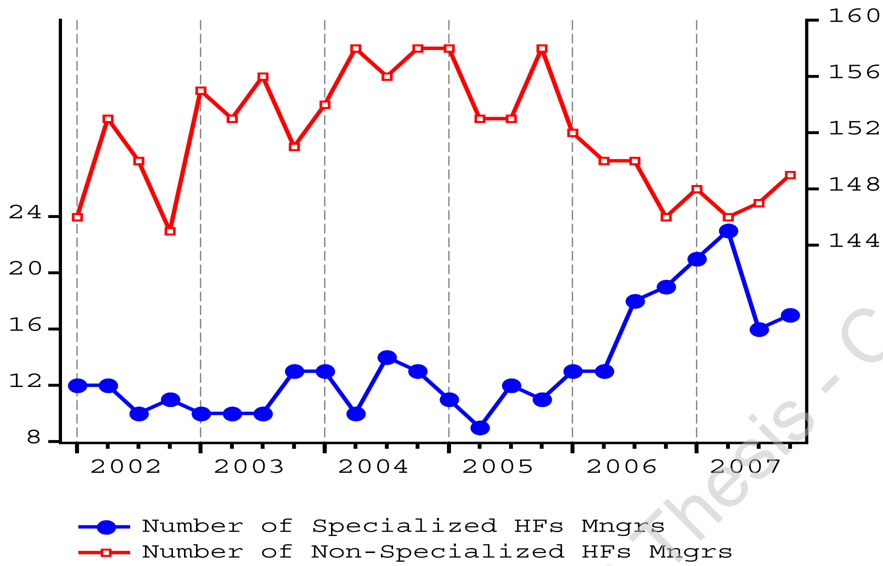
postpone for a while the answer to such a question and first examine if heterogeneity in managers size played a role in the determination of their behavior during the bubble period.

1.5.1 Heterogeneity Among Hedge Funds Managers - Specialization in REITs plays a role?

The distribution of holdings among the sample hedge funds managers is important. First of all, the REITs market - and the real estate market in general - is small and so it is expected to have only a small number of investors that regularly invest in it. Second, results based on the REITs holdings presented above, might be misleading if these holdings come from a small number of hedge funds managers that invest heavily in REITs and a large number of hedge funds that invest only a very small portion of their assets in REITs.

So as to unveil the distribution of hedge funds managers holdings in each quarter we split our sample hedge funds managers between those that specialize in REITs

Figure 1.4: Number of Specialized Hedge Funds Managers

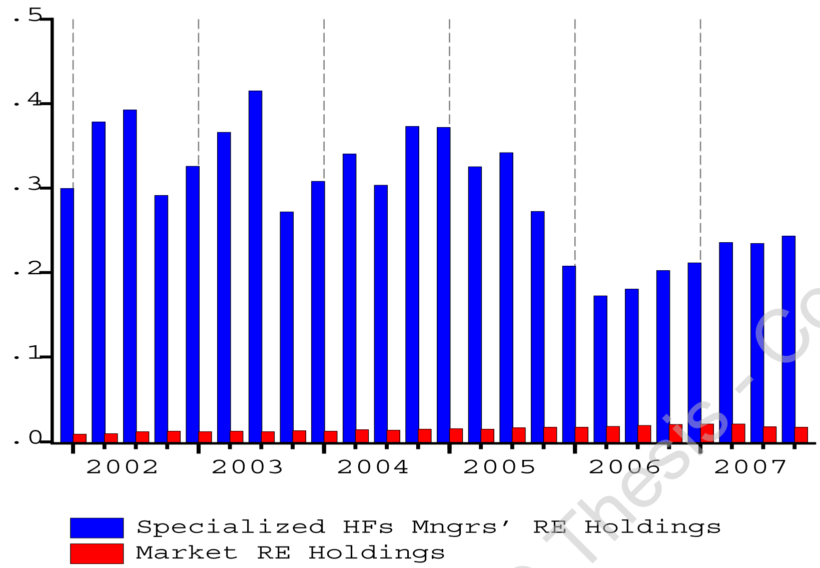


and those that do not. The groups construction is based solely on the proportion of real estate holdings in their total portfolio. We split the hedge funds managers holdings in two groups. The first - the specialized hedge funds managers - have holdings greater or equal to 10% and the second - the non - specialized hedge funds managers - includes the rest. The choice of the 10% was based purely on the data but it also has some empirical backing from the real estate literature. More specifically, Chun, Jarjisy & Shilling [32] estimate that the exposure of an institutional investor who faces no consumption risk is around $3\frac{1}{2}\%$ while the respective percentage rises to 15% and more when the institutional investor is exposed to consumption risk[11] .

Figure 1.4 presents the distinction between specialized and non - specialized hedge funds managers. For most of the period the number of specialized hedge funds managers remains stable with mean around 20. The only exception is in the 2005:Q4-

[11] Chun, Jarjisy & Shilling [32] in an asset allocation approach examine the existence of the so-called "underinvestment puzzle"n real estate. Their results are not in favor of the existence of the "underinvestment puzzle" Only investors who are exposed to consumption risk invest more than 15% in real estate while all the others invest around $3\frac{1}{2}\%$ of their portfolio. As consumption risk they define the possibility of poor performance of an institutional investor's portfolio when consumption growth opportunities are low.

Figure 1.5: Specialized Hedge Funds Managers Mean Real Estate Holdings



2007:Q1 period where there is an increase of almost 50% in the number of specialized funds. But as the price followed a decreasing pattern after 2007:Q1 participation of specialized funds falls too. There are 20 specialized hedge funds managers in the REITs sector on 2007:Q4, the same number with 2004:Q4.

The number of non - specialized hedge funds managers has a mean of 170 for most of the period. It increases before the 2004:Q1 and 2005:Q3 price peaks and decreases shortly after. Observe that the number of non - specialized hedge funds managers decreased prior to 2007:Q1 - from 2005:Q3 to 2006:Q4 - with the exception of the 2006:Q3 where an increase was observed. Moreover, this number increased after the price collapsed, indicating that a number of non - specialized hedge funds managers entered the market too late to profit from the price peak.

The question that arises here is if this behavior is verified by the hedge funds managers holdings. Again we use the ratios presented above but instead of the total hedge funds managers holdings of each group we present the mean hedge funds managers holdings for each group. The reason for doing this is to observe the difference in the average holdings behavior between the two groups.

Figure 1.5 presents the holdings of the specialized hedge funds managers. Again, the ratios presented above, were used but instead of the total holdings (%) compared with the benchmark market ratio (as in Figure 3) mean holdings were used. The main reason for doing this is to observe the difference in the average holdings behavior between the two groups.

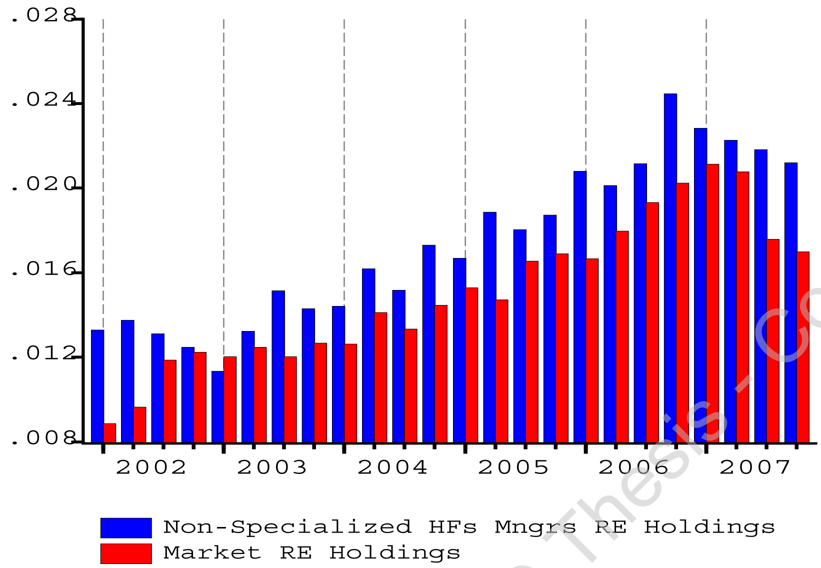
By construction specialized hedge funds managers holdings are more than 10% and reached 43% percent before the 2004:Q1 price peak. The behavior of their holdings is consistent with the anticipation of the price peaks in 2004:Q1 and 2005:Q3. They started building up their positions a year before the price peak and started unloading two or three quarters before it. But this is not the case for the 2007:Q1 price peak. Specialized hedge funds managers reduced their positions in the REITs sector after the 2005:Q3 peak and started to upload positions after 2006:Q2 and continued doing so until the end of the sample period.

This behavior is strange enough, in part of the specialized hedge funds managers, since it indicates an early exit from the market and then a late entry - when it was too late to profit from the price rise. It has to be mentioned here that 2005 was a tough period for REITs institutional investors. Reports[12] from he market pointed out that the three year run up of REITs prices could not cope with the rising interest rates (Federal Fund Rates rose from 1% to 3,75% for the first five months of 2005). Moreover the decreasing US growth and the peak in the US real estate market in 2006:Q1 is an indication that our specialized hedge funds managers placed their positions so as to gain from the real estate market peak. Sushko & Stamatiou [111] show that even though the Case-Shiller Housing Value Index peaked in 2006:Q1 the REITs index (see Figure 1.1 above) continued to move upwards. So it was a close call for the specialized hedge funds managers and they started to enter the REITs market again.

Figure 1.6 presents the holdings of the non - specialized hedge funds managers. Even though the threshold for dividing between the two groups was 10% the mean holdings of non - specialized hedge funds managers are well below that. Observe that for most of the period - from 2002:Q1 to 2007:Q4 - mean holdings are above the market threshold. Non - specialized hedge funds managers were overweighted

[12] There is a list of links to such reports and news in the Appendix.

Figure 1.6: Non - Specialized Hedge Funds Managers Mean Real Estate Holdings



in REITs stocks. Observe that their loadings in REITs reached a peak - compared with the respective market benchmark holdings - in 2006:Q4 and from then on this loadings started to decrease following the behavior of the market benchmark. Nevertheless this decrease was slow since in the last quarters of 2007 hedge funds managers holdings in REITs are above their market benchmarks. But this is not the end of the story. Below we will examine hedge funds managers short positions and in the next section we will examine their returns performance during the sample period.

1.5.2 What About Going Short?

Because of the 13f filings data nature we have no information on the hedge funds managers short positions. To address this problem we will use an indirect approach similar with that of Brunnermeier & Nagel [22]. Starting from the benchmark REITs market ratio above we have that:

$$m_{REITs} = \frac{REITs_{mv}}{TM_{mv}} \tag{1.2}$$

with $REITs_{mv}$,TM_{mv} being the REITs sector and total market value respectively. Assume that a hedge funds manager, allocates a fraction b of her total portfolio to the market portfolio and then allocates a fraction g of the total portfolio value from the market portfolio to the REITs sector. Then the return of this hedge fund is:

$$r_t = (b - g)r_M + gr_{REITs} + e_t \tag{1.3}$$

with r_M,r_{REITs} being the market and REITs sector returns respectively and e_t is the idiosyncratic return. On the other hand, the return of the market portfolio can be written as the sum of the (market value) weighted returns of the various market sectors:

$$r_M = r_{s1}w_{s1} + r_{s2}w_{s2} + ... + r_{sn}w_{sn}$$

with r_{si} and w_{si} the returns and weights of sector $i = 1, 2, ..., n$. For our analysis we indicate with A the sum of all the other sectors except the REITs sector and so we have:

$$r_M = A + r_{REITs}m_{REITs} \tag{1.4}$$

From equations (1.2), (1.3), (1.4) we have:

$$r_t = (b - g)A + (b - g)m_{REITs}r_{REITs} + gr_{REITs} + e_t \tag{1.5}$$

Using (1.5) we can observe that the net investment in REITs stocks is $W_{RE} = (b - g)m_{RE} + g$ and therefore the net investment in REITs stocks as a proportion of the total hedge fund portfolio invested in stocks b is:

Table 1.3: HFR Style Indices

HFR Style Indices
Equity Hedge
Equity Nonhedge
Equity Market Neutral
Market Timing
Macro
Short Shelling
Real Estate

These are the various hedge funds styles that HFR uses for distinguishing between the various hedge funds strategies

$$w_{REITs} = \frac{W_{REITs}}{b} =$$
$$= \frac{b-g}{b} m_{REITs} + g$$

and finally:

$$w_{REITs} = m_{REITs} + \frac{g}{b}(1 - m_{REITs}) \tag{1.6}$$

So as to calculate (1.2) we can estimate b and g using the following OLS regression:

$$r_t = \alpha + \beta r_M + \gamma(r_{REITs} - r_M) + \epsilon_t$$

The lack of specific hedge fund returns from our sample is circumvented partially by using data from Hedge Fund Research (HFR). These data consist of the various HFR style indexes.

So we estimate the above regression seven times - one for each style index. For the hedge fund return r_t we use the returns of the respective HFR index. For the return of the REITs sector we use a value weighted index of our sample stocks. For the market return the total US market index[13] is used.

[13] The source for the total market index is Thomson's Financial DataStream

Table 1.4: Regression Coefficients

Factor Loadings				
	coef. b	coef. g	Rsq.	factor loadings
eq.1	0.4892	0.0184	0.5187	0.0105
	0.00	0.67		
eq.2	0.9441	0.0247	0.6797	0.0105
	0.00	0.68		
eq.3	0.0845	0.0199	0.1347	0.0105
	0.00	0.29		
eq.4	0.5743	0.0388	0.4951	0.0105
	0.00	0.47		
eq.5	0.2794	0.0298	0.1694	0.0105
	0.00	0.58		
eq.6	-0.8062	-0.0535	0.6397	0.0105
	0.00	0.35		
eq.7	0.4203	0.2712	0.6166	0.6490
	0.00	0.00		

The table presents the results of the following regression $r_t = \alpha + \beta r_M + \gamma(r_{RE} - r_M) + \epsilon_t$ for the sample period 2002-2007 (monthly data). The depended variables are returns of the seven HFR indexes (i.e. Equity Hedge, Equity Nonhedge, Equity Market Neutral, Market Timing, Macro Short Selling, Real Estate). The first column presents the coefficient β, the second column the coefficient γ and the third column presents the R^2 for each regression. The fourth column presents the factor loadings (i.e. the total investment in REITs stocks) given by the following formula: $w_{RE} = m_{RE} + \frac{g}{b}(1 - m_{RE})$.

The behavior of market betas is almost as expected. Positive for most of the cases and significant. Moreover it is close to zero for the market neutral case and negative as expected for the short specialist case. Observe that the γ coefficient is positive and statistically significant only for the real estate index. And using the relation for w_{RE} the net investment in Real Estate relative to the hedge funds' portfolio is 0.64. A close look to the Figure of specialized hedge funds managers holdings reveals that the mean is around 0.25. This difference is attributed to the fact that our sample hedge funds only overlap with the HFR dataset.

The absence of negative γ coefficients is an indication that hedge funds short positions in the REITs market were not of a significant size or at least of a size to be a serious drawback for our analysis.

1.6 Hedge Funds Managers Returns

Until now we focused on the overloading of hedge funds managers with REITs stocks during the sample period. This by itself only partially can answer the question if the managers were rational investors or not. But *Conjecture 2* asks if hedge fund managers anticipated the bubble and placed their holdings accordingly. To get a more complete answer we have to examine directly the hedge fund portfolios during the sample periods. This will be done in two steps.

In the first step we will examine hedge funds managers behavior in the quarters before and after the REITs bubble. The second step will be to have a more direct look at the actual composition of the hedge fund managers REITs portfolios during the sample period.

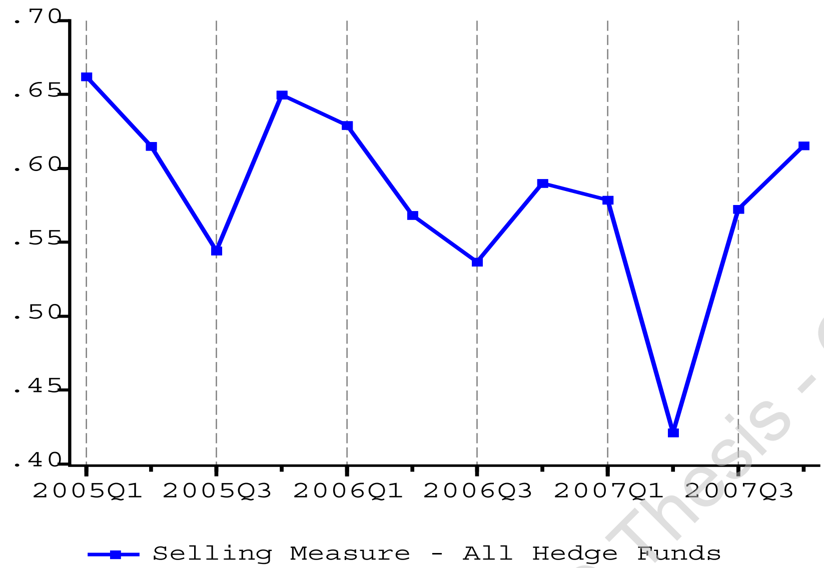
1.6.1 Hedge Funds Managers Anticipated the Bubble?

In order to observe the behavior of the hedge funds managers around the peak of the bubble we will examine their behavior in the REITs market. So as to accomplish this we will use the following measure:

$$\Delta_{k,t} = \frac{\#Hedge\ Funds\ Selling_{k,t}}{\#Hedge\ Funds\ Buying_{k,t}\ +\ \#Hedge\ Funds\ Selling_{k,t}} \tag{1.7}$$

The above measure - the selling measure in what follows - shows the number of hedge funds managers that sell REITs stocks in a specific quarter in relation with the total number of hedge funds managers that buy and sell stocks in that quarter. The selling measure is a modified version of Sias [99] herding measure. The difference is that in the latter, the number of institutional investors that bought stocks in each quarter was used in the numerator, instead of the number of investors selling stocks as in our measure. End of quarter holdings data were used for the period 2005:Q1 - 2007:Q4 for all hedge funds managers of our sample as well as for the breakdown of specialized and non - specialized managers. If end of quarter REITs holdings of a hedge fund manager are bigger than the respective holdings of the previous quarter then we classify the hedge fund manager in the buying side and the opposite holds

Figure 1.7: Selling Measure - All Hedge Funds Managers



for the selling side of the previous relation. We conjecture here that the selling measure will increase the quarters before the price peak. In other words, hedge fund managers knew that a bubble existed and started to exit before the price peak.

From Figure 1.7, we observe that in the case of all hedge funds managers there is little - even though increasing - variation in the selling measure in the quarters prior to the price peak of the REITs market (2007:Q1). The increase in the selling measure is not so obvious so as to give support to the argument that hedge funds managers anticipated the bubble and so they placed their positions accordingly in the quarters before it.

Figure 1.8 presents the breakdown of hedge funds managers in specialized and non - specialized ones. Observe the change in the picture. There is a decrease in the selling measure for the specialized hedge funds managers for the 2005:Q2 to 2006:Q2 period. They did not start to unload their positions until the quarters prior to the (real estate!market!peak) peak - from 2006:Q2 to 2006:Q4. It is interesting here that Sushko & Stamatiou [111] find that institutional investors started to unloading their positions from 2006:Q2 and afterwards. The selling measure for the non - specialized

Figure 1.8: Selling Measure - Specialized versus Non - Specialized Hedge Funds Managers

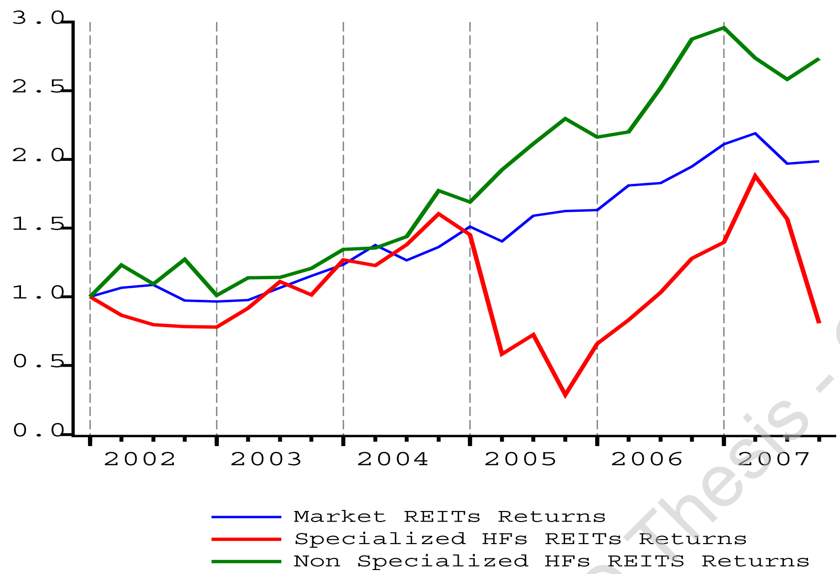
hedge fund managers shows a different behavior. It increases in the quarters prior to the bubble and until the end of the sample period - with the exception of 2007:Q2. So the argument(*Conjecture 2* that hedge funds managers anticipated the REITs bubble and placed their positions accordingly cannot be rejected yet. But still one crucial step remains. To examine if hedge funds managers profited from their behavior in the REITs market.

1.6.2 Hedge Funds Managers Portfolio Performance

Our main purpose in what follows is to observe the relations of hedge funds managers for the sample period so as to give a clear answer to the argument that hedge funds managers anticipated the bubble (or not). In order to achieve this we build copycat portfolios that mimic hedge fund managers behavior in the market and compare it with a portfolio that consists of all the REITs stocks of our sample.

So as to achieve this we obtain for the 13f filings files for each quarter the number of stocks that each hedge fund manager holds and calculate her total return for each

Figure 1.9: Copycat Portfolios - Growth of 1$ for the Sample Period (2002-2007)



quarter using the returns of the stock she owns. We use the end of quarter REITs prices for these returns as by definition 13f filings holdings refer to end of quarter prices. We do this for specialized and non - specialized hedge funds managers as well as for a (value weighted) portfolio that consists of our sample REITs stocks. Figure 1.9 below presents the growth of an investment of 1$ in each one of the three portfolios for the sample period.

The portfolio that copies the REITs market is out performed for most of the period by the portfolio of the non - specialized hedge fund managers but this is not the case for the specialized managers portfolio. Observe that this outperformance in relation to the REITs market copycat portfolio becomes more clear during 2005-2006. Non - specialized managers during that period did not buy the REITs market portfolio but instead they invested in REITs stocks that were still making profits as the peak of the bubble closed. This is evidence - in part of non - specialized hedge fund managers - of stock picking ability. Specialized hedge fund managers had also that stock picking ability after 2005:Q3 but their early exit from the market had consequences for their total return performance. The return of the 1$ goes to

Table 1.5: Performance Summary for the Copycat Portfolios

Performance Summary						
Panel A: All Hedge Funds Managers Portfolio						
	2002	**2003**	**2004**	**2005**	**2006**	**2007**
Mean	0.01	0.02	0.10	-0.06	0.12	0.00
St. Deviation	0.10	0.12	0.09	0.14	0.05	0.13
Annual Sharpe Ratio	0.14	0.26	2.31	-1.02	4.46	-0.17
Growth of 1$	1.02	1.08	1.58	1.18	1.83	1.54
Panel B: Specialized Hedge Funds Managers Portfolio						
Mean	-0.08	0.06	0.11	-0.43	0.37	-0.05
St. Deviation	0.06	0.13	0.11	0.58	0.30	0.39
Annual Sharpe Ratio	-2.64	0.93	2.05	-1.51	2.39	-0.31
Growth of 1$	0.77	0.97	1.47	0.01	0.04	0.01
Panel C: Non - Specialized Hedge Funds Managers Portfolio						
Mean	0.08	-0.01	0.10	0.06	0.08	0.02
St. Deviation	0.18	0.15	0.08	0.08	0.10	0.09
Annual Sharpe Ratio	0.88	-0.21	2.18	1.46	0.93	0.13
Growth of 1$	1.23	1.12	1.60	2.04	2.51	2.37
Panel D: Market Portfolio of Sample REITs						
Mean	-0.01	0.04	0.05	0.05	0.05	0.02
St. Deviation	0.09	0.05	0.09	0.09	0.05	0.07
Annual Sharpe Ratio	-0.50	1.40	0.71	0.32	0.00	-0.66
Growth of 1$	0.97	1.15	1.36	1.62	1.95	1.99

The table presents the performance summary for the copycat portfolios. Each portfolio was constructed using the 13f filings data (*i.e.* the end of quarter number of stocks that each hedge fund manager holds) and the respective end of quarter prices. performance is summarized using annual means, standard deviations, Sharpe ratios and the growth of 1$ invested at the start of 2002. In Panel A the results for the portfolio of all hedge fund managers are presented. In Panels B and C the results for the breakdown in specialized and non - specialized hedge fund managers portfolios are presented. In Panel D the performance summary for a value weighted REITs market portfolio is presented.

zero after 2005:Q2 and starts to rise after 2005:Q3 and until the peak of the REITs market (2007:Q1) and decreases thereafter.

Table 1.5 presents a more formal investigation of the performance of each one of our copycat portfolios. The first line of each panel presents the mean quarterly return for each year, the second line presents its standard deviation, the third line the Annual Sharpe Ratio. The fifth line presents the growth of 1$ invested in 2002:Q1. For Sharpe ratio's risk free asset the US 3-month Treasury Bill was used.

For 2006 - the year before the peak of the bubble - specialized hedge funds managers copycat portfolio returns are the highest. Nevertheless, these returns did not help in improving their poor performance caused by their 2005 early exit behavior. For the rest of the portfolios it is obvious that non - specialized hedge funds managers copycat portfolio outperforms the REITs market copycat portfolio. Mean returns, Sharpe ratios and Cumulative returns are higher for non - specialized hedge funds managers copycat than the REITs market portfolio. The values of the Sharpe ratios for the year 2006 are of interest. The respective values are 2.39 , 0.93 and 0.00 for the specialized, non - specialized and REITs market portfolios respectively. Such behavior is in favor of the stock picking ability of the hedge fund managers. In both cases they ensured highest mean returns with less risk than an investment in the REITs market portfolio.

All of the above are in favor of the argument that hedge fund managers placed their holdings in such a way so as to profit from the bubble in the REITs market in 2007:Q1 (*Conjecture 2*.

1.7 Conclusion

The main purpose of this study was to examine the behavior of a sample of hedge fund managers in the REITs sector of the NYSE, for the period 2002:Q1 to 2007:Q4. The REITs market followed the upwards move of the US Real Estate sector and more interestingly continued to move upwards even after the peak in the US Real Estate sector in 2006:Q1. A subset of the REITs sector (containing more than 90% of the NYSE REITs was constructed, and two conjectures were examined. *Conjecture 1* stated that the sample hedge fund managers were overweighted in REITs stocks during the sample period while *Conjecture 2* stated that hedge fund managers anticipated the bubble and placed their holdings accordingly. Using 13f filings data on institutional ownership we identified a sample of hedge fund managers that invested in the sample REITs for the period 2002-2007.

Our sample hedge fund managers for most of the period where overloaded with REITs stocks but placed their holdings in such a way that gained from the bubble. More interestingly non - specialized hedge fund managers outperformed specialized hedge fund managers during the sample period. The former choose to exit from the

REITs market early in 2005 and this behavior had consequences for their overall performance. Nevertheless, both types of hedge fund managers in the period before the bubble, performed in a way that shows their ability to gain from a bubble environment.

These results are in accordance with the theory work of DeLong et al [35] and Abreu & Brunnermeier [1] and the empirical results of Brunnermeier & Nagel [22]. Hedge fund managers anticipated the REITs bubble and ride it - instead of playing against it, as standard theory predicts - so as to gain from the price rise. It have to be mentioned though that we cannot draw general results for the hedge fund industry from our small sample of hedge fund managers.

Chapter 2

Distributional test for market-timing behavior:Evidence from REITs

This paper presents a testable model of market-timing behavior based on the essential elements of arbitrage and speculative attack theory. In equilibrium, heterogeneous investors find it optimal to herd. The equilibrium is characterized as a stochastic tâtonnement process with an empirically detectable distribution. We use institutional ownership data in real estate investment trusts (REITs) to find evidence of market-timing behavior implied by the model. In addition, based on the changes in distributions of the data we find that speculative attack by institutional investors began three quarters prior to the crash of REITs in February 2007 and that the likelihood of speculative attack steadily increased during the run-up to the crash.

2.1 Introduction

This paper presents a testable model of speculative attack by market-timing investors based on the essential elements of arbitrage and speculative attack theory. Speculators want to exit at the last instance before the market crashes. During each trading round a speculator updates his subjective probability of a crash based on the sum of sellers he observes in the market and his private signal about the market's capacity to absorb these sales without a crash. Since each speculator is more likely to attack when greater number of others attack, and since all speculator follow the same rule, this leads to strategic complementarity. In Bayesian equilibrium, the sum of attacking agents is drawn from a distribution that exhibits exponential rather than a Gaussian decay because of endogenous feedback (herding). In the empirical portion of the paper we examine whether the market-timing strategy implied by the model played a role in the crash of U.S. real estate stocks in early 2007.

The identification strategy is based on Nirei [89] and Nirei [90]. He shows that when heterogeneous agents follow complementary strategies with threshold adjustment then the distribution of aggregate action exhibits exponential rather than Gaussian decay. For identification we utilize two additional sources of variation in stock holdings not commonly found in data: the variation across individual investors and the variation across a group of closely related securities with high degree of substitutability – real estate investment trusts (REITs). This means that instead of observing one realization of the aggregate number of attackers during each period one can observe a sample of data points large enough to construct a distribution. Each observation in the sample is a group of institutional investors that fall with then same class (e.g. hedge funds, pension funds, etc.) holding the same REIT. If investors are unsure about the accuracy of their private signal about the fundamentals and are prone to follow the actions of others within the same stock-investor-type group, then, because of the complementarity of their market-timing strategies, the probability of observing large outliers is much higher compared to the case of investors acting independently.

The distribution of investor positions across stock-investor-type groups indicates that herding was a factor during the run-up to the crash in REITs. The distribution changes to Gaussian during the attack phase. Consistent with the model, this indicates a transition from a regime of uncertainty regarding market fundamentals to a regime of full certainty (of bad fundamentals). Finally, we examine the association between the empirical herding measure derived in the paper and the timing of the crash. The emphasis on herding behavior is motivated in part by Veldkamp [114] who identifies herding as an element of intrinsic instability because it makes markets respond disproportionally to seemingly trivial news. Furthermore, Gallegaty & Pietronero [43] argue that it is necessary to introduce new stabilization measures, like control of herding, into policy discussion.

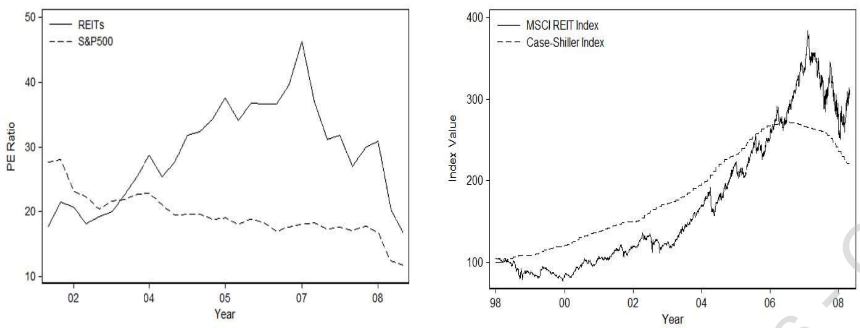
Related arbitrage literature includes DeLong et al [34] who show that rational traders will tend to ride the bubble because of risk aversion. Abreu & Brunnermeier [1] model a continuous time coordination game in which the market finally crashes when a critical mass of arbitrageurs synchronizes their trades. In such a setting, it is futile for well-informed rational arbitrageurs to act on some piece of information unless a mass of other arbitrageurs will do so also. This coordination element creates an incentive for arbitrageurs to base their actions on the actions of others, i.e. herd.[1].

Laboratory studies of market-timing and herding behavior include Brunnermeier & Morgan [21] and Cheung and Friedman [30], but empirical literature on the subject is scant. Also, most of the empirical literature on herding in financial markets[2] does not link herding directly to instability and market crashes, because testing the above models is complicated. For instance, it is hard to identify empirical counterparts to such theoretical constructs as arbitrageurs and noise traders. Furthermore, inference on market timing requires observations not only on prices, but also on investor positions. A number of empirical examinations of market crashes, such as Johansen et al [62], Sornette [105], Sornette et al [106], attribute such critical phenomena to herding, but lack microeconomic foundations and as such have been largely overlooked by mainstream economic literature.

[1] For theory on herding see Bikhchandani et al [10], Banerjee [9], and Avery & Zemsky [7] work on *Informational Cascades*

[2] Shiller & Pound [103] find that word-of-mouth communications are important for the trading decisions of both individuals and institutional investors, McNichols & Trueman [82] find herding on earnings forecasts, Welch [115] finds that security analysts herd, Sias [99] confirms herding among institutional investors in NYSE and NASDAQ, and Li & Yung [75] find evidence of institutional herding in the ADR market.

Figure 2.1: Price Earnings Ratios of REITs and S & P500 (Left) and MSCI REITs Index and Case-Shiller Housing Value Index (Right)



2.2 Data

2.2.1 Real Estate Investment Trusts

The analysis focuses on a class of securities called real estate investment trusts (REITs) traded on the New York Stock Exchange (NYSE). These are closed-end funds that specialize in real estate investments. More specifically REITsare firms that own and operate income producing real estate or/and financing real estate. Their main characteristic is their special tax status. Each year a REIT has to distribute at least 90% of its taxable income to its shareholders[3]. U.S. has the oldest and most developed REITs market in the world, with over 170 securities total at the end of 2007 [4]. This allows for an identification strategy that explores the variation in holdings across securities within this common class of stocks.

As the left panel of Figure 2.1 shows, REITs experienced a dramatic rise in their average P/E ratios relative to the market (proxied here by S&P500) beginning around 2003:Q1 then crashed dramatically during 2007:Q1. These events preceded the collapse of major investment banks, the 2008 credit crisis and the global recession that ensued soon after.

[3] For more information on REITs refer to the following web address `http://www.nareit.com`, and/or to Imperiale [61] and to the Appendix below.

[4] Source: National Association of Real Estate Investment Trusts (NAREIT))

The right panel of Figure 2.1 shows MSCI US REIT Index along with Case-Shiller Housing Value Index with 1998:Q1 values normalized to 100. The MSCI US REIT Index represents approximately 85% of U.S. REITs universe (Source: mscibarra.com). The index continued to rise for approximately one year after housing values in U.S. had peaked. This indicates that investors continued to demand REITs even while fundamentals were no longer sound. The figure suggests that while the long-run price movements of REITs appear consistent with fundamentals the exact timing of the collapse of the market for real estate stocks may have been determined by non-fundamental factors such as market-timing of investors who maximize short-term profits. In Chapter 1 above we found evidence for market-timing in the market for REITs. Overall the sample hedge funds timed the market correctly (*i.e.* they started to exit from REITs stocks before the peak of that market). Moreover, hedge funds with large holdings in REITs timed correctly the peak of the real estate market (*i.e.*they started to exit before 2006:Q1) but some of them reentered the market after that so as to gain from the continuing upwards time trend.

2.2.2 Institutional Ownership Data

Campbell et al [24] find that institutional investors behave like arbitrageurs, for example by employing contrarian strategies and anticipating earning surprises in advance, while Kaniel et al [66] find that individual investors behave more like momentum traders and accommodate short-run institutional demand for liquidity. Consistently with these findings, we treat institutional investors as empirical proxies to arbitrageurs. The data on institutional REITs holdings comes from the 13f filings database provided by Thomson Financial[5]. The data is compiled from quarterly 13f filings in which institutional investors are required to report their long positions in equities. This data also separates institutional investors into types such as pension funds, insurance companies, or hedge funds. Table 2.1 presents descriptive statistics for institutional ownership data in REITsfor selected quarters of the 1998-2008 sample period[6]. From panel A observe that there is an increase in institutional investors

[5] Other studies using 13f filings to infer institutional order flow include Gompers & Metrick [45], Sias [99], Brunnermeier & Nagel [22], and Campbell et al [24] and Chapter 1 above

[6] A table similar with Table 2.1 is presented in the Appendix but with the total capitalization of the institutional investors'ortfolios in Panel B instead of their REITs portfolios. Moreover in

Table 2.1: Distribution of 13f Holdings Among Institutional Investors

Descriptive Statistics						
	Mar 98	Mar 00	Mar 02	Mar 04	Mar 06	Mar 08
	Panel A: Number of Institutional Investors					
Bank and Trusts	72	88	103	120	126	118
Hedge Funds	195	195	281	354	460	586
Insurance Companies	17	16	16	21	19	19
Investment Advisors	544	599	736	851	947	1050
Pension Funds	29	30	40	43	46	47
All Others	28	115	217	866	1364	1420
Total	885	1043	1393	2255	2962	3240
	Panel B: Capitalization in Millions ($)					
Bank and Trusts	842.61	570.81	694.13	1974.98	1656.61	2089.54
Hedge Funds	11773.79	10228.03	19202.90	31191.91	59607.63	68196.88
Insurance Companies	468.50	711.39	1164.42	1819.87	2028.70	1840.06
Investment Advisors	26878.85	24581.41	44566.47	82207.80	142026.9	170815.4
Pension Funds	2135.88	2531.97	6815.96	11279.04	19130.56	23199.76
All Others	1015.25	4191.93	8705.01	13234.87	21509.47	20863.29
Total	43114.88	42815.55	81148.89	141708.48	245959.87	287004.93
	Pane C: Number of REITs with:					
¿ 1 trader	85	91	88	98	119	131
¿ 20 traders	73	73	79	96	116	126
¿ 50 traders	60	57	70	88	109	121
¿ 100 traders	30	36	50	73	93	114
Total Number of REITs	85	91	88	98	119	131

The table presents the distribution of 13f holdings among the various types of institutional investors. The types of institutional investors are: Bank and Trusts, Hedge Funds, Insurance Companies, Investment Advisors, Pension Funds and All Others (including Endowments, Research Firms, Other Firms, etc.). Panel A presents the number of institutional investors with holdings in the sample REITs for each year from 1998 to 2008. Panel B presents their REITs portfolio capitalization in Millions ($) for each year from 1998 to 2008. Panel C presents the total REITs holdings capitalization in Millions ($) for each year from 1998 to 2008. Panel D presents the breakdown of REITsbased on the number of institutional investors that trade in each year from 1998 to 2008.

that have REITs holdings as we move to the end of the sample period and the same holds also for the capitalization of the REITs portfolio.

the Appendix there is a table with the sample REITs. Beware that the sample REITs of this Chapter are different from the sample REITs of the previous one because we included REITsthat for various reasons (IPOS etc.) were excluded previously.

2.3 Model: Speculative Attack Under Endogenous Feedback

2.3.1 Setup

At some time t_0 the price of an asset begins to deviate from the fundamental value by some fraction $\beta(t)$. All "informed" investors know that following t_0 the price includes a bubble component that is not sustainable indefinitely. Nevertheless they continue to purchase or hold the asset because of relative performance considerations and short-term profit horizon.[7] The fundamental rate of return to holding this asset is r. Normalizing $p_0 = 1$ the shadow price is simply:

$$p^f(t) = e^{rt}$$

whereas following the onset of a bubble the rate of return increases to g, and the price becomes:

$$p^b(t) = p^f(t) + e^{g(t-t_0)} \tag{2.1}$$

with the bubble component then given by:

$$\beta(t) = 1 - e^{-(g-r)(t-t_0)} \tag{2.2}$$

where $g - r$ is the excess return during the bubble phase.

At any point in time there are N_t arbitrageurs in the market. At each point in time each arbitrageur i chooses whether to switch from passive mode, $a_{i,t} = 0$, to an attack mode, $a_{i,t} = 1$. Let $m_t = \sum_{i=1}^{N_t} a_{i,t}$ denote the total mass of attackers at t and $\alpha_t \equiv m_t/N_t$ the corresponding fraction. Further assume that the number of traders is sufficiently large, that is $\alpha_t \approx \alpha_{t,\neq i}$. The bubble bursts if:

$$\alpha_t \geq \theta \tag{2.3}$$

where θ represent the market's absorption capacity and is drawn from a uniform .

[7]See Shleifer & Vishny [104] and Vayanos [113]

Analogously to Morris & Shin [85] θ is best interpreted as a latent variable summarizing market fundamentals such as the availability of speculative funding, tolerance towards risk, or market liquidity. Alternatively, θ may be interpreted as the absorption capacity of noise traders who serve as liquidity providers to fundamentalists (Abreu & Brunnermeier [2]) . Higher value of θ corresponds to stronger fundamentals and implies a larger mass of sellers is necessary to cause the bubble to burst.

During each trading period arbitrageurs can credibly infer the fraction of sellers in the market, α_t. On the other hand, θ is unknown and each arbitrageur i only has a private signal of the true absorption capacity:

$$\theta_i = \theta + \epsilon_i \tag{2.4}$$

where ϵ_i is i.i.d across traders distributed according to twice differentiable smooth symmetric density $f(\cdot)$ with mean zero.

The decision whether or not to attack is based on each arbitrageur's subjective perception of the absorption capacity of the market, θ_i, and the sum of actions of other arbitrageurs, α_t.

2.3.2 Optimal Strategy

An arbitrageur would find it optimal to join a speculative attack in the next instant when he believes that $\alpha_{t+\Delta} \geq \theta > \alpha_t$. Given that the magnitude of the price change in case of a crash is $-\beta(t)p(t)$ whereas it is $(g-r)p(t)\Delta$ if the crash does not occur, each arbitrageur sets first order benefits of an attack at t versus $t+\Delta$ equal to first order costs of being out of the market for a short period Δ:

$$\Delta h(\alpha_t|\theta_i)[p(t)\beta(t)] = (1 - \Delta h(\alpha_t|\theta_i))[(g-r)p(t)\Delta] \tag{2.5}$$

where $h(\alpha_t|\theta_i)$ is the crash hazard rate (conditional failure rate). In other words, it is arbitrageur i's perceived probability that the crash will happen in the next instant conditioned on the fact that it has not yet occurred:

$$\begin{aligned} h(\alpha_t|\theta_i) &= \Delta t \overset{lim}{\rightarrow} 0 \; \frac{Pr\left(\alpha_{t+\Delta} > \theta > \alpha_t|\theta_i\right)}{\Delta} \\ &= \Delta t \overset{lim}{\rightarrow} 0 \; \frac{Pr(\alpha_{t+\Delta} > \theta > \alpha_t|\theta_i)}{1 - Pr(\alpha_t > \theta|\theta_i)} \\ &= \frac{f(\alpha_t|\theta_i)}{1 - F(\alpha_t|\theta_i)} \end{aligned} \tag{2.6}$$

where $Pr(\alpha_t > \theta|\theta_i)$ represents an arbitrageur's subjective conditional probability that the bubble bursts at time t given his belief about market's absorption capacity θ_i and the observed market-wide selling pressure. Hence, $Pr(\alpha_t > \theta|\theta_i) \equiv F(\alpha_t|\theta_i)$ corresponds to the conditional cumulative distribution function of θ_i truncated at α_t. It's derivative, $dPr(\alpha_t > \theta|\theta_i)$ is the associated probability density. Using the definition of $h(\alpha_t|\theta_i)$, divide both sides by $\Delta p(t)$ and let $\Delta \rightarrow 0$ to obtain the attack condition:

$$\frac{f(\alpha_t|\theta_i)}{1 - F(\alpha_t|\theta_i)} = \frac{g - r}{\beta(t)} \tag{2.7}$$

Accordingly, (6) implies the following threshold condition for attack:

$$h(\alpha_t|\theta_i) \geq \frac{g - r}{\beta(t)} \tag{2.8}$$

The resulting best-response strategy for a market-timing arbitrageur at each trading round may be expressed as follows:

$$a_{i,t} = \begin{cases} 1 & \text{if} \quad h(\alpha_t|\theta_i) \geq \frac{g-r}{\beta(t)} \\ 0 & \text{otherwise} \end{cases} \tag{2.9}$$

2.3.3 Static Equilibrium

Equation (8) implies that there exists a threshold value of private signal about the fundamentals, $\theta^*(\alpha)$, given the observed selling pressure, α, such that:

$$a_i = \begin{cases} 1 & \text{if} \quad \theta_i < \theta^*(\alpha) \\ 0 & \text{otherwise} \end{cases} \tag{2.10}$$

In equilibrium the threshold $\theta^*(\alpha)$ is determined by Bayesian inference based on the actions of all other arbitrageurs. To simplify the intuition define instantaneous probability of a crash conditional on private information and aggregate action as $Pr(C|\theta_i, \alpha) \equiv h(\alpha|\theta_i)$. The posterior probability of a crash is given by:

$$Pr(C|\theta_i, \alpha) = Pr(\theta_i, \alpha|C)Pr(C) \tag{2.11}$$

where the marginal probability of a signal equals 1. Since a_i is a binomial parameter, under the threshold rule (9) an attack by αN of arbitrageurs and the inaction of $(1-\alpha)N$ others implies:

$$\begin{aligned} Pr(C|\theta_i, \alpha) &= Pr(\theta_i \leq \theta^*(\alpha)|C)^{\alpha N} Pr(\theta_i > \theta^*(\alpha)|C)^{(1-\alpha)N} \\ &= h(\theta^*(\alpha))^{\alpha N}(1 - h(\theta^*(\alpha)))^{(1-\alpha)N} h'(\theta^*(\alpha)) \end{aligned}$$

Expression $h(\theta^*(\alpha))$ denotes the crash hazard rate revealed by an attacking arbitrageur j ($a_j = 1$):

$$\begin{aligned} h(\theta^*(\alpha)) &= \frac{Pr(\theta_j = \theta^*(\alpha)|\theta)}{1 - Pr(\theta_j \leq \theta^*(\alpha)|\theta)} \\ &= \frac{f(\theta^*(\alpha) - \theta)}{1 - F(\theta^*(\alpha) - \theta)} \end{aligned}$$

where the second line followed from the distribution of ϵ_j. Given a common prior about the fundamentals, θ_0, the posterior crash hazard rate is then expressed as:

$$h(\alpha|\theta_{i,1}) = h(\theta^*(\alpha))^{\alpha N}(1 - h(\theta^*(\alpha)))^{(1-\alpha)N} h'(\theta^*(\alpha))h(\theta_0) \tag{2.12}$$

Thus the optimal strategy follows the rule in equation (9) with $\theta^*(\alpha)$ implicitly determined by:

$$h(\theta^*(\alpha))^{\alpha N}(1 - h(\theta^*(\alpha)))^{(1-\alpha)N}h'(\theta^*(\alpha))h(\theta_0) = \frac{g - r}{\beta} \tag{2.13}$$

The static equilibrium is determined by θ^* which satisfies (9) and (13) and by α, which represents the fraction of all traders who receive private signal regarding the market's absorption capacity lower than θ^*.

In equilibrium the threshold value of the signal about fundamentals must be increasing in the observed proportion of sellers in the market. Intuitively, if a trader observes a panic in the market, then he will try to sell even if his prior perception about market fundamentals was strong, that is his threshold will be raised. Taking logarithm of both sides of (13) and totally differentiating:

$$\frac{d\theta^*}{d\alpha} = \frac{logh(\theta^*(\alpha)) - log(1 - h(\theta^*(\alpha)))}{-h'(\theta^*(\alpha))\left(\frac{\alpha}{h(\theta^*(\alpha))} - \frac{1-\alpha}{1-h(\theta^*(\alpha))} + \frac{h''(\theta^*(\alpha))}{h'(\theta^*(\alpha))^2 N}\right)} \tag{2.14}$$

(14) will be positive as long as the logit of the odds ratio of the crash (the numeraire) is less than zero, i.e. when the probability of the crash in the next instant is less 50%. By threshold (8) this means that if the rate of return approaches half of the accumulated bubble component to that point the strategy breaks down. Intuitively, this means that the asset price is growing so fast that, perceiving such growth rate as physically unsustainable, all arbitrageurs will find it optimal to exit irrespective of their private signal or the actions of others.

2.3.4 Distribution of Attackers

We follow Nirei [90][8] by characterizing equilibrium outcome of the model with a distribution that governs a tâtonnement process[9]: α^ν. Define $S = \{0, 1/N, 2/N, .., 1\}$ as the set of possible outcomes of α and $\Gamma : S \mapsto S$ as the reaction function for each realization of θ such that $\alpha' = \Gamma(\alpha)$ is a fraction of traders with $\theta_i < \theta^*(\alpha)$.

[8]Nirei (2008) defines stochastic tâtonnement process for traders choosing whether or not to *purchase* an asset based on the subjective likelihood of the asset's *value*: high versus low.

[9]Leon Walras described tâtonnement as the process by which markets find their way to equilibrium. For an informal description of the tâtonnement process refer to (O'Hara [92], p.4) and Stamatiou [108]. For a formal description of the process refer to (Mas-Collel et al [81], p.624)

Proposition 1 *Consider a tâtonnement process α^ν, where $\alpha^0 = 0$ and $\alpha^\nu = \Gamma(\alpha^{\nu-1})$ for $\nu = 1, 2, .., n$ where the stopping time n is the smallest ν such that $m^\nu - m^{\nu-1} = 0$. Then, i) α^ν converges to minimum equilibrium value α^* for each realization of θ and ii) $\theta^*(\alpha^{\nu+1}) > \theta^*(\alpha^\nu)$: the threshold increases over the information tâtonnement process for any realization of θ.*(See Nirei [90] for proof of the mirror case.)

By *i)* the analysis is restricted to the equilibrium reached via the most efficient tâtonnement path. That is, each selected equilibrium has the property of being the closest to the initial equilibrium. Also, by *ii)* there exists a non-trivial chance of chain-reaction because a trader who chooses to attack given ν will also have chosen to attack at $\nu + 1$. Define the conditional probability of an arbitrageur deciding to attack in response to $\alpha^\nu - \alpha^{\nu-1}$:

$$\begin{aligned}\pi^\nu &= \int_{\theta^{*\nu}}^{\theta^{*\nu-1}} f(\theta_i)d\theta_i / F(\theta^{*\nu-1}) \\ &= f(\theta^{*\nu-1})/F(\theta^{*\nu-1})\frac{d\theta^*}{dm}|_{m^{\nu-1}}(m^{\nu-1} - m^\nu)\end{aligned}$$

where π^ν is non-negative also by *ii)*. Thus, the number of new attackers at each stage of tâtonnement, $(m^{\nu+1} - m^\nu)$, conditional on $(m^\nu - m^{\nu-1})$ follows a binomial distribution with population parameter $N^\nu = (N - m^\nu)$ and probability parameter π^ν. Also, m^1 follows a binomial distribution with population N and probability $\pi^0 \equiv Pr(\theta_i < \theta_0^*) = 1 - F(\theta_0^*)$. The probability, π^ν, governing the emergence of new attackers at each tâtonnement step, ν, is of the order $1/N^\nu$. To see this, substitute (14) into (15), where also by (14) $d\theta^*/dm$ is:

$$\frac{d\theta^*}{dm} = \frac{logh(\theta^*(\alpha)) - log(1 - h(\theta^*(\alpha)))}{-h'(\theta^*(\alpha))\left(\frac{\alpha}{h(\theta^*(\alpha))} - \frac{1-\alpha}{1-h(\theta^*(\alpha))} + \frac{h''(\theta^*(\alpha))}{h'(\theta^*(\alpha))^2 N}\right)} \times \frac{1}{N^\nu} \tag{2.15}$$

Using (15) and (16), π^ν can be expressed as:

$$\pi^\nu = \frac{\lambda}{(N - m^\nu)} \tag{2.16}$$

where $\lambda \equiv G\left(h(\theta^*(\alpha))\right)$ is a function of threshold crash hazard rate.

Applying simple calculus and the definition of a binomial distribution it can be shown that the number of realizations of $a_i = 1$ with probability of $a_i = 1$ in N trials given by λ/N approaches a Poisson distribution with non-homogeneous mean λ as $N \to \infty$. Using (15), (16), and (17), the asymptotic mean of the binomial variable $(m^{\nu+1} - m^{\nu})$ conditional on $(m^{\nu} - m^{\nu-1}) = 1$ is:

$$\lambda =_{N\to\infty}^{plim} \pi^t|_{(m^{\nu}-m^{\nu-1})=1}(N - m^{\nu}) \tag{2.17}$$

According to (18) an attacking agent at ν induces a random number of other agents to attack at $\nu + 1$ according to Poisson distribution with mean λ. The next result follows from the *Interval Theorem* of Kingman [67]. Denote $a_+^{\nu+1} \equiv m^{\nu+1} - m^{\nu}$ the number of agents induced to attack at $\nu + 1$. If $a_+^{\nu+1}$ follows a Poisson process with mean rate λ, then the random variables denoting increments of the tâtonnement process:

$$y^1 = a_+^1, \text{ and, } y^{\nu+1} = a_+^{\nu+1} - a_+^{\nu};\ (\nu \geq 2)$$

are independent and each has a probability:

$$Pr(y = y^{\nu}) = \lambda e^{-\lambda y^{\nu}}$$

where $y^1 = a_+^1$ holds because $m^0 = 0$. It follows that the n^{th} point M of the homogeneous Poisson process on $(0, \infty)$, the new equilibrium reached via the tâtonnement described above, may be written as the sum of independent exponentially distributed random variables:

$$M = y^1 + y^2 + .. + y^n$$

with the corresponding probability accordingly given by (for a general proof see Kingman [67], p.42):

$$
\begin{aligned}
Pr(M = m) &= \frac{\lambda^n}{(n-1)!} m^{n-1} e^{-\lambda m} \\
&= \frac{\lambda^n}{\Gamma(n)} m^{n-1} e^{-\lambda m}
\end{aligned}
$$

where the second line follows from the definition of the Gamma function. Conditioning (19) on $m^{\nu} - m^{\nu-1} = 1$ and $m^1 = 1$:

$$
Pr(M = m) = \frac{\lambda^m}{\Gamma(m)} m^{m-1} e^{-\lambda m} \tag{2.18}
$$

(20) falls in the family of distributions known as Borel-Tanner distributions in queuing theory Kingman [67] that describe the processes that govern the arrival of descendants over successive generations where reproduction itself follows a Poisson process. Finally conditioning (20) on m^1 having been drawn from a Poisson distribution with some mean μ we arrive at the asymptotic result of Nirei [90]:

$$
\begin{aligned}
Pr(M = m|m^1) &= \frac{(\lambda m + \mu)^{m-1}}{m\Gamma(m)} \mu e^{-(\lambda m + \mu)} \\
&= \frac{(\lambda m + \mu)^{m-1}}{m!} \mu e^{-(\lambda m + \mu)} \\
&\propto (\lambda e^{1-\lambda})^m m^{-1.5}
\end{aligned}
$$

where the third line is obtained by applying Stirling's formula to the denominator and holds proportionally as $m \to \infty$. (21) is a gamma-type distribution that approaches power-law with exponential truncation in the limit. Since the exponential distribution declines faster than the power function, the tail of the distribution is dominated by the exponential part. The speed of exponential truncation is determined by $1 - \lambda$. The distribution exhibits criticality, because at the points where $\lambda = 1$ the exponential part vanishes. Nirei [90] shows that the branching process has zero probability of surviving indefinitely if $\lambda \leq 1$.

2.4 Evidence from Institutional Transactions

Institutional ownership data from 13f filings with Securities and Exchange Commission (SEC) allows to construct a sample of the proportion of attackers, α, for each quarter instead of observing only one realization. The quarterly sample size is Number of REITs $\times$ Number of Institutional Investor Types. We denote the empirical counterpart as $\alpha(t)_k$, where, depending on the desired frequency, t denotes quarter or year and k denotes stock-investor-type group. Table B.3 and Table B.4 in the appendix show summary statistics for both conditional and unconditional $\alpha(t)_k$ respectively. The empirical analysis focuses on the distributional characteristics of $\alpha(t)_k$.

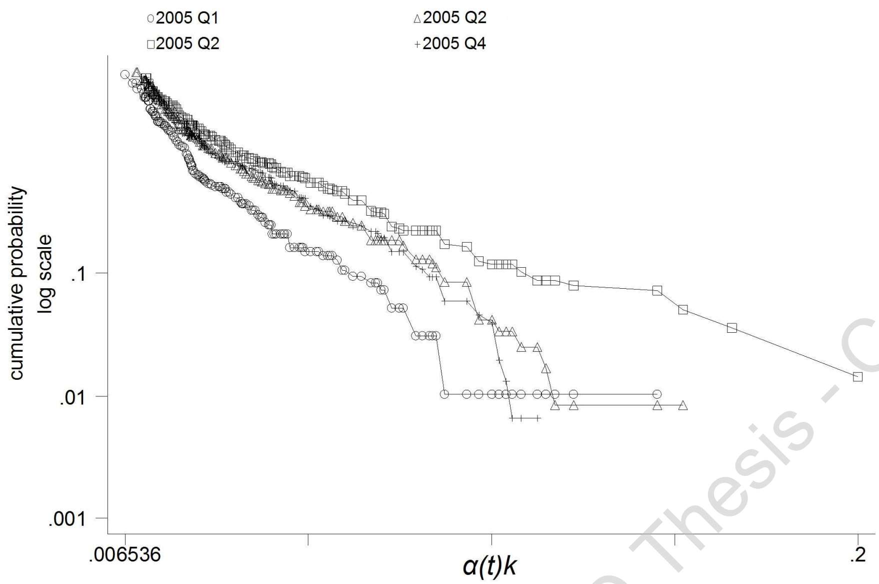
2.4.1 Cumulative Probability Plots

Figure 2.2 plots the fractions of institutional REITs investors selling over 80 % of their holdings by each stock-investor-type group against the cumulative distribution (log rank over number of observations). Only groups with 10 traders or more are included in the sample. A concave line would roughly correspond to a Gaussian distribution while a straight line implies a highly non-normal distribution with very long tail. The market-timing strategy outlined in (9) would result in exponential decay and upon a visual inspection is consistent with the distributions plotted in Figure 2.2.

The plot also shows a convex deviation from the exponential tail as the size of observations approaches zero. Moreover, notice a small number of observations that lie very far from the probability mass. A Gamma distribution would produce such outliers because for small values of the shape parameter all observations drawn from a Gamma distribution will have the same expectation of the order $1/N$, but there is high probability that at least one observation will be much greater than the average (Kingman [67])).

The intuition behind semi-log plots in Figure 2.2 is as follows. Suppose the average perception of the value of fundamentals is strong and the mean fraction of attackers is small. In the absence of selling cascades within some stock-investor-type groups, generated by the tendency to time the market based on the selling actions of others

Figure 2.2: Semi-log plot of cumulative distribution of fraction of attackers in 2005



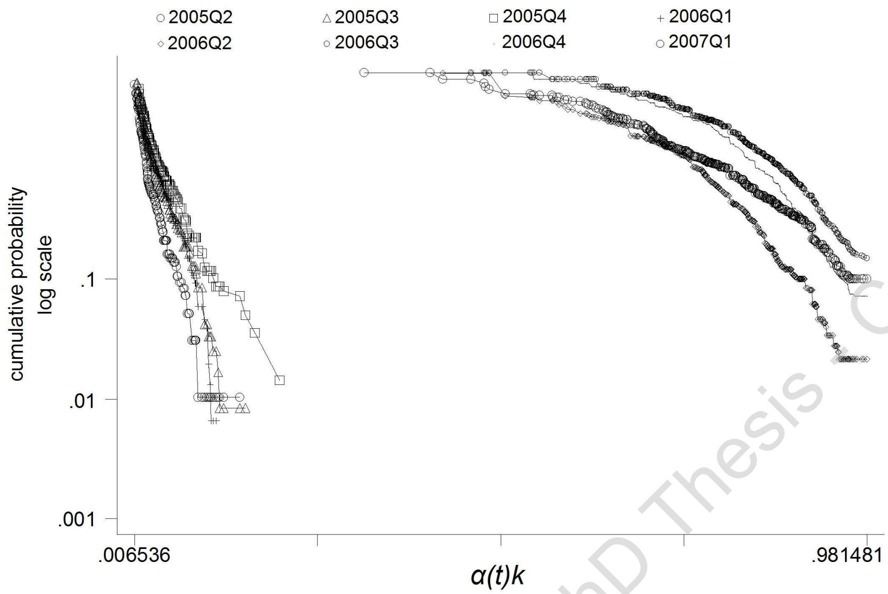
within the same group, the probability of observing a given fraction of attackers would be declining at an increasing rate as we move further away from the mean. In this case we should observe a concave line in the semi-log plot indicating Gaussian decay. On the other hand, suppose investors are attempting to time the market by basing their actions on the actions of others. For example, within stock investor-type group called "hedge funds holding stock X" a hedge fund manager having observed 5% of other hedge fund managers selling 80% or more of their holdings of stock X interprets this as the beginning of a speculative attack and is induced to sell himself. If the conditions are so fragile that even in the absence of major change in the fundamentals a number of investors are inclined to act as this hypothetical hedge fund manager, then we would observe selling cascades within some stock-investor-type groups. Hence, even though the mean of aggregate fraction of attackers may still be 5%, the probability of observing large deviations from the mean remains much higher than predicted by Gaussian decay, with some major outliers, such as the point corresponding to 20% in 2005:Q2, having the probability of occurrence well within the 99% confidence interval.

It is important to emphasize that the best response strategy exhibiting strategic complementarity described by equation (9) is only one out of many possible strategies investors may follow. Other strategies include trading solely based on private information or based on past price movements (such as momentum or contrarian trading). The model only shows a market timing strategy that prevails during the bubble environment when "informed" investors are set to eventually attack but are uncertain of the ability of the market to absorb a given order flow. Figure 2.3 shows similar plots to Figure 2.2 for 8 quarters approaching the crash quarter (2007:Q1). The figure suggests different distributional properties during the quarters when major sellers were relatively scarce (2005:Q2, 2005:Q3, 2005:Q4, and 2006:Q1) and the quarters when institutional investors appear to be dumping real estate stocks in large numbers in most stock-investor-type categories (2006:Q2, 2006:Q3, 2006:Q4, and 2007:Q1). During the quarters when the upper bound on fraction of major sellers is below 25%, with majority concentrated in the $1-5\%$ region, the distribution exhibits exponential decay as predicted by the model. On the other hand, when the probability mass for fraction of major sellers is approaching 90% the distribution of aggregate propagation sizes appears Gaussian.

Figure 2.3 conveys two things. First, the attack ensued as early as 2006Q2 and continued for approximately 4 quarters. Second, institutional investors in the REITs market operated according to two different regimes during the duration of the bubble. During the run-up phase, the distribution of their actions exhibits exponential decay, as predicted by the model, then it is roughly Gaussian during the attack phase. Such regime switching can be understood in the context of aggregate uncertainty. When arbitrageurs are uncertain about the strength of the fundamentals, they each assign different probabilities to a crash occurring in the next instant and accordingly follow a trading strategy described by equation (9). On the other hand, when uncertainty vanishes, that is broadly speaking all arbitrageurs become convinced that fundamentals are good or fundamentals are bad, $\theta_i = \theta_j = \theta$, then $\lambda^t \to 1$ and all institutions act in unison. The transition from from one family of distributions to another depicted in Figure 4 is consistent with criticality at $\lambda^t = 1$.

The finding that institutional investors began their attack on REITs stocks three quarters ahead of the actual crash is consistent with recent empirical finding of Campbell et al [24] who find that institutional sells predict higher returns in the

Figure 2.3: Semi-log plot of cumulative distribution of fraction of attackers approaching the crash time



short-run, but are consistent with lower returns in medium to long-run. They interpret the short-run inconsistency of returns with the direction of institutional trades as a compensation to individual investors for meeting institutional liquidity needs.

2.4.2 Distribution Parameter Estimates

Table 2.2 shows the results of maximum likelihood estimations of exponential, gamma, and normal distribution parameters for the fraction of attackers in each stock-investor-type category. Each panel is a four-quarter period sliced so that the four attack quarters fall within the same panel.

Based on log likelihoods, the empirical distributions in all the panels except for 1998:Q2-1999:Q1 and 2006:Q2-2007:Q1 favor a model that generates exponential decay (such a exponential of gamma distributions) rather than a model that generates normal distribution. The first period of exception corresponds to the four quarters before the onset of the bubble (see Figure 2.1). The distribution has a well

Table 2.2: Maximum Likelihood Estimates of Distribution Parameters

	Stock-Investor-Type Group: $\alpha(t)_k$						Log Likelihood		
	Exponential		Gamma		Normal		Exponential	Gamma	Normal
1998Q2-1999Q1	λ	17.800	α	3.372	μ	0.056	417.186	482.733	444.695
		(1.195)		(0.305)		(0.002)			
			β	0.017	σ	0.033			
				(0.001)		(0.002)			
1999Q2-2000Q1	λ	21.531	α	2.630	μ	0.046	378.720	421.496	373.34
		(1.592)		(0.206)		(0.002)			
			β	0.018	σ	0.031			
				(0.002)		(0.002)			
2000Q2-2001Q1	λ	20.093	α	2.282	μ	0.050	602.106	649.149	586.170
		(1.158)		(0.160)		(0.002)			
			β	0.022	σ	0.035			
				(0.002)		(0.001)			
2001Q2-2002Q1	λ	19.073	α	2.510	μ	0.052	633.200	694.211	625.140
		(1.058)		(0.210)		(0.002)			
			β	0.021	σ	0.035			
				(0.002)		(0.001)			
2002Q2-2003Q1	λ	20.449	α	2.120	μ	0.047	701.071	697.710	608.958
		(1.100)		(0.151)		(0.002)			
			β	0.022	σ	0.036			
				(0.002)		(0.001)			
2003Q2-2004Q1	λ	22.830	α	1.885	μ	0.044	629.914	659.267	554.104
		(1.327)		(0.141)		(0.002)			
			β	0.023	σ	0.037			
				(0.002)		(0.001)			
2004Q2-2005Q1	λ	22.485	α	1.794	μ	0.044	832.460	866.331	743.898
		(1.133)		(0.097)		(0.002)			
			β	0.025	σ	0.037			
				(0.002)		(0.001)			
2005Q2-2006Q1	λ	21.546	α	1.658	μ	0.046	840.494	867.469	733.120
		(1.069)		(0.081)		(0.002)			
			β	0.028	σ	0.040			
				(0.002)		(0.001)			
2006Q2-2007Q1	λ	1.221	α	68.049	μ	0.819	-736.095	824.314	872.293
		(0.040)		(7.437)		(0.003)			
			β	0.012	σ	0.094			
				(0.001)		(0.002)			
2007Q2-2008Q1	λ	23.792	α	2.282	μ	0.042	1190.961	1276.804	1153.763
		(1.015)		(0.112)		(0.001)			
			β	0.018	σ	0.030			
				(0.002)		(0.001)			

Maximum likelihood estimates of distribution parameters; standard errors in parentheses. Note: exponential: $Pr(x;\lambda) = \lambda e^{-\lambda x}$; gamma: $Pr(x;\alpha,\beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$. Estimations of gamma distribution parameters conducted allowing for conditional dependence within each stock.

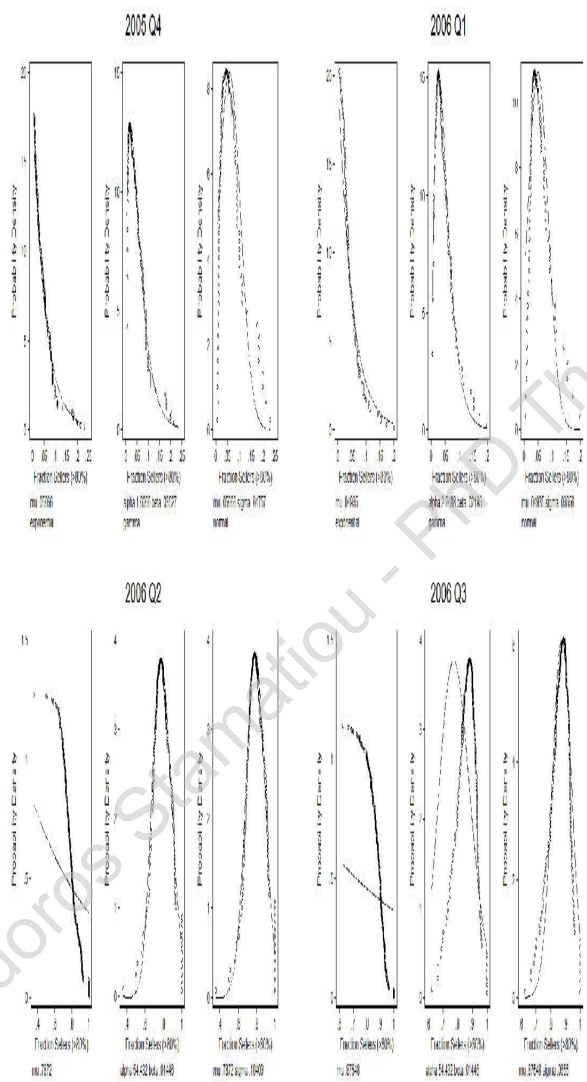
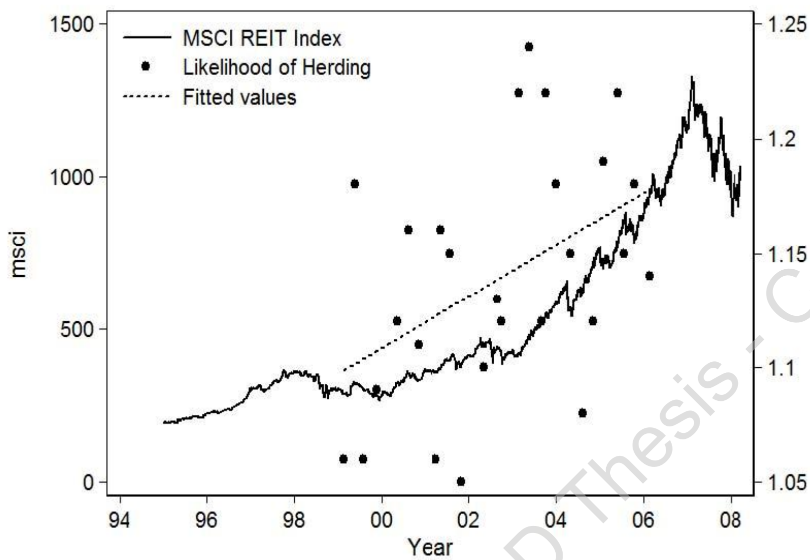


Figure 2.4: Distribution of fractions of major sellers before and during the attack phase

Figure 2.5: MSCI US REIT Index and herding, as proxied by the relative likelihood of exponentially distributed $\alpha(t)_k$



defined mean for fraction of major sellers in stock-investor-type group of 5.6%. This indicates low level of uncertainty about market fundamentals, low level of sales, and low level of imitative behavior. The second period corresponds to the four quarters of attack. Consistently with semi-log plots in Figure 2.4, the distribution has a well defined mean of 81.9% indicating low level of uncertainty but very high level of liquidation.

Figure 2.4 shows best fits of the densities to the empirical data with parameters estimated via maximum likelihood. The figure shows quarterly fits of exponential, gamma, and normal distributions to the data for 2005:Q4 through 2006:Q3. Quarters 2005:Q4 and 2006:Q1 are before the attack ensued, while 2006:Q2 and 2006:Q3 are the first two of the four quarters over which the attack persisted. Both exponential and gamma distributions fit the data much better than normal distribution during 2005:Q4 and 2006:Q1. However, the fit of the exponential began to deteriorate during 2006:Q1, one quarter prior to the attack. Also distributional fits change during the first two quarters of the attack, 2006:Q2 and 2006:Q3. As normal distribution fit locks on, the exponential is completely unable to fit empirical data, while gamma distribution still performs fairly well during 2006:Q2 but is dominated by a symmetric distribution during 2006:Q3. Figure 2.5 is consistent with the regime change depicted by the semi-log plots in Figure 2.4 and with changes in the log likelihood value of the three distributions before and during the attack phase depicted in Table B.3.

2.4.3 Herding

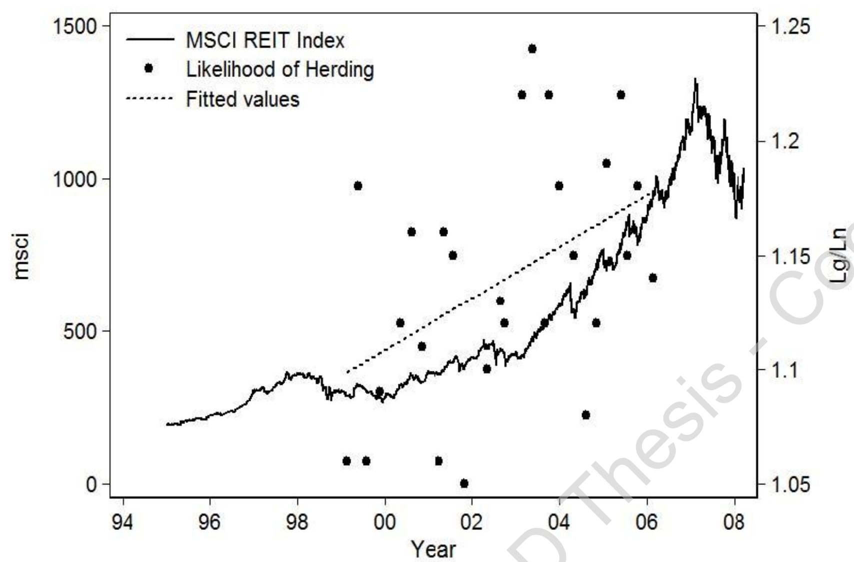
This section presents a simple metric based on distribution parameters to examine whether institutional ownership data in REITs provided any leading indications on the likelihood of market collapse. The likelihood of market-timing regime with intensity λ^t is depicted by the likelihood that empirical data fits the gamma-type distribution implied by the model better than a normal distribution. Since the best response strategy implied by the model results in imitative behavior, the associated likelihood ratio between the two types of distributions is intended to proxy for the degree of herding behavior among institutional investors:

$$Herding(t) \equiv \prod_{k=1}^{K} \frac{f^{E,G}(\alpha(t)_k)}{f^N(\alpha(t)_k)} \tag{2.19}$$

where $f^E(\cdot)$, $f^G(\cdot)$, and $f^N(\cdot)$ are exponential, gamma, and normal probability density functions respectively. $\alpha(t)_k$ is the percentage of major sellers within stock-investor-type group k. The measure is increasing when investors within group k are more likely to sell when others are selling within the same group, generating cascades and long-tailed distribution of aggregate selling propagation size across groups. The measure is decreasing if investors within each group tend to act independently, resulting in a Gaussian distribution of selling pressure across groups.

Figure 2.5 shows daily price history of the MSCI US REIT Index and the herding measure based on (22) for exponential distribution as a benchmark along with the associated best linear fit. The figure shows a steady increase in the likelihood of exponential decay in the distribution of fraction of attackers. The figure also shows that the criticality in arbitrageurs'actions was reached prior to the peak of the bubble. Figure 6 shows a similar results for gamma distribution as a benchmark. Plausible explanations for the delay between the onset of attack by institutional

Figure 2.6: MSCI US REIT Index and herding, as proxied by the relative likelihood of gamma distributed $\alpha(t)_k$



investors and the market crash may be found in market microstructure. First, the delay could be due to the inability of the market-maker to distinguish between order-flow from informed traders from that of the uninformed ones. Avery & Zemsky [7]call this *composition uncertainty.* Second, the delay is also consistent with Campbell et al [24] notion of implicit short-term compensation to individual investors for acting as liquidity providers to the selling institutional investors. Overall, the herding measure in (22) shows some potential for measuring the degree of market fragility or the risk of a speculative attack, however, the magnitudes of change are small and further research and refinement is needed.

2.5 Conclusion

The model of market-timing behavior with a binary decision rule based on crash hazard rate developed in this paper leads to a tâtonnement process characterized by a gamma-type distribution. Therefore, market-timing behavior implied by the model is detectable given the right data. We analyze empirical distributions in institutional ownership data to show that market-timing was a factor in the collapse of the U.S. REITs bubble in February of 2007. Also, consistent with market-timing hypothesis, the distributional characteristics in the data indicate that speculative attack by institutional investors ensued three quarters prior to the collapse of REITs. Finally, based on the log likelihoods of the fitted distributions we find that the degree of herding motivated by market-timing behavior consistent with the model steadily increased approaching the attack phase.

As a possible extension to the model one might consider variable transaction costs. In the current setup transaction cost grows at a constant rate r and is therefore irrelevant for the arbitrageur's optimization problem. The introduction of variable transaction costs into the model, for instance a Tobin tax, will directly affect arbitrageurs'first order condition and therefore may provide useful insight into possible policy measures to control herding.

Chapter 3

Price Limits, Volatility and Overreaction: An Event Study from the Athens Stock Exchange

Price limits are automated mechanisms that pre-specify the maximum daily percentage range - upwards and downwards- in which security prices are allowed to move within a single day. I examine if the price limits ($\pm 8\%$) of the Athens Stock Exchange (ASE) for the "bubble" period 1998-2001 had an effect on volatility, liquidity and abnormal returns. I test three conjectures. The first is that price limits cause a decrease in - close to close or close to open - volatility the day(s) following a price limit hit against the alternative. The second is that price limits cause an increase in liquidity the day(s) following a price limit hit against the alternative. The third is that price limits cause market overreaction the day(s) following a price limit hit against the alternative. I use daily data for the period 01/06/1998- 31/05/2001. The open to close volatility and the liquidity hypothesis are new to the price limits literature. My results are against price limits. I reject both volatility and liquidity conjectures while the overreaction conjecture is rejected for the Up limits.

3.1 Introduction

Informational efficiency - the concept of how much information is revealed by the price process - is central to the analysis of financial economics. According to Fama [38] a market in which prices always fully reveal all available information is called efficient and moreover prices change only in response to relevant new information. The above statement gives no role to the direction and / or the magnitude of price changes in response to new information.

Nevertheless, the magnitude of price change - irrespective of the direction - is a crucial parameter in which stock markets around the world focus their attention. This is based on the fact that (large) price changes are not welcomed by market participants. So large price changes are banned from the daily picture of stock markets. This ban takes the form of a price limit. This is a market mechanism that specifies the upward or downward price movements in which stock prices are allowed to move within a single day. The allowed price change can take the form of a percentage change on the previous day's price. This percentage may be fixed but in same cases maybe a varying one.

Price limits are a common case in stock markets around the world but their use is recent[1]. After the October 1987 crash, the Brady Report [13] suggested that price limits might be useful in preventing excess market volatility. The adoption of price limit mechanisms became apparent. Currently, the stock market of all the EU countries (except UK), Taiwan, Thailand, Japan, China etc. use various forms of price limit mechanisms[2].

Even though in actual markets price limits are a common case there is a strong academic debate concerning the usefulness of this mechanism. The first argument in favor of price limits is that in days of high uncertainty in the market they stop

[1] Price limits exist in future markets for a long time in the past. Japan used futures contracts price limits in the eighteenth century while for the US futures contract price limits were first established on 1917. Brennan [14], Chodhry & Nanda [29] and Kodres & O'Brien [72] develop theoretical rationales for the existence of price limits in future markets.

[2] Kim & Yang [70] distinguish between automated and non-automated circuit breakers. The former are usually referred as price limits while the latter are referred as trading halts. In addition they examine market wide trading halts. Table 3.1 of Kim & Yang [70] presents various price limits in futures markets while Table 3.2 includes a list of (outdated) price limits regulations from various stock markets around the world.

the price resolution process and so they give time to market participants to "digest" new information and so reassess their investment decisions. Similarly the second argument in favor of price limits is concerned with high market volatility. In days of high market uncertainty price limits define the bounds of price movement and so they construct artificial bounds for volatility.

Empirical evidence in favor of price limits is scant. Ma, Rao & Sears [80] examine the price overreaction and volatility arguments in the Treasury Bonds, silver, corn and soybean future contracts using event study methods. Their results are in favor of the price overreaction hypothesis. There is no price change between pre and post limit hit days or at least prices reverse in the post limit hit day.

It is obvious from the above discussion that the arguments in favor of the price limits mechanism abstract from the efficient markets hypothesis (Fama [38]) and are based on a behavioral approach. With respect to that, Harris [58] mentions the psychological power that price limits might have. The empirical results do not agree with the behavioral approach. Several studies (Gay, Kale, Kolb & Noe [44], Chen [27]) find no support for systematic overreaction by market participants. Moreover, Kim & Rhee [69]using an event study approach for the Tokyo Stock Exchange (TSE) price limit mechanism find evidence of price continuation after a price limit hit.

For the volatility reduction hypothesis results are also not encouraging. Only Ma, Rao & Sears [80] find a volatility reduction following a price limit hit. However, according to Harris [58] the volatility result is statistical and not due to the price limit use (i.e. high volatility days are followed by low volatility days - mean reversion in volatility). In addition, Kim & Rhee [69] find abnormally high volatility in days following a price limit hit. The volatility reduction hypothesis is not supported either by Chen [28], Phylaktis et al [96], Kim [68], Henke & Voronkova [60] and Stamatiou [107].

The basic argument that underlies all these papers is that price limits only delay the price discovery process (Fama [39]). If the price change is due to new fundamental information, a price limit hit will only delay the price from reaching its equilibrium level for one (or more in the case of successive price lit hits) day(s). Moreover, as Fama [39] argues, rational prices are not necessarily less volatile prices. As long as price volatility comes from rational responses to changes in fundamental values, high volatility per se in not a bad thing for the market. Again the difference is between rational and behavioral approaches to the market.

This difference is not answered by the theory studies on price limits either. Subrahmanyam [110] builds a model with risk neutral traders, risk averse market makers and liquidity traders. His result show that price limits increase volatility and act like magnets. This happens because informed traders place their trades in such a way so as the price limit mechanism will not affect their ability to trade. As a result, even if the stock price won't hit its price limit, the existence of it will increase volatility. In the event that prices are close to their limits, the behavior of the informed traders will push them to hit the levels.

In a more recent paper, Brunnermeier & Pedersen [23] examines the behavior of predatory traders and derives results in favor of price limits. "Predators" buy (sell) shares when their "prey" buys (sells) so they drive the price upwards (downwards) and when the latter stops buying (selling) they sell (by) and so they gain the difference. This is achieved because the "predator" drains liquidity from the market. The introduction of price limits permits other traders to enter the market in the opening clearing mechanism and as result liquidity draining stops. This leads to the break-up of the predatory game if only a single "predator" exists or decreased profits for the surviving "predators" in the case of multiple predators.

My paper now has three objectives. The first one is to test if the price limit mechanism cause a decrease in volatility the day(s) following a price limit hit. For this I am using the event study approach of Kim & Rhee [69]for a sample of stock prices from the Athens Stock Exchange (ASE) for the period 1998-2001. The main advantage of this approach is the examination of volatility not only for the stocks that hit their price limit but also for the stocks that reached their limit but did not hit it. The control groups permit the distinction between the excess volatility that comes from general market conditions and the one that comes from the price limit mechanism. I use close to close volatility and close to open volatility. The former's use is not new to the literature but it is the first time it is used in the ASE. The latter type of volatility in new to the price limit literature and originates from the Amihud & Mendelson [6] study of the TSE trading system.

The second objective is to test if price limits cause an increase in liquidity the day after a price limit hit. The liquidity examination arises from Brunnermeier & Pedersen's [23] argument that liquidity is increased after a price limit hit. I, implicitly, measure liquidity using Amihud's [5] illiquidity measure. Again I use the control groups described above. The liquidity objective is new - at least in my knowledge - in the price limit literature.

The third objective of the paper is to test if the price limit mechanism causes price overreaction in the ASE. I am using the abnormal returns approach of Brown & Warner [16]. Diakogiannis et al [36] used a similar method for the ASE. Compared with theirs my analysis has two advantages. First, my sample period includes the bubble period of 1999-2000 and price limits are mechanisms made to work in such environments. Diakogiannis's et al. [36] sample period was 1995-1998 a relatively calm period for the ASE. Second, I use control samples - as in Kim & Rhee [69]- so as to control their abnormal returns behavior with those of the stocks that hit their limit.

In summary, the decreased volatility conjecture the day(s) following a price limit hit is rejected for stocks that hit their up or down price limits. For the liquidity results are not better either. The liquidity conjecture the day following a price limit hit is less than the liquidity of the control groups for both up and down limits. The overreaction conjecture cannot be rejected for both up and down limit cases while is rejected for the respective control groups.

The reminder of the paper goes as follows. Section 2 gives some details for the ASE during the sample period and also presents the descriptive statistics of the sample stock. Section 3 includes the testing of the excess volatility hypothesis. Section 4 presents the liquidity conjecture and section 5 shows the price continuation hypothesis. Finally Section 6 concludes the paper.

3.2 The ASE and the Sample Stocks

The ASE is the sole official stock market in Greece. For the sample period ASE operated from Monday to Friday between 10.45 and 1.30 p.m.. The opening price of each day was determined by a preopening period between 10.15 and 10.45. Limit and market orders enter the system. During the trading session the electronic system is used on the matching of orders according to price and time priorities. An order was executed whenever a counter order existed at the same price with the first order entered into the system executed first.

Price limitsprice limits!first imposed were first imposed on the ASE on August 1992. Initially there was a $\pm 4\%$ price limit for heavily traded stocks and a $\pm 8\%$ for less heavily traded stocks. The percentage was based on the previous day closing price. In the following years for all the stocks listed in the ASE the $\pm 8\%$ was adopted. Phylaktis et al [96] work refers to that regime. My sample period belongs to the $\pm 8\%$ regime also.

From 1998 to September 1999 there was a tremendous increase in the ASE stock prices. The General Index (GI) of the ASE was 2060 units in 01/04/1998 and reached 6335 units in 17/09/1999. This was due mainly to the expectations that were created after the devaluation of the drachma in March 1998. This, in turn, created expectations that Greece will join the EURO in 2001 and also created great expectations concerning the future growth of the Greek economy. At the same time the convergence of this period inflation and interest rates to the EU levels, created an excess demand for risky assets.

Obviously there was a self-fulfilling expectation element in all the above that led to the creation of a "bubble environment" in the ASE. The turning point was in 17/09/1999 which was the higher level ever reached by the GI. From there a gradual decrease started that accelerated from mid-2000 onward. As a result the GI reached its 1998 levels in 2001.

The sample period of the paper covers the time span from 1/6/1998 to 31/5/2001. The stocks that are included in the analysis satisfy the following criteria:

- Positive number of price limits (either upwards or downwards).
- Stocks first entered the ASE before the start of the sample period.
- There is sufficient trading for the stocks in the sample period.

There is no need to state why the first criterion is needed (it's a price lit analysis after all). The second criterion is needed not only because it help us to avoid problems by IPOs etc. but also because in Section 4 a control period of 90 days is needed before the price limit hit. The third criterion is needed because after the "bubble" crash of the 11th of September 1999 the trading volume of - almost all - the small capitalization stocks dropped to zero. Only 168 of the 376 ASE stocks satisfy the above criteria.

There is no database that records the price limit hits so an indirect method is used. The first step is to find the days for which $P_t \geq P_{t-1} + 0.079P_{t-1}$ for the Up limits or $P_t \leq P_{t-1} - 0.079P_{t-1}$ for the Down limits where P_t is the price of the stock i on day t. The price data come from Datastream. The second step to observe in the ASE database if on day t the closing bid price and the respective volume was zero for the Up limits or the closing ask price and the respective volume was zero for the Down limits.

Moreover for each day t for which I have an Up or Down price limit hit - following Kim & Rhee [69]- I construct four additional groups, two for the Up limits and two for the Down limits. For the Up limits the first group consists of the stocks that on day t at least reached the 90 percent of their price limit but did not hit it i.e. the stocks for which the following relation holds on day t

$$P_t < P_{t-1} + 0.079P_{t-1}\, and\, P_t \geq P_{t-1} + 0.90 * 0.079P_{t-1}$$

The second group consists of the stocks that at least reached the 80 percent of their price limit but where smaller from the 90 percent of their limit.

$$P_t < P_{t-1} + 0.90 * 0.079P_{t-1}\, and\, P_t \geq P_{t-1} + 0.80 * 0.079P_{t-1}$$

For the Down limits the 90 and 80 percent groups are those that satisfy the following relations respectively.

$$P_t > P_{t-1} - 0.079P_{t-1}\, and\, P_t \leq P_{t-1} - 0.90 * 0.079P_{t-1}$$

$$P_t > P_{t-1} - 0.90 * 0.079P_{t-1}\, and\, P_t \leq P_{t-1} - 0.80 * 0.079P_{t-1}$$

Table 3.1 presents the summary statistics for the sample of the identified (Up or Down) price limit cases and the respective 90 and 80 percent groups. This sample is important because it is the first time it is constructed for the ASE and for a small

Table 3.1: Summary Statistics

	HIT-UP	90	80	HIT-DOWN	90	80
1-day	1992	4202	5111	1208	9600	1516
2-days	629	1235	3355	248	1886	492
3-days	249	420	1238	79	596	246
4-days	112	246	660	29	299	660
5-days	113	984	843	29	645	98
6-days	30	85	168	9	84	26
$\succeq$7-days	109	229	28	15	170	123
Total	3233	7351	11403	1617	13280	3161

The left-hand side of the table presents the case of the Up Limits while the right-hand side presents the case of the Down Limits. The criteria for the selection of the the limits are:

- $P_t \geq P_{t-1} + 0.079P_{t-1}$ for the Up Limits and $P_t \leq P_{t-1} - 0.079P_{t-1}$ for the Down Limits.
- if on day t the closing bid price and the respective volume was zero for the Up Limits and the closing ask price and the respective volume was zero for the Down Limits

For the Hit-Up and Hit-Down columns only the first price limit is the event. The columns labeled 90 and 80 include the stocks that reached at least the 90 percent (80 percent respectively) of their limit but did not hit the limit (where below the 90 percent respectively). The criteria for the inclusion are the following:

- $P_t < P_{t-1} + 0.079P_{t-1}$ *and* $P_t \geq P_{t-1} + 0.90 * 0.079P_{t-1}$ (Group 90) and $P_t < P_{t-1} + 0.90 * 0.079P_{t-1}$ *and* $P_t \geq P_{t-1} + 0.80 * 0.079P_{t-1}$ (Group 80) for the Up Limits.
- $P_t > P_{t-1} - 0.079P_{t-1}$ *and* $P_t \leq P_{t-1} - 0.90 * 0.079P_{t-1}$ (Group 90) and $P_t > P_{t-1} - 0.90 * 0.079P_{t-1}$ *and* $P_t \leq P_{t-1} - 0.80 * 0.079P_{t-1}$ (Group 80) for the Down Limits.

emerging market in a bubble period. Observe that the number of the Up price limits (3233) is almost double that of the Down price limits (1617). This is similar with of Kim & Rhee [69] Price limits prevent more stock price increases than decreases.

In addition for the Up limit cases Group 80 cases (11463) are greater than Group 90 cases (7351) and the latter are greater than Group Hit cases (3233). This does not hold for the Down limit cases. There Group 80 cases (3161) are less than Group 90 (13280) cases and the latter are greater than Group Hit cases (1617). This combined with the number of Up and Down price limits may be attributed to the existence of asymmetric feedback effects as in Shen & Wang [102]. Asymmetric feedback traders tend to believe that the price will be higher the following day when a price goes up while when prices go down they tend to believe that prices will go down but at a slower rate.

Using the above three groups in what follows I will examine if there is:

- a decrease in - close to close and / or close to open - volatility the day(s) following a price limit hit. (Conjecture 1
- an increase in liquidity the day(s) following a price limit hit. (Conjecture 2
- No overreaction exists the day(s) following a price limit hit. (Conjecture 3

3.3 Price limits and Volatility in the ASE

3.3.1 Price limits and Close to Close Volatility

As already mentioned one of the basic arguments in favor of the price limit mechanism is the reduction of volatility in times of high market turbulence. So as to test this an event study approach is used similar with Kim & Rhee [69] A window of ten days is constructed around the hit day for the group that hit its price limit (Group Hit) and for the groups that reached their price limits on Day 0 but did not hit it.

For each day volatility is calculated using the following formula:

$$V_t = (r_{t,j}^{CC})^2$$

where $r_{t,j}$ is the close to close return for stock j between day $t-1$ and t. This volatility event study is similar to the one used by Kim & Rhee [69]and Nath [88]. Differences in volatility across the three groups may lead to results concerning the implementation of the price limit mechanism in the ASE. More specifically increased volatility the days following Day 0 for the Hit Group might be translated as volatility spillover from Day 0 to the following days. This evidence will be reinforced if the volatility spillover for the Hit Group will be significantly greater from the respective volatilities of the 90 and 80 Groups for the days following the price limit hit.

I include in the analysis that follows price limit cases that:

- Experienced no limit hits from Day -10 to Day -1.
- Had similar volatility with group Hit volatilities for Day -10 to Day -1.

I distinguish both Up and Down limit cases in two groups. The first one includes cases with only one limit hit (Day 0) and the second includes cases with successive limit hits. There I count only the first price limit as the event (Day 0). This distinction is made because I want to examine if the single hit cases have similar behavior with the successive hit cases.

Table 3.2 presents the results for the Up limits close to close volatility. Volatility is multiplied by 10^3. Panel A presents the simple limit hit case while Panel B presents the successive limit hits case. The first column presents the volatility from Day -10 to Day 10 for the group of stocks that hitted their price limit (GroupHit). The second and third columns present the respective volatilities for the groups that reached the 90 (Group90) and the 80 (Group80) percent of their price limits. The symbols $>>$ and $>$ indicate that the left-hand side figure is greater than the right-hand figure at the 0.01 and 0.05 levels of significance using the Wilcoxon signed-rank test.

From Panel A note that on Day 0 volatility for Group Hit is greater than volatility for Group 90 and the latter is significantly greater than the respective volatility for Group 80. But this is a trivial result. The three volatilities have this ordering by construction. The interesting results of the analysis lay before and after Day 0.

Observe that there is a substantial decrease in volatility from Day 0 to Day 1. Volatility continuous a decreasing pattern for Days 2 and 3. Group 90 volatility from Day 0 to Day 1 shows a substantial decrease also. Moreover volatilities for Days 1 to 3 are significantly greater for Group Hit than for Group 90. Since the only difference between the two groups is the price limit hit of the first one the previous result provides evidence that cannot reject the hypothesis that price limits cause excess volatility. The fact that excess volatility of Group Hit relative to Group 90 is attributed to price limit hits is reinforced from the pattern of volatilities of the two groups for Days -10 to -1. During this period both groups have similar daily volatilities (means) and for five days volatilities are significantly greater for Group Hit and for the rest period are greater for Group 90. In addition observe that there is no pattern in the behavior of Group 80 towards Group 90. For the [-10,10] period only Day -7, Day -2 and Day 10 are significantly grater for Group 90 than for Group 80.

From Panel B note that the same pattern with the single hit case exists for the Day 0 volatilities of the three groups. The crucial point here is that again a decrease in volatility is observed for Days 1 to 3 for Group Hit. The same behavior holds

Table 3.2: Up Limits and Close to Close Volatility

Panel A: Case One UP					
Days	**GroupHit**	**Wilc.Hit-90**	**Group90**	**Wilc.90-80**	**Group80**
-10	1.614	>>	1.733		1.292
-9	1.631		1.467		1.504
-8	1.475		1.363		1.087
-7	1.666		1.679	>>	0.926
-6	1.564		1.124		1.288
-5	1.660	>>	1.882		1.402
-4	1.826		2.309		1.919
-3	1.751		1.569		2.001
-2	1.912		1.908	>>	1.467
-1	1.809		2.582		1.712
0	**5.911**	>>	**5.264**	>>	**4.311**
1	2.156	>>	1.885		1.052
2	2.112	>	2.003		2.061
3	2.148	>>	2.766		3.127
4	1.973		2.178	>>	1.273
5	2.165		2.198		2.467
6	2.205	>>	2.692		3.331
7	1.877		1.937		1.479
8	5.669	>	1.736	>	3.174
9	2.185		2.247		2.380
10	2.189		2.060	>>	3.325
Panel B: Case Two UP					
Days	**GroupHit**	**Wilc.Hit-90**	**Group90**	**Wilc.90-80**	**Group80**
-10	1.694		1.751		1.635
-9	1.76	>	1.168		1.626
-8	1.646		1.739		1.245
-7	1.867		2.161		2.063
-6	1.617		1.146	>>	1.588
-5	1.83		2.013		1.618
-4	1.938		1.903		2.551
-3	1.791		1.636		1.631
-2	2.065		2.709	>>	1.689
-1	1.875	>>	3.017		1.77
0	**5.894**	>>	**5.261**	>>	**4.33**
1	3.353	>>	2.549		1.924
2	2.833	>>	2.209		1.936
3	2.652	>>	2.682	>>	2.08
4	2.296		2.374		1.984
5	2.333		2.053		2.207
6	2.379	>>	2.808		2.67
7	2.149		2.007		1.532
8	4.624	>>	1.62		2.041
9	2.428		2.838		20.457
10	2.205	>>	1.566		1.818

For the three groups I calculate the close to close volatility for a window of -10 to +10 around the event according to the following formula: $V_t = (r_{t,j}^{CC})^2$ I include in the analysis stocks that experienced no price limit hits for the (-10,-1) period and had similar volatilities for the same period across the three groups. Panel A presents the case of a single price limit while Panel B presents the case of the successive price limits where only the first price limit is counted as an event (Day 0). Volatility is multiplied by 10^3. The symbols >> and > indicate that the left-hand side figure is greater than the right-hand figure at the 0.01 and 0.05 levels of significance using the Wilcoxon signed-rank test.

for Group 90. Volatilities for Group Hit are significantly higher than volatilities for Group 90. This pattern of behavior does not hold for the volatilities between Group 90 and Group 80. Only for Days -6, -2 and -3 volatilities of Group 90 are significantly greater than the respective volatilities for Group 80.

In both panels the difference between Group Hit and Groups 90 and 80 are the price limit hits (for Group Hit) and the price increase (for Group Hit, Group 90 and Group 80). Because the post Day 0 days are only significantly greater between Group Hit and Group 90 it seems safe to attribute this behavior to price limit hits. So I conclude that there are enough evidence for rejecting Conjecture 1.

Table 3.3 presents the results for the down limits close to close volatility. Volatility is multiplied by 10^3. In Panel A for the single limit hit case the Day 0 trivial result of Table 3.2 is also true. Group Hit Day 0 volatility is significantly greater from Group 90 Day 0 volatility and the latter is significantly greater from Group 80 Day 0 volatility. For Group Hit volatility decreases for Day 1 and the same holds for Group 90 Day 1 volatility with the former being significantly greater than the latter. Day 2 volatilities increase compared with the previous day but again the same pattern holds. Group Hit volatility is significantly greater than Group 90 volatility. Day 3 volatilities decreased for both groups. For Days 4 to 6 volatilities decreased for Group Hit and moreover there are significantly greater than volatilities for Group 90. As in the case of Table 3.2 Group 80 shows no specific pattern. Only Day -7, Day -6, Day -3 and Day 8 volatilities of Group 90 are significantly greater than those of Group 80.

From Panel B the trivial result for Day 0 volatilities for Group Hit, Group 90 and Group 80 also holds. For Day 1 volatile is decreased for both Group Hit and Group 90 with the former being significantly greater than the latter. In addition for Days 3, 4 and 6 volatilities for Group Hit are significantly greater than those of Group 90. From both Panel A and Panel B the results are similar with those of Panels A and B of Table 3.2. The greater volatilities of Group Hit from the respective of Group 90 in the post limit hit days for both panels are attributed to the limit hit and not to the price increase. So again I conclude that there are enough evidence for rejecting Conjecture 1. This rejection is similar to the results of Kim & Rhee [69]for the TSE and only partially differs from Nath [88] for the NSE.

Table 3.3: Down Limits and Close to Close Volatility

Panel A: Case One DOWN					
Days	**GroupHit**	**Wilc.Hit-90**	**Group90**	**Wilc.90-80**	**Group80**
-10	2.680		2.010		1.579
-9	2.522		1.632		1.415
-8	2.286		1.830		1.655
-7	2.838		2.803	>>	2.187
-6	6.663		2.247	>	1.830
-5	3.263	>>	4.432		1.955
-4	2.909		3.118		1.870
-3	3.022		2.417		2.196
-2	2.794	>>	1.635		1.817
-1	2.538		2.509		1.940
0	**7.100**	>>	**5.986**	>>	**4.942**
1	2.747	>>	1.941		4.247
2	3.666	>>	3.711		3.100
3	2.843		3.015	>>	2.026
4	3.493	>>	2.757	>>	3.751
5	3.174	>>	3.538		2.942
6	2.838	>>	2.547		2.584
7	2.917		3.362		3.182
8	2.289	>>	3.501	>>	2.888
9	2.709		2.849		2.619
10	2.838		2.659		2.390

Panel B: Case Two DOWN					
Days	**GroupHit**	**Wilc.Hit-90**	**Group90**	**Wilc.90-80**	**Group80**
-10	3.522		2.099	>	1.422
-9	2.546		1.715	>>	1.363
-8	2.47		1.838		1.781
-7	2.843		2.819		2.312
-6	6.024		2.31		1.856
-5	3.373	>>	5.304		1.718
-4	3.012		3.536		1.819
-3	3.179	>>	2.066		2.38
-2	2.976		1.864		1.791
-1	2.512		2.435		2.078
0	**7.026**	>>	**5.991**	>>	**4.933**
1	3.533	>>	2.388		4.8676
2	3.567		3.899		3.253
3	3.153	>>	3.018	>	2.122
4	3.603	>>	2.951	>	3.546
5	3.433		3.294		2.89
6	3.016	>>	2.305		2.659
7	2.918		2.902		3.262
8	2.508		2.884		3.109
9	2.712		2.59		2.763
10	2.842		2.373		2.522

For the three groups I calculate the close to close volatility for a window of -10 to +10 around the event according to the following formula: $V_t = (r^{CC}_{t,j})^2$ I include in the analysis stocks that experienced no price limit hits for the (-10,-1) period and had similar volatilities for the same period across the three groups. Panel A presents the case of a single price limit while Panel B presents the case of the successive price limits where only the first price limit is counted as an event (Day 0). Volatility is multiplied by 10^3. The symbols >> and > indicate that the left-hand side figure is greater than the right-hand figure at the 0.01 and 0.05 levels of significance using the Wilcoxon signed-rank test.

3.3.2 Price limits and Close to Open Volatility

Another approach for testing the effect of price limits on volatility is the one using the close to open volatility. This concept - at least in my knowledge - is new to the price limits literature and originates from Amihud & Mendelson [6] study of the TSE trading system. They use among other things close to open volatility so as to examine the periodic clearing mechanisms and the closing transactions of the various TSE trading sessions. The basic idea behind their analysis is that any differences between volatilities it might be attributed - excluding new information - to the price disturbances among them resulting from trading frictions. In other words the framework will be the same with close to close volatility.

For each day volatility is calculated using the following formula:

$$V_t = (r_{t,j}^{CO})^2$$

where $r_{t,j}$ is the close to open return for stock j between day $t-1$ and t. One caveat of the close to open volatility analysis has to do with data availability. There are no opening prices data available prior to September 1999. So I have to exclude a large portion of the initial sample described in Table 3.1 above.

Nevertheless, Table 3.4 presents the Up Limits close to open volatility. Volatility is multiplied by 10^2. Again results of the single limit hit are shown on Panel A. There for Day 0 volatility for Group Hit is significantly greater than Day 0 volatility for Group 90 and the latter is significantly greater than Day 0 volatility for Group 80. Again this is a trivial result made by the construction of the three groups.

Observe that close to open volatility for Group Hit increases from Day 0 to Day 1 and this increase continuous until Day 4. A decrease in close to open volatility starts from Day 5 downwards. One might argue here that this increase is in favor of the price limits implementation. In other words close to open returns do not have a price limit and so their volatility increases. This is not true. Close to open volatility for Group 90 decreases from Day 0 to Days 1 and 2. Even though there is an increase in volatility for Days 3 and 4 the decreasing pattern continuous from Day 5 downwards. Moreover volatility for Days 1 to 5 of Group Hit is significantly greater than volatility for Days 1 to 5 for Group 90. This pattern of behavior can

Table 3.4: Up Limits and Close to Open Volatility

Panel A: Case One UP					
Days	**GroupHit**	**Wilc.Hit-90**	**Group90**	**Wilc.90-80**	**Group80**
-10	1.770		1.070		1.670
-9	1.770	>>	2.360	>>	1.430
-8	2.040	>>	1.290	>>	1.440
-7	1.570		1.450		1.430
-6	1.510		2.660		1.430
-5	2.000	>>	5.400	>>	1.470
-4	5.700		4.920		3.400
-3	2.150		0.814		1.480
-2	1.780		1.240		1.330
-1	1.530		1.750		1.070
0	1.610	>	2.500	>	1.410
1	0.892	>>	0.384	>>	0.620
2	1.420		0.396		1.120
3	1.200		0.321		1.010
4	1.160	>>	0.185	>>	0.948
5	0.929		0.620		0.978
6	1.200		0.285		1.080
7	0.906	>>	0.571		0.813
8	2.260	>>	0.383	>>	1.330
9	1.470		0.654		1.500
10	1.870	>>	0.273	>>	2.040
Panel B: Case Two UP					
Days	**GroupHit**	**Wilc.Hit-90**	**Group90**	**Wilc.90-80**	**Group80**
-10	2.410		0.748		1.610
-9	1.730		1.570		1.420
-8	1.870		0.886		1.340
-7	1.530	>>	0.955	>>	1.360
-6	1.740		1.720		1.500
-5	2.270	>	3.380		1.720
-4	4.580		3.110		2.890
-3	1.990	>>	0.589	>>	1.470
-2	1.870		0.885		1.420
-1	1.510		1.310		1.110
0	1.680	>>	1.760	>>	1.470
1	1.170	>>	0.391		0.898
2	1.360		0.359		1.070
3	1.210	>>	0.328		0.950
4	1.190	>>	0.223		0.977
5	0.907	>	0.531		0.908
6	1.120		0.414		0.989
7	0.871		0.489		0.804
8	1.910	>>	0.376	>>	1.300
9	1.330		0.622		1.340
10	1.580	>>	0.364		1.660

For the three groups I calculate the close to open volatility for a window of -10 to +10 around the event according to the following formula: $V_t = (r_{t,j}^{CO})^2$ I include in the analysis stocks that experienced no price limit hits for the (-10,-1) period and had similar volatilities for the same period across the three groups. Panel A presents the case of a single price limit while Panel B presents the case of the successive price limits where only the first price limit is counted as an event (Day 0). Volatility is multiplied by 10^2. The symbols >> and > indicate that the left-hand side figure is greater than the right-hand figure at the 0.01 and 0.05 levels of significance using the Wilcoxon signed-rank test.

not be observed for Group 80. According to Amihud & Mendelson [6] the greater volatility of Group Hit it might be attributed to the difference of the trading system between these groups. The difference between Group Hit and Groups 90 and 80 is the limit hits of the first group. Note that there is no difference between post Day 0 days for Group 90 and Group 80.

From Panel B and successive limit hits I have again that Day 0 volatility for Group Hit is significantly greater than Day 0 volatility for Group 90 and the latter is significantly greater than Day 0 volatility for Group 80. Close to open volatility decreases for Group Hit from Day 0 to Day 1 and this decrease continuous downwards. For Group 90 volatility decreases from Day 0 to Day 1 and there is no clear pattern of behavior from Day 2 downwards. Group Hit volatility is significantly greater than Group 90 volatility for Days 1, 3, 4, 5, 8 and 10 while this is not true between Group 90 and Group 80. Again the results is that the post Day 0 difference in volatilities for Group Hit and Group 90 is attributed to the limit hit of Group Hit. As a result Conjecture 1 is rejected for both single and successive Up limits.

Table 3.5 presents the results for the Down Limit close to open volatility. Volatility is multiplied by 10^3. From Panel A for the single limit hit Group Hit Day 0 volatility is significantly greater than Group 90 Day 0 volatility and the latter is significantly greater than Group 80 Day 0 volatility. Close to open volatility increases from Day 0 to Day 1 and it follows a more or less increasing pattern from Day 2 downwards for Group Hit and Group 90. For Group 80 close to open volatility even though again increases from Day 0 to Day 1 it follows a decreasing pattern downwards. Group Hit close to open volatility is significantly greater than the respective volatility of Group 90 for Days 1,3,6 and 8. Group 90 volatility is significantly greater from Group 80 volatility only for Day 8. Again the results is that the post Day 0 difference in volatilities for Group Hit and Group 90 is attributed to the limit hit of Group Hit.

From Panel B for the successive limit hit case Group Hit Day 0 volatility is significantly greater than Group 90 Day 0 volatility and the latter is significantly greater than Group 80 Day 0 volatility. Close to open volatility for Group Hit decreases from Day 0 to Day 1 and there is no clear pattern downwards. On the other hand close to open volatility increases from Day 0 to Day 1 for Group 90 and Group 80 and here too there is no clear pattern for the following days. Group Hit close to open

Table 3.5: Down Limits and Close to Open Volatility

Panel A: Case One DOWN					
Days	**GroupHit**	**Wilc.Hit-90**	**Group90**	**Wilc.90-80**	**Group80**
-10	2.746	>	3.832		1.134
-9	2.949		5.432		1.091
-8	3.131		3.906		1.764
-7	3.191		3.192		1.111
-6	3.722		0.785	>>	0.765
-5	4.281		1.450		0.966
-4	4.488	>>	0.466	>>	2.299
-3	3.635	>>	0.374	>>	1.517
-2	3.689		0.813		1.349
-1	3.505		0.954		0.864
0	**2.768**	>>	**0.676**	>>	**2.115**
1	2.875	>>	1.414		2.190
2	2.857		2.495		1.678
3	2.973	>>	1.837		1.506
4	2.942		2.238		1.656
5	2.985		1.984		0.971
6	3.155	>>	1.797		1.192
7	3.148		1.236		0.951
8	2.780	>>	1.672	>>	0.759
9	2.881		1.808		0.904
10	3.114		1.870		1.780
Panel B: Case Two DOWN					
Days	**GroupHit**	**Wilc.Hit-90**	**Group90**	**Wilc.90-80**	**Group80**
-10	2.793	>>	4.463	>	1.337
-9	2.943		5.843		1.165
-8	3.097		4.926		1.529
-7	3.158		3.988		0.964
-6	3.717		0.819		0.723
-5	4.326		1.415		1.012
-4	4.660	>>	3.690		2.200
-3	3.876	>>	0.322	>>	1.496
-2	3.985		0.703		1.142
-1	3.873		0.783		0.752
0	**2.874**	>>	**0.609**	>>	**1.828**
1	2.728	>>	1.159		1.894
2	2.841		2.064		1.544
3	3.052	>>	1.373		1.321
4	3.002		2.006		1.544
5	2.858		1.698		0.944
6	2.964	>>	1.578	>>	1.109
7	2.990		1.182		0.924
8	2.766	>>	1.697	>>	0.642
9	2.872		1.999		0.843
10	2.946		1.855		1.637

For the stock groups I calculate the close to open volatility for a window of -10 to +10 around the event according to the following formula: $V_t = (r_{t,j}^{CO})^2$ I include in the analysis stocks that experienced no price limit hits for the (-10,-1) period and had similar volatilities for the same period across the three groups. Panel A presents the case of a single price limit while Panel B presents the case of the successive price limits where only the first price limit is counted as an event (Day 0). Volatility is multiplied by 10^2. The symbols >> and > indicate that the left-hand side figure is greater than the right-hand figure at the 0.01 and 0.05 levels of significance using the Wilcoxon signed-rank test.

volatility is significantly greater than the respective volatility of Group 90 for Days 1,3,6 and 8. Group 90 volatility is significantly greater from Group 80 volatility for Days 6 and 8. Again the results is that the post Day 0 difference in volatilities for Group Hit and Group 90 is attributed to the limit hit of Group Hit. For both single and successive Down price limits Conjecture 1 is rejected.

3.4 Price Limits and Liquidity

Brunnermeier & Pedersen's [23] argument in favor of price limits is that "predators" cannot gain from their "prey" under a price limit mechanism. This happens because "predators" gain from their "prey" by draining liquidity from the market. A price limit hit on the other hand first stops liquidity draining on the limit hit day and second the day after limit hit the open clearing mechanism of the trading session permits all market participants to provide liquidity in the market. So it stops or reduces the predators impact on price and thus eliminate or at least reduce their profits. So according to Brunnermeier & Pedersen [23] price limits will lead to increased liquidity - or in other words decreased illiquidity - the day (s) after a limit hit.

There are two issues arising for the price limit analysis from the Brunnermeier & Pedersen [23] argument. The first is that a predator (or a group of predators) is needed. There is no explicit answer in this paper for this. Only an implicit answer on the existence of predators might be given. During the 1999 Bubble period, rumors circulated in the market concerning the growth, investment plans, possible mergers and acquisitions of a large number of the sample firms. One can find this rumors, tips etc. in the Greek Financial/Economic Press of that period. A big part of these rumors started from insiders of the firms and after the bubble some of them were prosecuted by the Greek Exchanges and Securities Commission.

The second issue that arises here is liquidity measurement. Usually in studies of liquidity and asset returns intra-day data are used. Here intra-day ASE data are not available for the sample period under question. So as to circumvent this problem I use daily data and the illiquidity measure proposed by Amihud [5] which is described as the absolute (percentage) price change per euro of daily trading volume and is given by the following formula:

$$illiq_t = \frac{\mid r_{t,j}^{CC} \mid}{vol_{t,j,e}}$$

where $\mid r_{t,j}^{CC} \mid$ is the absolute value of close to close return for stock j between day t-1 and t and $vol_{t,j,e}$ is the respective daily volume in euros (e). The illiquidity measure is closely related with Kyle's [74] result for liquidity i.e. the order flow necessary to induce prices to rise or fall by one euro.

Table 3.6 presents the results for the Up limits illiquidity. Illiquidity is multiplied by 10^7. From panel A for the single limit hit Day 0 illiquidity for Group Hit is significantly grater from Day 0 illiquidity for Group 90 and the latter is significantly greater than Day 0 illiquidity for Group 80. Observe that the Day 0 illiquidity is greater from Day -1 illiquidity for all three groups. This is similar with Brunnermeier & Pedersen's [23] result that "predators" cause a liquidity drain in the market - and thus creating illiquidity - before the price limit hit. For Group Hit, Group 90 illiquidity for Day 1 compared with Day 0 is decreased which again agrees with Brunnermeier & Pedersen [23]. Illiquidity decreases also for Group 80 from Day 0 to Day 1. In addition Group Hit Day 1 illiquidity is significantly greater than Group 90 Day 1 illiquidity but the latter is also significantly greater than Group 80 Day 1 illiquidity. Consequently it is not possible to determine if the increased illiquidity between Group Hit and Group 90 is due to the price limit mechanism or to the difference in price increase between the groups.

From Panel B for the successive price limits Day 0 illiquidity for Group Hit is significantly greater than Day 0 illiquidity for Group 90 and the latter is significantly greater than Group 80 Day 0 illiquidity. Again there is an increase between Day -1 and Day 0 illiquidity and a decrease in illiquidity from Day 0 to Day 1 for all three groups. But this time only Group Hit Day 1 illiquidity is significantly greater than Group 90 Day 1 illiquidity. As a result the liquidity conjecture cannot be rejected for the single Up limit case while it is rejected for the successive Up limit case.

Table 7 presents the results for the Down limits illiquidity. Illiquidity is multiplied by 10^7. From Panel A for the single price limit hit Group Hit Day 0 illiquidity is significantly greater than Group 90 and the latter is significantly greater than

Table 3.6: Up Limits and Liquidity

Days	GroupHit	Wilc.Hit-90	Group90	Wilc.90-80	Group80
Panel A: Case One UP					
-5	2.000	>>	5.400	>>	1.470
-4	5.700		4.920		3.400
-3	2.150		0.814		1.480
-2	1.780		1.240		1.330
-1	1.530		1.750		1.070
0	**1.610**	>	**2.500**	>	**1.410**
1	0.892	>>	0.384	>>	0.620
2	1.420		0.396		1.120
3	1.200		0.321		1.010
4	1.160	>>	0.185	>>	0.948
5	0.929		0.620		0.978
Panel B: Case Two UP					
Days	**GroupHit**	**Wilc.Hit-90**	**Group90**	**Wilc.90-80**	**Group80**
-5	2.270	>	3.380		1.720
-4	4.580		3.110		2.890
-3	1.990	>>	0.589	>>	1.470
-2	1.870		0.885		1.420
-1	1.510		1.310		1.110
0	**1.680**	>>	1.760	>>	1.470
1	1.170	>>	0.391		0.898
2	1.360		0.359		1.070
3	1.210	>>	0.328		0.950
4	1.190	>>	0.223		0.977
5	0.907	>	0.531		0.908

For the three groups I calculate the close to close illiquidity for a window of -5 to +5 around the event according to the following formula: $illiq_t = \frac{|r_{t,j}^{CC}|}{vol_{t,j,e}}$ where $| r_{t,j}^{CC} |$ is the absolute value of close to close return for stock j between day t-1 and t and $vol_{t,j,e}$ is the respective daily volume in euros (e). I include in the analysis stocks that experienced no price limit hits for the (-10,-1) period and had similar illiquidities for the same period across the three groups. Panel A presents the case of a single price limit while Panel B presents the case of the successive price limits where only the first price limit is counted as an event (Day 0). Volatility is multiplied by 10^7. The symbols >> and > indicate that the left-hand side figure is greater than the right-hand figure at the 0.01 and 0.05 levels of significance using the Wilcoxon signed-rank test.

Group 80 illiquidity. Moreover from Day -1 to Day 0 there is a substantial increase in illiquidity while for Day 1 there is a decrease in illiquidity for all three groups. For Days 2 to 4 illiquidity decreases for Group Hit and is significantly greater from the respective illiquidity for Group 90. This does not hold between the respective days of Group 90 and Group 80 except for Day 2.

From Panel B for the successive limit hits the previous result for Days 0 illiquidity holds. Again there is an increase from Day -1 to Day 0 and a decrease for Day 1 for all three groups. Finally for Day 2 to 4 illiquidity for Group Hit is greater from illiquidity for Group 90 and the latter is greater from illiquidity of Group 80 only for

Table 3.7: Down Limits and Liquidity

Panel A: Case One DOWN					
Days	**GroupHit**	**Wilc.Hit-90**	**Group90**	**Wilc.90-80**	**Group80**
-5	1.490		0.382		1.220
-4	2.060	>>	0.021	>>	1.420
-3	1.410		0.232		1.250
-2	1.360		0.158		0.968
-1	1.260		0.141		1.150
0	**6.920**	>>	**0.364**	>>	**7.890**
1	2.650		0.435		3.150
2	3.260	>>	0.145	>>	3.710
3	2.470	>>	0.095		2.640
4	2.180	>>	0.029		2.170
5	2.460		0.388		2.810
Panel B: Case Two DOWN					
Days	**GroupHit**	**Wilc.Hit-90**	**Group90**	**Wilc.90-80**	**Group80**
-5	1.75		0.382		1.520
-4	1.99	>>	0.021		1.470
-3	1.38		0.232		1.220
-2	1.29	>	0.158		0.977
-1	1.22		0.141		1.170
0	**6.28**	>>	0.364	>>	7.390
1	3.13		0.435		3.620
2	3.18	>>	0.145		3.670
3	2.54	>>	0.0948		2.690
4	2.11	>>	0.0289	>>	2.140
5	3.15		0.388		3.640

For the three groups I calculate the close to close illiquidity for a window of -5 to +5 around the event according to the following formula: $illiq_t = \frac{|r^{CC}_{t,j}|}{vol_{t,j,e}}$ where $\mid r^{CC}_{t,j} \mid$ is the absolute value of close to close return for stock j between day t-1 and t and $vol_{t,j,e}$ is the respective daily volume in euros (e). I include in the analysis stocks that experienced no price limit hits for the (-10,-1) period and had similar illiquidities for the same period across the three groups. Panel A presents the case of a single price limit while Panel B presents the case of the successive price limits where only the first price limit is counted as an event (Day 0). Volatility is multiplied by 10^7. The symbols >> and > indicate that the left-hand side figure is greater than the right-hand figure at the 0.01 and 0.05 levels of significance using the Wilcoxon signed-rank test.

Day 4. So the liquidity conjecture is rejected for both single and successive Down limit cases.

In summary, the liquidity conjecture is not rejected for the single hit price limits case while it is rejected for all the other cases. Illiquidity is increased - and so liquidity is decreased - the day after a price limit hit.

3.5 Price Limits and Overreaction

In this section the question of whether the price limits mechanism causes stock price overreaction or not will be answered. By the term overreaction I mean that the behavior of stock prices surrounding an event - a price limit hit in this analysis - can be decomposed in two terms. The first ones describes the normal behavior of stock prices and the second term describes the "non-normal" behavior of stock prices. The normal behavior could be addressed either by a statistical or an economic model (MacKinley [78]). The statistical model might be the mean stock returns or the market adjusted returns (Brown & Warner [16]) or an economic model for example the Capital Asset Pricing Model (CAPM) of Sharpe [101], Lintner [76]and Mossin [86]. Usually economic models have more constraints than the statistical ones making the analysis of overreaction more complicated.

The "non-normal" term of stock prices behavior can be attributed to investor cognitive biases as those described by Kahneman & Tversky [64] or by the limits to arbitrage literature as is reviewed in Barberis & Thaler [8]. The former provides psychological reasoning while the latter an economic argument on the existence of "non-normal" returns. In fact the Subrahmanyam [110] and Brunnermeier & Pedersen [23] papers belong to the limits of arbitrage area. In what follows I will not try to relate "non-normal" returns with a theory model. Rather I will try to examine if these returns exist using an event study methodology as the one described by Brown & Warner ([15], [16]) and MacKinley [78].

Usually in studies of this form the efficient market price is disturbed either upwards or downwards by an information driven event. Then the speed of adjustment to the fully informational price is examined. According to Fama [38] this adjustment is instantaneous. But according to the behavioral (psychological or limits to arbitrage) approach this adjustment is slower and may give ways of profits for informed investors.

The key difference of the common event studies with what follows is the nature of the event. Usually the events are information driven (earnings announcements, stock splits etc.) and so the event study is a semi-strong test of the efficient market hypothesis (Dimson et al [37]). Here the price limit hit is not information driven but it can be considered as containing information (or at least noise) implicitly.

Fama [39] argues that the limits only delay the price adjustment process after the new information while the arguments in favor state that limits give time to investors to "digest" this information.

In what follows the sample of the 168 stocks from the ASE is used. An event window of -10 to 10 days around each price limit and an estimation window of 200 days is used also. I use all the price limit cases with up to 4 price limit hits without excluding those that hit their price limit from Day - 10 to -1. This is done because I want to include as many price limits cases as possible in the abnormal returns analysis and because using the single and successive hit samples of the analysis above gives no different results. Nevertheless for the successive price limit cases only the first limit is counted as an event.

For the estimation period the market model is used with $r_{t,m}$ being the return of the GI for the estimation window. The market model takes the form:

$$r^{estw}_{t,j} = \alpha_j + b_j r_{t,m} + e_{t,j}$$

with $E[t,j] = 0$ and $Var[e_{t,j}] = \sigma^2_e$. The abnormal returns are given by:

$$r^{abn}_{t,j} = r^{evw}_{t,j} - (\bar{\alpha}_j + \bar{b}_j r^{evw}_{t,j})$$

where r^{estw}, r^{evw}, r^{abn} are the actual returns for the estimation period, the actual returns for the event window and the abnormal returns respectively.

Table 3.8 gives the results for the abnormal returns. Note that the asterisk denotes significance of the abnormal return using a t-test as this is described in Brown & Warner [16] and MacKinley [78]. The symbols $>>$ ($<<$) and $>$ ($<$) denote that the left hand figure is greater (less) than the right-hand figure at the 0.01 and 0.05 levels of significance using the Wilcoxon signed rank test.

From Panel A for the Up Limit case Group Hit Day 0 abnormal returns are positive and significantly different from zero and this also holds for Group 90 and Group 80 Day 0 abnormal returns. For Group Hit Day 0 returns are positive and significantly greater than zero while this is not true between Group 90 and Group 80 abnormal returns. For Group Hit Day 1 abnormal returns are positive and significant while this is not true for Group 90 or Group 80 Day 1 abnormal returns. For Group Hit

Table 3.8: Price Limits and Abnormal Returns

Panel A: The Up Limit Case					
Days	**GroupHit**		**Group90**		**Group80**
-10	-2.466		-2.123		-2.182
-9	-2.723	>>	-2.164		-1.93
-8	-1.662		-2.195		-1.504
-7	-1.988		-2.471		-2.161
-6	-2.047		-2.521		-2.4
-5	-2.122		-2.307		-2.379
-4	-1.744		-2.129		-1.835
-3	-1.974		-1.331		-0.951
-2	-0.212		0.525		0.762
-1	0.202		3.447		3.247
0	9.77**	>>	5.328**	>>	4.698**
1	4.326**	>>	1.821*		1.196*
2	0.149		-0.399		-1.367
3	−2.947*	<<	-1.383		-2.483
4	−3.216*	<	-1.958		-3.112
5	−3.292*	<<	-1.877		-3.016
6	−3.237*	<<	-1.898		-3.265
7	−3.154*	<	-2.25	>	-3.406
8	−3.316**	<<	-2.186		-3.253
9	−3.11*	<<	-2.174	>>	-3.19
10	−3.553**	<<	-2.136		-3.241

Panel B: The Down Limit Case					
Days	**GroupHit**		**Group90**		**Group80**
-10	-1.242		-2.318		-2.629
-9	-2.787		-3.088		-3.719
-8	-3.928		-3.751		-4.272
-7	-3.676		-4.23		-3.774
-6	-2.498		-3.894		-3.618
-5	-3.323		-3.889		-3.167
-4	-4.194		-4.364		-4.286
-3	-3.202		-6.148		-5.991
-2	−6.581*	<<	−8.990**	<	−8.406**
-1	−8.441**	<<	−9.834**	<<	−9.461**
0	−17.623**	<<	−11.113**	<<	−10.446**
1	−6.794**	<<	−7.069**	<<	−6.509**
2	−7.314**	<<	-6.453		-6.466
3	−6.458*		-5.233		-5.534
4	-4.948		-3.814		-3.974
5	-3.933		-2.973		-3.168
6	-2.877		-3.331		-3.072
7	-4.427		-4.095		-4.194
8	-3.367		-4.436		-4.276
9	-4.129		-4.196		-3.539
10	-3.566		-4.231		-3.814

For the three groups I calculate abnormal returns according to the methodology described in Brown & Warner [16] and MacKinley [78]. I include in the analysis stocks that experienced no price limit hits for the (-10,-1) period and had similar abnormal returns for the same period across the three groups. Panel A presents the case of the Up Limits while Panel B presents the case of the Down Limits. Here I include bot single and successive price limit hits in the same analysis as results are qualitatively the same for all cases. Again for the successive price limits where only the first price limit is counted as an event (Day 0). Volatility is multiplied by 10^3. The asterisk denotes significance of the abnormal return using a t-test as this is described in Brown & Warner [16] and MacKinley [78]. The symbols >> (<<) and > (<) denote that the left hand figure is greater (less) than the right-hand figure at the 0.01 and 0.05 levels of significance using the Wilcoxon signed rank test.

and for Days 3 to 10 abnormal returns are negative and significant while this is not true for the abnormal returns of the other two groups. By observing Group Hit I can conclude that an overreaction exists.

In addition from the Wilcoxon test Group Hit Day 0 abnormal returns are significantly greater than Group 90 Day 0 abnormal returns and the latter are significantly greater than Group 80 Day 0 returns. Abnormal returns of Group Hit for Day 1 are greater from the respective returns for Group 90 and this does not hold between Group 90 and Group 80. Moreover for Days 3 to 10 - the reversal period for Group Hit - abnormal returns for Group Hit are significantly less than abnormal returns for Group 90 while there is no difference between returns for Group 90 and Group 80. All these lead to the result that Conjecture 3 - no overreaction exists for Group Hit - is rejected for the Up Limits case and this is attributed to the price limit hit.

From Panel B for the Down Limits case Group Hit Day 0 abnormal returns are negative and significant and this also holds for Group 90 and Group 80 Day 0 abnormal returns. But Day -2 and Day -1 results are negative and significant for Group Hit and Groups 90 and 80. For Group Hit abnormal returns are negative and significant for Days 1 to 3 while for Group 90 and Group 80 only Day 1 abnormal returns are negative and significant. In addition, there is no reversal pattern for all three groups since returns from Day 4 downwards are insignificant for Group Hit and this is also true for Group 90 Day 2 and Group 80 Day 2 downwards.

From the Wilcoxon test Group Hit Day 0 abnormal returns are significantly less than Group 90 Day 0 returns and the latter are significantly less from Group 80 abnormal returns. For Group Hit abnormal returns are less than abnormal returns of Group 90 for Days -2 and -1 and this also holds between Group 90 and Group 80. Group Hit Day 1 abnormal returns are significantly less than Group 90 abnormal returns and this also holds between Group 90 and Group 80 Day 1 abnormal returns. For Group Hit Day 2 abnormal returns are significantly less than Group 90 Day 2 abnormal returns but there is no difference between Group 90 and Group 80 abnormal returns. As a result Conjecture 3 is not rejected for the Down Limit cases.

So overreaction is present for the case of Up Limits and is not present for the Down Limits. This result is consistent with the general notion of a "bubble" where the frenzy usually takes place in the upward side and is consistent with the asymmetric feedback effect mentioned by Shen & Wang [102]. In other words traders buy stocks when prices go up but are more reluctant to sell stocks when prices go down.

3.6 Conclusion

Even though the use of price limits is widespread in stock markets around the world their usefulness is doubtful. My results support this position. In summary two out of the three conjectures that were posed at the beginning of the paper were rejected while the third was at least half rejected. There is no decrease in - close to close or close to open - volatility after a (Up or Down) price limit hit. At the same time there is no increase in liquidity the day following a price limit. Finally, overreaction exists only for the case of the Up price limits while this is not true for the Down limits.

In addition there is a number of additional features of the analysis that need to be mentioned. First of all is the large sample of price limits hits and the groups that reached but did not hit their limits. The main characteristic of this sample is that it refers to a volatile bubble period and includes much more price limits cases than that of Kim & Rhee [69] The bubble period is important because price limits are mechanisms made especially for such environments. The tightness of the price limit mechanism ($\pm 8\%$) contributes also to the great number of price limit cases.

The second contribution of the paper is the introduction of the close to open volatility and liquidity measures. The former gives new insights to an old question on price limits that of the reduction of volatility the day following a price limit hit. At the same time it does not carry the price limit bounds that close to close volatility carries. The liquidity measure on the other hand gives an answer to a newly posed question concerning price limits that of Brunnermeier & Pedersen [23] that price limits increase liquidity the day after a price limit hit under a "predatory" setting. In this direction Amihud's [5] illiquidity measure helps in circumventing the lack of intra-day data and at the same time it captures Kyle's [74] definition of liquidity *i.e.* the order flow necessary to induce prices to rise or fall by one euro.

Among the weaknesses of the paper is the lack of opening prices for the entire sample period and the lack of intra-day data. The conjecture concerning asymmetric feedback traders remains without answer also. Nevertheless the result on price limits is not encouraging. price limits seem to fail serving the purposes for which they were made for.

Conclusion

In the preceding chapters we examined how the rational investors' behavior could reinforce the crisis in a market - as a crisis we define a bubble environment. At the same time we examined the efficiency of an exogenously imposed market mechanism - the upwards and downwards price limits - in relation with investors protection in a bubble period.
In the 1st Chapter we examined the behavior of rational investors - hedge funds managers - in the Real Estate Investment Trusts (REITs) bubble of the New York Stock Exchange for the 2002-2007 period. The basic result from the examination of hedge fund holdings in the specific sector and their respective returns, is that hedge funds instead of moving against the bubble they ride it. Moreover hedge fund managers that exited the market because of the bubble had significant losses in their cumulative returns and then tried to enter the market again.
In the 2nd Chapter we build a theory approach for the investigation of the op-

Στα προηγούμενα κεφάλαια εξετάσαμε πως η συμπεριφορά των ορθολογικών επενδυτών μπορεί να επιτείνει την κρίση σε μια αγορά - όπως αυτή εκδηλώνεται μέσω μιας χρηματιστηριακής φούσκας. Παράλληλα εξετάσθηκε η αποτελεσματικότητα ενός εξωγενούς μηχανισμού - των ορίων διαπραγμάτευσης - όσον αφορά την προστασία των επενδυτών σε συνθήκες φούσκας.
Στο 1ο Κεφάλαιο εξετάστηκε η συμπεριφορά των ορθολογικών επενδυτών - hedge funds - στο πλαίσιο της κερδοσκοπικής φούσκας στον κλάδο των Εταιρειών Διαχείρισης Περιουσιακών Στοιχείων του Χρηματιστηρίου της Νέας Υόρκης για την περίοδο 2007-2007. Το βασικό συμπέρασμα από την εξέταση των τοποθετήσεων των hedge funds στο συγκεκριμένο κλάδο και των αντίστοιχων αποδόσεων τους είναι ότι αντί να κινηθούν ενάντια στην κερδοσκοπική φούσκα κινήθηκαν στην ίδια κατεύθυνση με αυτή. Επιπλέον όσοι από τους ορθολογικούς επενδυτές εξήλθαν από την αγορά εξαιτίας της ύπαρξης της κερδοσκοπικής φούσκας απλά είχαν σημαντικές απώλειες στις συσ-

timal strategy of an investor in a bubble environment and under the presence of heterogeneity among investors in the market. The basic result of our analysis is that the optimal strategy for an investor under this circumstances is to mimic the strategies of the other market participants. This result is in accordance with the theory approaches of DeLong et al [35] and Abreu & Brunnermeier [1]. The empirical examination of this strategy in the REITs sector of the NYSE for the period 1998-2008 for all the institutional investors (that are included in the 13f database) confirms the theory result. The central role in the previous two empirical studies goes to the 13f filings database. This database offers substantial information for the institutional investors' holdings in the US equity market. It is not a coincidence that recently a series of empirical studies use the 13f filings database.

In the 3rd Chapter the interest is focused in the Athens Stock Exchange and the bubble of the 1998-2001 period. During that period the operation of upwards and downwards price limits did not prove useful for the investors' protection.

In conclusion, the previous empirical studies despite their strong limitations (the small rational investors -hedge fund managers sample (for the 1st and the

σωρευμένες αποδόσεις τους και προσπάθησαν να εισέλθουν το γρηγορότερο δυνατό.

Στο 2ο Κεφάλαιο αναπτύχθηκε ένα θεωρητικό υπόδειγμα για την διερεύνηση της βέλτιστης στρατηγικής ενός επενδυτή σε μια αγορά υπό συνθήκες κερδοσκοπικής φούσκας και με δεδομένο ότι υπάρχει ετερογένεια μεταξύ των συμμετεχόντων στην αγορά. Βασικό αποτέλεσμα της συγκεκριμένης ανάλυσης είναι ότι η βέλτιστη στρατηγική για έναν επενδυτή υπό αυτές τις συνθήκες είναι η μίμηση της στρατηγικής των υπολοίπων στην αγορά. Κάτι τέτοιο ενισχύει την θεωρητική προσέγγιση των DeLong et al [35] και των Abreu & Brunnermeier [1]. Η εμπειρική εξέταση της συγκεκριμένης στρατηγικής στον κλάδο των Εταιρειών Διαχείρισης Περιουσιακών Στοιχείων του Χρηματιστηρίου της Νέας Υόρκης για την περίοδο 1998-2008 και με τη χρήση των τοποθετήσεων του συνόλου των θεσμικών επενδυτών (που περιλαμβάνονται στη βάση δεδομένων 13f) επιβεβαιώνει το θεωρητικό αποτέλεσμα.

Κρίσιμο ρόλο και στις δύο εμπειρικές προσεγγίσεις παραπάνω κατέχει η χρήση της βάσης δεδομένων 13f. Η συγκεκριμένη βάση παρέχει σημαντική πληροφόρηση για τις τοποθετήσεις των θεσμικών επενδυτών στη χρηματιστηριακή αγορά των ΗΠΑ. Δεν είναι τυχαίο ότι τον τελευταίο καιρό μια σειρά από εμπειρικές μελέτες χρησιμοποιούν τη συγκεκριμένη βάση δεδομένων.

2nd Chapter) and the examination of price limits efficiency in a small emerging stock market like the Athens Stock Exchange (for the 3rd Chapter) shows that the stabilizing role of the rational investors in a market is disputable.

Στο 3ο Κεφάλαιο το ενδιαφέρον στρέφεται στο Χρηματιστήριο Αξιών Αθηνών και στην κερδοσκοπική φούσκα της περιόδου 1998-2001. Στη συγκεκριμένη περίοδο αποδεικνύεται εμπειρικά ότι η χρήση ανώτατων και κατώτατων ορίων διαπραγμάτευσης δεν ανταποκρίθηκε στον κύριο ρόλο τους, την προστασία των επενδυτών.

Συνοψίζοντας οι παραπάνω εμπειρικές εργασίες πέρα από τους υπαρκτούς εμπειρικούς περιορισμούς (όπως το μικρό δείγμα των ορθολογικών επενδυτών - hedge funds (για τα δύο πρώτα κεφάλαια) και η εξέταση της αποτελεσματικότητας των ορίων διαπραγμάτευσης σε ένα μικρό περιφερειακό χρηματιστήριο όπως το ΧΑΑ (3ο Κεφάλαιο)) δείχνουν πως ο σταθεροποιητικός ρόλος των ορθολογικών επενδυτών σε μια αγορά μπορεί να αμφισβητηθεί.

Bibliography

[1] Abreu, D., and M. K. Brunnermeier, (2003), Bubbles and crashes, *Econometrica 71*, pp.173-204

[2] Abreu, D. and M. K. Brunnermeier (2002), Synchronization risk and delayed arbitrage, *Journal of Financial Economics*, Vol. 66, pp.341-360

[3] Alfarano, S. and T. Lux, (2007), A noise trader model as a generator of apparent financial power laws and long memory, *Macroeconomic Dynamics*, Vol. 11, pp.80-101

[4] Akerlof, A. G., and R. J. Shiller, (2009), Animal Spirits - How Human Psychology Drives the Economy, and why it Matters for Global Capitalism, *Princeton University Press, Princeton and Oxford*

[5] Amihud, Y., (2002), Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets*, 5, pp.31-56

[6] Amihud, Y., and H. Mendelson,(1991), Volatility, Efficiency, and Trading: Evidence from the Japanese Stock Market, *Journal of Finance*, 46, pp.1765-1789

[7] Avery, C. and P. Zemsky, (1998), Multidimensional uncertainty and herd behavior in Financial markets, *American Economic Review* , Vol. 88, pp.724-48

[8] Barberis, N., and R. Thaler, (2002), A Survey of Behavioral Finance, *NBER Working Paper No. 9222*

[9] Banerjee, A. V., (1992), A Simple Model of Herd Behavior, *The Quarterly Journal of Economics*, Vol. 107, pp. 797-817

[10] Bikhchandani, S., Hirshleifer, D. and I. Welch, (1992), A Theory of Fads, Fashion, Custom, and Cultural Change in Informational Cascades, *Journal of Political Economy* , Vol. 100, pp.992-1026

[11] Biais, B., Bjork, T., Cvitanic, J., Karoui, E. N., and E. Jouini, (1997), Lectures Notes in Mathematics,(Edited by Runggaldier, J. W.,), *Springer, Berlin*

[12] Blaug, M., (2006), The Methodology of Economics or How Economist Explain, (2nd edition), Cambridge Surveys of Economic Literature, *Cambridge University Press, Cambridge*

[13] Brady Commission, (1988), *Report of the Presidential Task Force on Market Mechanisms*

[14] Brennan, M.J., (1986), A Theory of Price Limits in Futures Markets, *Journal of Financial Economics*, 16, pp.213-233

[15] Brown,S.J. and B. J. Warner, (1980), Measuring Security Price Performance, *Journal of Financial Economics*, 8, pp.205-258

[16] Brown,S.J. and B. J. Warner, (1985), Using Daily Stock Returns: The Case of Event Studies, *Journal of Financial Economics*, 14, pp.3-31

[17] Brunnermeier, K. M., (2001), Asset Pricing under Asymmetric Information: Bubbles, Crashes, Technical Analysis and Herding, *Oxford University Press, Oxford*

[18] Brunnermeier, K. M., (2009), Deciphering the Liquidity and Credit Crunch 2007ΰ2008, *Journal of Economic Perspectives*, Vol. 23, 1,pp.77-100

[19] Brunnermeier, K. M., (2009), Bubbles, *The New Palgrave Dictionary of Economics,* (Edited by S. Durlauf and L. Blume), (2nd edition), Palgrave Macmillan, New York

[20] Brunnermeier, M. K. and C. Julliard, (2008), Money Illusion and Housing Frenzies, *Review of Financial Studies*, 21(1), pp. 135-180

[21] Brunnermeier, M. K. and J. Morgan, (2004), Clock games: Theory and experiments, *Games and Economic Behavior*, Vol. 68, 2, pp.532-550

[22] Brunnermeier, K. M., and S. Nagel, (2004), Hedge Funds and the Technology Bubble, *Journal of Finance*, Vol LIX, 5, pp.2013-2040

[23] Brunnermeier, K.M., and Pedersen, H,L., (2005), Predatory Trading, *Journal of Finance*, LX,4, pp.1825-1863

[24] Campbell, J., Ramadorai, T. and A. Schwartz, (2009), Caught on tape: Institutional Trading, Stock Returns, and Earnings Announcements, *Journal of Financial Economics*, Vol. 92, pp. 66-91

[25] Chen, H-L., Jegadeesh, N., and R. Wermers, (2000), The Value of Active Mutual Fund Management: An Examination of the Stockholdings and Trades of Fund Managers, *Journal of Financial and Quantitative Analysis*, Vol.35, 3, pp.343-368

[26] Chancellor, E., (2000), Devil Take the Hindmost: A History of Financial Speculation, *Plume, New York*

[27] Chen, H., (1993), Price Limits, Overreaction and Price Resolution in Futures Markets, *The Financial Review*, 37, pp.243-263

[28] Chen, Y.M., (1993), Price Limits and Stock Market Volatility in Taiwan, *Pacific-Basin Finance Journal*, 1, pp.139-153

[29] Chodhry, B., and V. Nanda, (1998), Leverage and Market Stability: The Role of Margin Rules and Price Limits, *Journal of Business*, 71, pp.179-210

[30] Cheung, Y.-W. and D. Friedman, (2009), Speculative Attacks: A Laboratory Study in Continuous Time, *Journal of International Money and Finance*, Vol.28, 6, pp.1064-1082

[31] Chiang, C. A., (1984), Fundamental Methods of Mathematical Economics, *McGraw-Hill Book Company, London*

[32] Chun, H.G., Jarjisu, S-A, and J. D. Shilling, (2004) The Role of Real Estate in an Institutional Investor's Portfolio Revisited, *Journal of Real Estate Finance and Economics*, Vol. 29, 3, pp.295-320

[33] Cohrane, H. J., (2001), Asset Pricing, *Princeton University Press, Princeton*

[34] DeLong, J. B., Shleifer, A., Summers, L., and R. Waldmann, (1990a), Noise trader risk in financial markets, *Journal of Political Economy*, 98, pp.703-738

[35] DeLong, J. B., Shleifer, A., Summers, L., and R. Waldmann, (1990b), Positive feedback investment strategies and destabilizing rational speculation, *Journal of Finance*, 45, pp.375-395

[36] Diakogiannis, P.G., Patsalis, N., Tsangarakis, V.N., and E. D. Tsiritakis, (2005), Price Limits and Overreaction in the Athens Stock Exchange, *Applied Financial Economics*, 15, pp.53-61

[37] Dimson, E., and M. Mussavian,(1998), A Brief History of Market Efficiency, *European Financial Management*, 4, pp.91-193

[38] Fama, E.F., (1970), Efficient Capital Markets: A Review of Theory and Empirical Work, *Journal of Finance*, 25, pp.383-417

[39] Fama, E.F., (1989), Perspectives on October 1987, Or, What Did We Learn from the Crash?, (Edited by Kamphuis, R.W.Jr., Kormendi, R.C., and H.W.J. Watson), *Black Monday and the Future of Financial Markets*, Mid America Institute for Public Policy Research, Chicago

[40] Friedman, M., (1953), The case for flexible exchange rates, in Essays in Positive Economics, *University of Chicago Press, Chicago*

[41] Fuente, A., de la., (2000), Mathematical Methods and Models for Economists, *Cambridge University Press, Cambridge*

[42] Galbraith, K., J., (1992), The Great Crash 1929, *Penguin Books, London*

[43] Gallegati, M. and L. Pietronero, (2008), Why financial markets are unstable?, *Department of Economics Working Papers*, Department of Economics, University of Trento, Italia

[44] Gay. G., Kale, J., Kolb, R., and T. Noe, (1994), Fads in Asset Prices:Evidence from the Future Market, *Journal of Futures Markets*, 14, pp.243-263

[45] Gompers A. P., and A. Metrick, (2001), Institutional Investors and Equity Prices, *The Quarterly Journal of Economics*, Vol. 116, No. 1., pp.229–259

[46] Glosten, L., and P. Milgrom, (1985), Bid, Ask, and Transaction Prices in a Specialist market with Heterogeneously Informed Traders, *Journal of Financial Economics*, Vol. 13, pp.71-100

[47] Gorton, G., (2009), Information, Liquidity, and the (Ongoing) Panic of 2007, *NBER Working Paper No. 14649*

[48] Grossman S., (1992), The Information Role of Upstairs and Downstairs Trading, *The Journal of Business*, Vol.65, pp.509-528

[49] Grossman, S., (1976), On the Efficiency of Competitive Stock Markets Where Trades Have Diverse Information, *Journal Finance*, Vol. 31, pp.573-585

[50] Grossman, S., (1981), An Introduction to the Theory of Rational Expectations Under Asymmetric Information, *Review of Economic Studies*, Vol. 48, pp.541-559

[51] Grossman, S., and M. Miller, (1987), Liquidity and Market Structure, *The Journal of Finance*, Vol. 43, pp.617-633

[52] Grossman, S., and J. Stiglitz, (1980), On the Impossibility of Informationally Efficient Markets, *The American Economic Review*, Vol. 70, pp. 393-408

[53] Guimaraes, B. (2008), Vulnerability of currency pegs: Evidence from brazil, *CEP discussion papers*, Centre for Economic Performance, LSE

[54] Hardouvelis, G., and R., Craine, (1983), Are Rational Expectations for Real?, *Greek Economic Review*, Vol.5, pp.5-32.

[55] Hardouvelis, G., and S. Peristiani, (1992), Margin Requirements, Speculative Trading and Stock Price Fluctuations: The Case of Japan, *Quarterly Journal of Economics*, Vol 107, pp.1333-1370

[56] Hardouvelis, G. and T. Stamatiou, (2009), Hedge funds and the us real estate bubble: Evidence from Nyse Real Estate Companies, *University of Piraeus Working Paper.*

[57] Hardouvelis, G., and P. Theodossiou(2002), The Asymmetric Relation between Margin Requirements and Stock Market Volatility across Bull and Bear Markets, *The Review of Financial Studies*, Winter 2002, Vol.15, 5, pp.1525-1559

[58] Harris, L., (1998), Circuit Breakers and Program Trading Limits: What have we learned, *Brookings - Wharton Papers on Financial Services*

[59] Hasbrouck, J., (2007), Empirical Market Microstructure: the Institutions, Economics, and Econometrics of Securities Trading, *Oxford University Press, New York*

[60] Henke, H., and S. Voronkova, (2005), Price Limits on a Call Auction Market: Evidence from the Warsaw Stock Exchange, *International Review of Economics and Finance*, 14, pp.439-453

[61] Imperiale, R., (2006), Real Estate Investment Trusts, *John Wiley & Sons, Inc, New Jersey*

[62] Johansen, A., Sornette, D. and O. Ledoit, (1999), Predicting Financial Crashes Using Discrete Scale Invariance, *Journal of Risk*, Vol. 1, pp.5-32

[63] Jordan, S. J., and R. Radner, (1982), Rational Expectations in Microeconomic Models: An Overview, *Journal of Economic Theory*, 26, pp. 201-23

[64] Kahneman, D., and A. Tversky, (1982), Judgment under Uncertainty: Heuristics and Biases, (Edited by Kahneman,D., Slovic, P., and A. Tversky), *Cambridge University Press, London, pp.3-20*

[65] Keynes M. J., (1997),The General Theory of Employment, Interest, and Money, The Great Mind Series, *Prometheus Books, New York*

[66] Kaniel, R., Saar, G. and S. Titman, (2008), Individual Investor Trading and Stock Returns, *Journal of Finance* , Vol. 63, pp.273-310

[67] Kingman, J. F. C., (1993), Poisson Processes, *Oxford, NY*

[68] Kim, A.K., (2001), Price Limits and Stock Market Volatility, *Economic Letters*, 71,pp.131-136

[69] Kim, A.K., and G. S. Rhee, (1997), Price Limit Performance: Evidence from the Tokyo Stock Exchange, *Journal of Finance*, 52,pp.865-901

[70] Kim, H.Y., and J.J. Yang, (2004), What Makes Circuit Breakers Attractive to Financial Markets? A Survey, *Financial Markets, Institutions and Instruments*, 13, pp.109-146

[71] Kindleberger, P. C., and R.Z. Aliber, (2005), Manias, Panics and Crashes: A History of Financial Crises, *Palgrave–MacMillan, New York*

[72] Kodres, L.E., and D. P. OBrien, (1994), The Existence of Pareto Superior Price Limits, *American Economic Review*, 84, pp.919-932

[73] Kreps, D. M., (1990), A Course in Microeconomic Theory, *Harvester Wheatsleaf, London*

[74] Kyle, S. A., (1985), Continuous Auctions and Insider Trading, *Econometrica*, Vol. 53, pp.1315-1336

[75] Li, D. D. and K. Yung, (2004), Institutional Herding in the ADR market, *Review of Quantitative Finance and Accounting*, Vol. 23, pp.5ỏ17

[76] Lintner, J., (1965), The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, *The Review of Economics and Statistics*, 47, pp.13-37

[77] Lo, W. A., (2008), Hedge Funds: An Analytic Perspective, *Princeton University Press, Princeton*

[78] MacKinlay, A. G., (1999), Event Studies in Economics and Finance, *Journal of Economic Literature*, 35, pp.13-39

[79] Madhavan, A., (2000), Market Microstructure: A Survey, *Journal of Financial Markets*, Vol.3, pp.205-228

[80] Ma, K.C., Rao,P.R., and R.S. Sears, (1989), Volatility, Price Resolution, and the Effectiveness of Price Limits, *Journal of Financial Services Research*, 3, pp.165-199

[81] Mas-Colell, A., Whinston, D. M., and R.J. Green, (1995), Microeconomic Theory, *Oxford University Press, New York*

[82] McNichols, M. and B. Trueman, (1994), Public Disclosure, Private Information Collection, and Short-Term Trading, *Journal of Accounting and Economics*, Vol. 17, pp. 69-94

[83] Micosch, T., (1998), Elementary Stochastic Calculus, Advanced Series on Statistical Science & Applied Probability, *World Scientific, London*

[84] Miller H. M., Modigliani, F., (1961), Dividend Policy, Growth, and the Valuation of Shares, *The Journal of Business*, Vol. 34, 4, pp. 411-433

[85] Morris, S. and Shin, H., (1998), Unique Equilibrium in a Model of Self-Fulfilling Currency Attacks, *American Economic Review*, Vol. 88, pp.587-597

[86] Mossin, J., (1966), Equilibrium in a Capital Asset Market, *Econometrica*, Vol. 34, No. 4 (Oct., 1966), pp. 768-783

[87] National Association of Real Estate Investment Trusts, (2007), *Frequently Asked Questions About REITS*, NAREIT, Washington DC

[88] Nath P., (2004), Are Price Limits Always Bad?, *Journal of Emerging Market Finance*, 4, pp.281-313

[89] Nirei, M., (2006), Threshold Behavior and Aggregate Fluctuation, *Journal of Economic Theory*, Vol. 127, pp. 309-322

[90] Nirei, M., (2008), Self-Organized Criticality in a Herd Behavior Model of Financial Markets, *Journal of Economic Interaction and Coordination*, Vol. 3, pp. 89-97

[91] Obstfeld, M., (1996), Models of currency crises with self-fulfilling features, *CEPR Discussion Papers 1315.*

[92] O'Hara, M., (1997), Market Microstructure Theory, *Blackwell Publishing, Oxford*

[93] Ofek, E., and M. Richardson, (2002), The valuation and market rationality of Internet Stock Prices, *Oxford Review of Economic Policy*, Vol. 18, pp.265-287

[94] Osborne, J. M., and A. Rubinstein, (1994), A Course in Game Theory, *The MIT Press, Cambridge, MA*

[95] Payne, E. J., and A.G. Waters, (2007), Have Equity REITs Experienced Periodically Collapsing Bubbles?, *Journal of Real Estate Finance and Economics*, 34, pp.207-224

[96] Phylaktis, K.,Kavussanos, M., and G. Manalis, (1999), Price Limits and Stock Market Volatility in the Athens Stock Exchange, *European Financial Management*, 5, pp.69-84

[97] Rothschild, M., and J. Stiglitz, (1976), Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information, *Quarterly Journal of Economics*, Vol.90, pp.629-649

[98] Rubinstein, A., (1998), Modeling Bounded Rationality, *The MIT Press, Cambridge, MA*

[99] Sias, R. W., (2004), Institutional Herding, *Review of Financial Studies*, Vol. 17, pp.165-206

[100] Soros, G., (2003), The Alchemy of Finance, *Wiley Investment Classics, Wiley, London*

[101] Sharpe, F.W., (1964), Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *Journal of Finance*, 19, pp.425-442

[102] Shen, C.-H., and L.-R. Wang, (1998), Daily Serial Correlation, Trading Volume and Price Limits: Evidence from the Taiwan Stock Market, *Pacific-Basin Finance Journal*, 6, pp.251-273

[103] Shiller, R. J. and J. Pound, (1989), Survey Evidence on Diffusion of Interest and Information Among Investors,*Journal of Economic Behavior & Organization*, Vol. 12, pp.47–66

[104] Shleifer, A. and R. W. Vishny, (1997), The limits of arbitrage, *Journal of Finance*, Vol. 52, pp. 35ů55

[105] Sornette, D., (2003), Critical market crashes, *Physics Reports*, Vol. 378, p.1-98

[106] Sornette, D., Woodard, R. and W. Zhou, (2008), The 2006 through 2008 Oil Bubble and Beyond, *ETH Working Paper*

[107] Stamatiou, T., (2009), Price Limits, Volatility and Price Continuation in the Athens Stock Exchange, *Unpublished Working Paper, University of Piraeus*

[108] Stamatiou, T., (2006), Market Microstructure, Noise & Overconfidence, *Unpublished Working Paper, University of Piraeus*

[109] Stamatiou, T., (2008), Price Limits, Volatility and Overreaction: An Event Study from the Athens Stock Exchange, *New Developments in Financial Modeling*, (Edited by Soares, O. J., Pina, J., and M. Catalao-Lopes,), Cambridge Scholars Publishing, Newcastle UT

[110] Subrahmanyam A., (1994), Circuit Breakers and Market Volatility: A Theoretical Perspective, *Journal of Finance*, 49, pp.232-254

[111] Sushko, V., Stamatiou, Th., (2009), Market Timing and Market Crashes: Evidence from Real Estate Stocks, *Working Paper, University of California, Santa Cruz*

[112] Taylor, J. S., (2007), Asset Price Dynamics, Volatility and Prediction, *Princeton University Press, Princeton*

[113] Vayanos, D., (2004), Flight to Quality, Flight to Liquidity, and the Pricing of Risk, *NBER Working Paper No. W10327*

[114] Veldkamp, L. L., (2006), Information markets and the Comovement of Asset Prices, *Review of Economic Studies*, Vol. 73, pp.823-845

[115] Welch, I., (2000), Herding Among Security Analysts, *Journal of Financial Economics*, Vol. 58, pp.369-396

Appendices

Appendix A

A.1 The Sample Stocks

Before we proceed with the sample stocks we think that is useful to give some details on the nature of a Real Estate Investment Trust, its legal structure and the size of the REIT industry. So according to the National Association of Real Estate Investment Trusts [87] a REIT is a company that mainly owns and in most cases also operates income-producing real estate such as apartments, shopping centers, offices, hotels and warehouses. Some REITS also engage in financing real estate. Moreover, REITS can be classified in exchange traded around 170 REITS by the end of 2007 mostly traded in the NYSE) and non-exchange traded[1]

The basic characteristic of a REIT is that it has most of its assets and income in real estate and must distribute each year at least 90% of its taxable income to its shareholders.

The Sample stocks are Real Estate Investment Trusts (REITS) included in the respective market sector of the NYSE. We did not include all the REITS that were traded in the NYSE but followed a more indirect process. We used a list of REITS that was published in Imperiale [61] – a textbook on the REITS industry. We excluded the REITS that were subjects of takeover and so did not survive until the end of the sample period. Moreover using Thomson's Financial Datastream we included in our list the REITS that entered the NYSE until 2005:Q1. The main reason for this was to avid IPO problems during the final quarters of our sample

[1]the following *forbes.com* article provides an interesting introduction to REITs:`http://www.forbes.com/2005/02/14/cz_sf_0214reits.html`.

that will increase our holdings for reasons other than those described in the main part of the paper. A complete list of the 111 REITS is presented below in Table A.1.

A.2 The Modigliani–Miller Formula

According to Miller & Modigliani's [84] approach and for a firm (named in what follows *Super Normal*) that for a period T years has supernormal returns r^* (relative to normal returns r) and with a fraction κ of the earnings invested the following formula holds for its $\frac{P}{E}$ ratio:

$$(\frac{P}{E})^{\text{Super Normal}} = \frac{1}{r}\{1 + \frac{\kappa(r^* - r)}{r - \kappa r^*}[1 - (\frac{1 + \kappa r^*}{1 + r})^T]\}$$

Assuming that $\kappa = 1$ (*i.e.* all the earnings are retained within the firm) we have that:

$$\begin{aligned}
(\frac{P}{E})^{\text{Super Normal}} &= \frac{1}{r}\{1 + \frac{(r^* - r)}{r - r^*}[1 - (\frac{1 + r^*}{1 + r})^T]\} \Rightarrow \\
(\frac{P}{E})^{\text{Super Normal}} &= \frac{1}{r}\{1 - \frac{(r - r^*)}{r - r^*}[1 - (\frac{1 + r^*}{1 + r})^T]\} \Rightarrow \\
(\frac{P}{E})^{\text{Super Normal}} &= \frac{1}{r}\{1 - 1 + [\frac{1 + r^*}{1 + r})^T]\} \Rightarrow \\
(\frac{P}{E})^{\text{Super Normal}} &= \frac{1}{r}(\frac{1 + r^*}{1 + r})^T \qquad \text{(A.1)}
\end{aligned}$$

Moreover for a firm with no supernormal profit (named in what follows *Normal*) opportunities we know that the following formula holds for the $\frac{P}{E}$:

$$(\frac{P}{E})^{\text{Normal}} = \frac{1}{r} \qquad \text{(A.2)}$$

(*i.e.* the price of the firm is equal with the discounted earnings $P^{\text{Normal}} = \frac{E^{\text{Normal}}}{r} \Rightarrow (\frac{P}{E})^{\text{Normal}} = \frac{1}{r}$)

Table A.1: List of the 111 Sample REITS

Sample Stocks			
AMB Property Corp	AMB-N	Host Hotels & Resorts Inc	HST-N
Acadia Realty Trust	AKR-N	Inland Real Estate Corp	IRC-N
Agree Realty Corp	ADC-N	Kilroy Realty Corp	KRC-N
Alexanders Inc	ALX-N	Kimco Realty Corp	KIM-N
Alexandria Real Estate Equities Inc	ARE-N	Kite Realty Group Trust	KRG-N
American Campus Communities Inc	ACC-N	LTC Properties Inc	LTC-N
Annaly Capital Management Inc	NLY-N	Lasalle Hotel Properties	LHO-N
Anthracite Capital Inc	AHR-N	Lexington Realty Trust	LXP-N
Anworth Mortgage Asset Corp	ANH-N	Liberty Property Trust	LRY-N
Apartment Investment & Management Co	AIV-N	MFA Financial Inc	MFA-N
Ashford Hospitality Trust Inc	AHT-N	Macerich Co	MAC-N
Associated Estates Realty Corp	AEC-N	Mack Cali Realty Corp	CLI-N
AvalonBay Communities Inc	AVB-N	Maguire Properties Inc	MPG-N
BRE Properties Inc	BRE-N	Medical Properties Trust Inc	MPW-N
BRT Realty Trust	BRT-N	Mid-America Apartment Communities Inc	MAA-N
BioMed Realty Trust Inc	BMR-N	National Health Investors Inc	NHI-N
Boston Properties Inc	BXP-N	National Retail Properties Inc	NNN-N
Brandywine Realty Trust	BDN-N	Nationwide Health Properties Inc	NHP-N
CBL & Associates Properties Inc	CBL-N	Newcastle Investment Corp	NCT-N
Camden Property Trust	CPT-N	NorthStar Realty Finance Corp	NRF-N
Capital Trust Inc MD	CT-N	Omega Healthcare Investors Inc	OHI-N
CapitalSource Inc	CSE-N	One Liberty Properties Inc	OLP-N
Caplease Inc	LSE-N	Parkway Properties Inc	PKY-N
Capstead Mortgage Corp	CMO-N	Pennsylvania Real Estate Investment Trust	PEI-N
Cedar Shopping Centers Inc	CDR-N	Plum Creek Timber Co Inc	PCL-N
Cogdell Spencer Inc	CSA-N	Post Properties Inc	PPS-N
Colonial Properties Trust	CLP-N	Potlatch Corp New	PCH-N
Corporate Office Properties Trust Inc	OFC-N	Prime Group Realty Trust	PGE.B-N
Cousins Properties Inc	CUZ-N	ProLogis Trust	PLD-N
Deerfield Capital Corp	DFR-A	Public Storage	PSA.E-N
Developers Diversified Realty Corp	DDR-N	RAIT Financial Trust	RAS-N
Diamondrock Hospitality Co	DRH-N	Ramco-Gershenson Properties Trust	RPT-N
Digital Realty Trust Inc	DLR-N	Rayonier Inc	RYN-N
Duke Realty Corp	DRE-N	Realty Income Corp	O-N
Dynex Capital Inc	DX-N	Redwood Trust Inc	RWT-N
EastGroup Properties Inc	EGP-N	Regency Centers Corp	REG-N
Education Realty Trust Inc	EDR-N	SL Green Realty Corp	SLG-N
Entertainment Properties Trust	EPR-N	Saul Centers Inc	BFS-N
Equity Lifestyle Properties Inc	ELS-N	Senior Housing Properties Trust	SNH-N
Equity One	EQY-N	Simon Property Group Inc	SPG-N
Equity Residential	EQR-N	Sovran Self Storage Inc	SSS-N
Essex Property Trust	ESS-N	Strategic Hotels & Resorts Inc	BEE-N
Extra Space Storage Inc	EXR-N	Sun Communities Inc	SUI-N
Federal Realty Investment Trust Inc	FRT-N	Sunstone Hotel Investors Inc	SHO-N
Felcor Lodging Trust Inc	FCH-N	Tanger Factory Outlet Centers Inc	SKT-N
First Industrial Realty Trust Inc	FR-N	Taubman Centers Inc	TCO-N
First Potomac Realty Trust	FPO-N	U Store It Trust	YSI-N
Getty Realty Corp New	GTY-N	UDR Inc	UDR-N
Glimcher Realty Trust	GRT-N	Universal Health Realty Income Trust	UHT-N
HCP Inc	HCP-N	Ventas Inc	VTR-N
HRPT Properties Trust	HRP-N	Vornado Realty Trust	VNO-N
Health Care REIT Inc	HCN-N	Washington Real Estate Investment Trust	WRE-N
Healthcare Realty Trust Inc	HR-N	Weingarten Realty Investors	WRI-N
Highwoods Properties Inc	HIW-N	Winthrop Realty Trust Inc	FUR-N
Home Properties Inc	HME-N	iStar Financial Inc	SFI-N
Hospitality Properties Trust	HPT-N		

Combining equations (A.1) and (A.2) we have that:

$$(\frac{P}{E})^{\text{Super Normal}} = (\frac{1+r^*}{1+r})^T(\frac{P}{E})^{\text{Normal}}$$

A.3 The Distribution of 13f Holdings Among Institutional Investors

In Table A.2 below the distribution of 13f Filings holdings data among the various types of institutional investors that are obliged to disclose their positions in the sample stocks. Data were obtained from Thomson Financial's 13f – Ownership utility. Panel A presents the number of institutional investors that are in the market at the last quarter of each year in our sample. Panel B presents the total value of the portfolio of each type of institutional investor for the same time span. Panel C presents the total value of the REITS each type of institutional investor has in his portfolio. Finally Panel D presents the number of institutional investors that hold each stock. The table is similar with the respective tables presented in Gompers & Metrick [45].

From Panel A above observe that the number of all institutional investors reached its highest point at 2006:Q4 and the same is true for the total value of institutional investors' REITS portfolio in Panel C.

A.4 The Sample Hedge Fund Managers

Below the construction of the sample Hedge Fund Managers is described. The main part of the construction is described in the paper but below we repeat it and clarify some details as well as presenting the table with the names of the sample hedge fund managers.

We obtained the files with the 13f filings for each quarter of the sample period (2001:Q1-2007:Q4) for the sample 111 REITS. Each file contains the list of institutional investors (firm level) that hold the 111 REITS, their 13f categorization, the value of each investor's holdings in REITS, the number of REITS shares he owns,

Table A.2: Distribution of 13f Holdings Among Institutional Investors

Descriptive Statistics						
	Dec 02	Dec 03	Dec 04	Dec 05	Dec 06	Dec 07
Panel A: Number of Institutional Investors						
Bank and Trusts	101	111	124	123	125	115
Hedge Funds	349	403	455	504	586	562
Insurance Companies	22	21	18	18	20	19
Investment Advisors	784	824	867	903	1046	1007
Pension Funds	47	46	42	45	49	47
All Others	205	264	888	1072	1260	1210
Total Number of Inst.Inv.	1508	1669	2394	2665	3086	2960
Panel B: Total Portfolio Capitalization in Millions ($)						
Bank and Trusts	279353.2	282189.8	291367.1	298808.3	292880.3	300612.3
Hedge Funds	1746690.0	1882660.0	1965653.0	1947031.0	1971660.0	2040728.0
Insurance Companies	58701.1	66618.4	55257.7	55927.6	57446.3	57592.8
Investment Advisors	5100468.0	5308982.0	5302486.0	5703678.0	5871000.0	6457841.0
Pension Funds	470058.1	466757.4	423874.1	492771.0	496904.7	513424.3
All Others	212456.4	253331.6	332152.2	351425.0	360841.5	364000.3
Total Capitalization	7867726.8	8260539.2	8370790.1	8849640.9	9050732.8	9734198.7
Panel C: REITS Portfolio Capitalization in Millions ($)						
Bank and Trusts	767.8	1504.0	1839.1	1207.3	2169.6	2264.8
Hedge Funds	19092.8	23977.9	36842.1	45358.8	74497.2	62568.8
Insurance Companies	1389.4	1596.1	1273.4	1676.3	2149.0	1518.2
Investment Advisors	43198.7	67092.0	99417.3	112776.9	181706.3	159077.1
Pension Funds	7693.1	9629.1	12716.4	15509.6	21691.4	20545.3
All Others	8750.8	10318.6	13293.9	15957.6	23794.0	21145.5
Total Capitalization	80892.6	114117.7	165382.2	192486.5	306007.4	267119.7
Pane D: Number of REITS with:						
> 1 trader	82	88	105	111	111	111
> 20 traders	79	86	99	103	109	109
> 50 traders	72	80	94	100	107	108
> 100 traders	51	67	76	86	99	103
Total Number of REITS	82	88	105	111	111	111

The table presents the distribution of 13f holdings among the various types of institutional investors. The types of institutional investors are: Bank and Trusts, Hedge Funds, Insurance Companies, Investment Advisors, Pension Funds and All Others (including Endowments, Research Firms, Other Firms, etc.). Panel A presents the number of institutional investors with holdings in the sample REITs for each year from 2002 to 2007. Panel B presents the total portfolio capitalization in Millions ($) for each year from 2002 to 2007. Panel C presents the total REITs holdings capitalization in Millions ($) for each year from 2002 to 2007. Panel D presents the breakdown of REITs based on the number of institutional investors that trade in each year from 2002 to 2007.

the number of securities held in his portfolio and the total value of his stock portfolio. For example in 2007:Q4, 1st Global Advisors Inc., an investment advisor with 15 securities in his portfolio which had total value of \$ 141.51 million, owned \$ 0.22 millions of the AMB Property Corp REIT (3,803 of AMB Property Group shares).

From 2001:Q1 to 2001:Q4 we identified the Institutional investors categorized as "Hedge Funds" or "Hedge Funds / Investment Advisors" and filtered these results using information from the SEC (Form ADV) and Thomson Financial. There is a difference between the "Hedge Funds" and "Hedge Funds / Investment Advisors" 13f Filing categorization. "Hedge Funds / Investment Advisors" are operating firms that not only own hedge funds but also mutual funds. Because the 13f Filing reporting is done at the firm level the equity holdings that appear in the 13f file for a "Hedge Fund / Investment Advisor" include all the holdings of the firm irrespectively of their source (if they come from the hedge fund or mutual fund branch of the firm). In order to distinguish between the firms whose income comes mainly from hedge funds (and not mutual funds) we use SEC's Form AVD.

These are the hedge fund managers investing in REITS prior to 2002:Q1. 283 hedge fund managers were identified in this way. This identification process is needed because we do not want my sample to biased by "latecomers".

Using the above list we examined which of them still invested (i.e. existed in the 13f Filing file of the respective quarter) as the "bubble" unfolded (period 2002:Q1-2007:Q4). We obtained the value of their holdings in the 111 sample REITS, the number of REITS shares they owned, the number of securities they held in their portfolio and its total value for each quarter. Tables A.3 and A.4 provide the list of the hedge fund managers of our sample.

A.5 Reports on the US REITS sector during 2005

Below we present links to news and reports about the situation of the REITS sector in 2005. The list is only indicative of the end of 2005 condition in the market. Thousands of similar reports are still out there.

http://www.forbes.com/2006/01/27/reits-vornado-camden-in_ps_0130adviserqa_inl.html

http://www.forbes.com/2005/11/22/reits-slatin-in_ps_1122soapbox_inl.html

http://www.forbes.com/2005/07/13/reit-investing-insider-cz_sf_0713reits2.html http://www.forbes.com/2006/01/27/reits-vornado-camden-in_ps_0130adviserqa_inl.html

http://nreionline.com/news/REITs/

http://www.forwardua.com/pdf/FlashReport_2005_12.pdf

http://home.flash.net/~factoids/fact4/r0503c.htm

http://www.ml.com/media/67216.pdf

Table A.3: The List of the Sample Hedge Fund Managers

Sample Hedge Fund Managers		
Zweig-Di Menna Associates Inc.	Schroder Investment Management Ltd. (SIM)	Oak Brook Investments LLC
Zimmer Lucas Partners L.L.C.	Schroder Investment Management (Japan) Ltd.	North American Management Corp.
York Management & Research Inc.	Schneider Capital Management Corporation	Neuberger Berman LLC (Oscar Capital Mgmt.)
York Capital Management	Schafer Cullen Capital Management Inc.	Neptune Capital Management L.L.C.
Wyper Capital Management L.P.	Sand Hill Advisors Inc.	Munder Capital Management
Wynnefield Capital Inc.	San Francisco Sentry Investment Group	Morgens Waterfall Vintiadis & CoInc.
Williams Jones & Associates LLC	SSI Investment Management Inc.	Morgan Stanley Investment Management Inc. (US)
Westfield Capital Management Company LP	SPO Partners & Co.	Morgan Stanley Investment Management (MAS)
Westchester Capital Management Inc.	SCM Advisors LLC	Moore Capita lManagement Inc.
West Highland Capital Inc.	S.A.C. Capital Advisors LP	Monatair Investments LLC
Wells Capital Management (Strong)	Rydex Investments	Metropolitan Capital Advisors Inc.
Welch & Forbes LLC	Royce & Associates LLC	McKinley Capital Management LLC
Warfield Associates Inc.	Roxbury Capital Management L.L.C.	Maverick Capital Ltd.
Wall Street Associates LLC	Rockview Management LLC	Mastrapasqua Asset Management Inc.
Wafra Investment Advisory Group Inc.	Rochdale Investment Management LLC	Martingale Asset Management L.P.
Vinik Asset Management L.P.	Robeco Investment Management Inc.	Martin Currie Investment Management Ltd.
Van Eck Associates Corporation	Robeco Investment Management Inc. (WPG)	Mark Asset Management Corp
Tyndall Management L.L.C.	River Source Investments LLC	Mainstream Investment Advisers LLC
Twin Capital Management Inc.	Rice Hall James & Associates LLC	Magten Asset Management Corp.
Tweedy Browne Company LLC	Renaissance Technologies Corp.	MacKay Shields LLC
Turner Investment Partners Inc.	Reich & Tang Asset Management L.L.C.	MAI Wealth Advisors LLC
Tudor Investment Corporation	RH Capital Associates L.L.C.	M.D. SassInvestors Services Inc.
Titan Capital Management L.L.C. (NJ)	RCM Capital Management LLC	M&R Capital Management Inc.
Timucuan Asset Management Inc.	Prospector Partners LLC	M&I Investment Management Corp.
Tilney Private Wealth Management	Promark Investment Advisors Inc.	Luther King Capital Management Corp.
Third Point L.L.C.	Private Capital Management LP	Los Angeles Capital Management And Equity Rese
Third Avenue Management LLC	Porter Orlin L.L.C.	Loomis Sayles & Company L.P.
The Dreyfus Corporation	Pioneer Investment Management Ltd.	Lone Pine Capital L.L.C.
The Boston Company Asset Management LLC	Pin Oak Investment Advisors Inc.	Loeb Partners Corp.
The Baupost Group L.L.C.	Petersen Flynn & Dinsmore Inc.	Lazard Asset Management L.L.C.
Talon Asset Management Inc.	Performance Capital L.L.C.	Kingdon Capital Management L.L.C.
T.Rowe Price Associates Inc.	Pequot Capital Management Inc.	Keefe Managers L.L.C.
Symphony Asset Management LLC	Paradigm Asset Management Company LLC	James Investment ResearchInc.
Summit Capital Management L.L.C.	Para Advisors LLC	Jacobs Levy Equity Management Inc.
Strome Investment Management L.P.	Paloma Partners Management Company	JP Morgan Asset Management U.K. Limited
Straus Capital Management L.L.C.	Palisade Capital Management LLC	JMG Capital Management LLC
State Street Global Advisors (UK) Ltd.	PNC Capital Advisors Inc.	JL Advisors LLC
Standard Pacific Capital LLC	PEA Capital LLC	JF Asset Management (HK) Ltd.
Southeastern Asset Management Inc.	PAR Capital Management Inc.	Ingalls & Snyder LLC (AssetManagement)
Soros Fund Management L.L.C.	Osterweis Capital Management LLC	Independence Investments LLC
Smith Asset Management Group LP	Oracle Investment Management Inc.	Ignis Asset Management Limited
Smith & Williamson Investment Management Limited	Oppenheimer Funds Inc.	INTECH Investment Management LLC
Seneca Capital Advisors L.L.C.	Oppenheimer Capital L.L.C.	ING Investment Management Co. (NY)
Segall Bryant & Hamill Investment Counsel	Omega Advisors Inc.	ING Investment Management Co.
Section H Partners L.P.	Och-Ziff Capital Management L.P.	ING Clarion Real Estate Securities L.P.
Schwerin Boyle Capital Management Inc.	Oaktree Capital Management L.P.	ICM Asset Management Inc.
Schwartz Investment Counsel Inc.	Oakmont Corporation	Hoefer & Arnett Capital Management Inc.

Table A.4: The List of the Sample Hedge Fund Managers

Sample Hedge Fund Managers		
Highland Capital Management L.P.	Eagle Asset Management Inc.	Brahman Capital Corp.
Highfields Capital Management L.P.	EOS Partners L.P.	Bowman Capital Management L.L.C.
Highbridge Capital Management LLC	EGS Partners L.L.C.	Boston Provident L.P.
Hermes Fund Managers Limited	EBF & Associates L.P.	Black Rock Investment Management (UK) Ltd.
Henderson Global Investors Ltd.	E.S. Barr & Company	Black Rock HPB Management L.L.C.
Hellman Jordan Management Company Inc.	Double Alpha Group Inc.	Black Rock Financial Management (Value)
Heartland Advisors Inc.	Dickstein Partners Inc.	Birinyi Associates Inc.
Harvest Management LLC	Dexia Asset Management Belgium S.A.	Bentley Capital Management Inc.
Handelsbanken Asset Management	Deutsche Asset Management Americas	Benchmark Capital Advisors Inc.
Halbis Capital Management (UK) Limited	Deltec Asset Management L.L.C.	Bel Air Investment Advisors LLC
HHR Asset Management LLC	Delta Asset Management LLC	Bedford Oak Advisors L.L.C.
Gruber & McBaine Capital Management L.L.C.	Dawson-Herman Capital Management Inc.	Bear Stearns Asset ManagementInc.
GrisantiBrown&Partners LLC	Davidson Kempner Capital Management L.L.C.	Beach Investment Counsel Inc.
Greenlight Capital Inc.	Dalton Greiner Hartman Maher & Co LLC	Batterymarch Financial Management Inc.
Granum Capital Management L.L.C.	DSI International Management Inc.	Basswood Partners L.L.C.
Grantham Mayo Van Otterloo & Co L.L.C.	DIAM Co Ltd.	Baring Asset Management Asia Ltd.
Granite Capital International Group L.P.	D. E. Shaw & Co L.P.	Baldwin Brothers Inc.
Goodman & Company Investment Counsel	Cypress Tree Investment Management LLP	Baker Nye Advisors Inc.
Gilder Gagnon Howe & Co. LLC	CreditS uisse Asset Management LLC (US)	Babson Capital Management LLC
George Weiss Associates Inc.	Cramer Rosenthal McGlynn LLC	BKF Asset Management Inc.
Gateway Investment Advisers L.L.C.	Cooper Neff Alternative Managers	Aviva Investors Global Services Limited
Gartmore Investment Management Limited	Connors Investor Services Inc.	Avery Capital Management LLC
Gardner Russo & Gardner	Columbus Circle Investors	Atticus Capital L.P.
Gabriel Capital L.P.	Columbia Partners L.L.C. Investment Management	Atlantic Trust Private Wealth Management
GE Asset Management Inc.	Cohen & Steers Capital Management Inc.	Atalanta Sosnoff Capital LLC
Fuller & Thaler Asset Management Inc.	Cobalt Capital ManagementI nc.	Ashford Capital Management Inc.
Friedman Billings Ramsey Investment Management	Citadel Investment Group L.L.C.	Ashburton (Jersey) Ltd.
Franklin Templeton Investment Management Ltd	Chilton Investment Company LLC	Aronson + Johnson + Ortiz L.P.
Franklin Street Advisors Inc.	Chartwell Investment Partners L.P.	Arnholdand S. Bleichroeder Advisers LLC
Franklin Mutual Advisers LLC	Charter Oak Partners	Ardsley Partners
Franklin Advisers Inc.	Cerberus Capital Management L.P.	Appaloosa Management L.P.
Foster Dykema Cabot & CoInc.	Centurion Investment Group L.P.	Apollo Investment Management L.P.
Fortis Investments France	Centurion Counsel Inc.	Apex Capital LLC
Fortis Investments (Nederland)	Cedar Hill Associates Inc.	Angelo Gordon & Co L.P.
Formula Growth Ltd.	Cazenove Capital Management Limited	Analytic Investors LLC
First State Investments (UK) Ltd.	Caxton Associates L.L.C.	Alliance Bernstein L.P.
First Quadrant L.P.	Catalyst Investment Management Co L.L.C.	Alex. Brown Investment Management
First Pacific Advisors LLC	Carlson Capital L.P.	Albion Financial Group
Fiduciary Asset Management LLC	Capital Partnership	Advisory Research Inc.
Falcon Point Capital LLC	Capital Counsel LLC	Abner Herrman & Brock Asset Management
Falcon Fund Management Ltd.	Canyon Capital Advisors LLC	AXA Rosenberg Investment Management LLC
Fairview Capital Investment Management L.L.C	Cambiar Investors LLC	AXA Investment Managers UK Ltd.
FSI Group Inc.	Calamos Advisors LLC	AXA Investment Managers Paris
F&C Asset Management plc	CIInvestments Inc.	AXA Framlington Investment Management Ltd.
Essex Investment Management Company LLC	Buckingham Capital Management Inc.	ARAssetManagementInc.
Elliott International Capital Advisors Inc.	Buchanan Parker Asset Management	AG Asset Management LLC
Edgewood Management LLC	Bricoleur Capital Management L.L.C.	AEW Capital Management L.P.

Appendix B

B.1 Institutional Ownership based on 13f holdings

Under Section 13F of the Securities Exchange Act of 1934 every institutional investment manager with more than $100 million under discretionary management are required to disclose their holdings in "Section 13(f) Securities". The later include: Exchange traded quoted stocks (traded in NYSE, AMEX or NASDAQ), equity options and warrants, shares of closed-end investment companies, and certain convertible debt securities. Institutional investment managers now include banks and trusts, hedge funds, insurance companies, investment advisors who manage private accounts, mutual fund assets, pension plan assets and hedge fund assets, pension funds, research firms, corporations, individual investors.[1]

Table B.1 below presents the distribution of 13f holdings among the various types of institutional investors. The table is complementary to Table 2.1 above. Their only difference is that Pane B below includes the capitalization of institutional investors total portfolio while Panel B in table 2.1. includes only the portion of institutional investors portfolio that is invested in REITs.

Table B.2 presents the list of the 130 sample REITS. For the selection we used Thomson Financials' Datastream tool. Observe that the list has differences with the respective list of Chapter 1. This is because in the previous list we excluded REITS on the basis of resent IPOS etc.

[1] For more information on the 13F filling refer to the following web address: http://www.sec.gov/divisions/investment/13ffaq.htm

Table B.1: Distribution of 13f Holdings Among Institutional Investors

	Mar-98	Mar-00	Mar-02	Mar-04	Mar-06	Mar-08
Panel A: Number of Institutional Investors						
Bank and Trusts	71	87	102	116	122	114
Hedge Funds	49	37	63	105	164	216
Insurance Companies	17	16	16	21	19	19
Investment Advisors	781	972	1097	1246	1363	1470
Pension Funds	29	30	39	43	45	47
All Others	30	107	195	786	1243	1248
Panel B: Capitalization in Millions ($)						
Bank and Trusts	834.9	557.9	667.1	1,787.3	1,248.8	1,953.4
Hedge Funds	337.8	255.6	721.6	2,213.0	5,044.2	8,929.4
Insurance Companies	456.3	708.9	1,117.3	1,720.1	1,967.4	1,776.0
Investment Advisors	37,330.6	33,204.5	60,463.9	104,264.1	185,948.6	271,138.4
Pension Funds	2,128.2	2,475.9	6,668.2	10,896.2	18,306.1	21,980.5
All Others	999.7	3,934.6	8,439.8	12,169.1	19,229.0	18,265.4
Panel C: Number of Real Estate Securities with:						
> 1 trader	84	89	86	93	130	125
> 20 traders	72	69	75	88	104	109
> 50 traders	59	55	68	83	101	108
> 100 traders	29	35	50	71	90	104
Total Real Estate Securities	84	89	86	93	130	125

The table presents the distribution of 13f holdings among the various types of institutional investors. The types of institutional investors are: Bank and Trusts, Hedge Funds, Insurance Companies, Investment Advisors, Pension Funds and All Others (including Endowments, Research Firms, Other Firms, etc.). Panel A presents the number of institutional investors with holdings in the sample REITs for each year from 1998 to 2008. Panel B presents the total portfolio capitalization in Millions ($) for each year from 1998 to 2008. Panel C presents the total REITs holdings capitalization in Millions ($) for each year from 1998 to 2008. Panel D presents the breakdown of REITs based on the number of institutional investors that trade in each year from 1998 to 2008.

Table B.2: List of the 130 REITs

Name	Ticker	Name	Ticker	Name	Ticker	Name	Ticker
Acadia Realty Trust	AKR	Developers Diversified Realty Corp.	DDR	Income Opportunity Realty	IOT	Rait Financial Trust	RAS
Agree Realty Corp.	ADC	Diamondrock Hospitality Company	DRH	Inland Real Estate	IRC	Ramcogershenson Properties Trust	RPT
Alexander's Inc	ALX	Digital Realty Trust Inc	DLR	Investors Real Estate Trust	RET	Rayonier Inc	RYN
Alexandria Real Estate Equities Inc	ARE	Duke Realty Corporation	DRE	Istar Financial Inc	SFI	Realty Income Corp.	O
AMB Property Corp.	AMB	Dupont Fabros Technology Inc	DFT	JER Investors Trust Inc	ERT	Redwood Trust Inc	RWT
American Campus Communities Inc	ACC	Dynex Capital Inc	DX	Kilroy Realty Corp.	KRC	Regency Centers Corp.	REG
Annaly Capital Management Inc	NLY	Eastgroup Properties Inc	EGP	Kimco Realty Corp.	KIM	Resource Capital Corp.	RSO
Anthracite Capital Inc	AHR	Education Realty Trust Inc	EDR	Kite Realty Group Trust	KRG	Saul Centers Inc	BFS
Anworth Mortgage Asset Corp.	ANH	Entertainment Properties Trust	EPR	Lasalle Hotel Properties	LHO	Senior Housing Properties Trust	SNH
Apartment Investment and Management Company	AIV	Equity Lifestyle Properties Inc	ELS	Lexington Realty Trust	LXP	Simon Property Group Inc	SPG
Arbor Realty Trust Inc	ABR	Equity One Inc	EQY	Liberty Property Trust	LRY	SL Green Realty Corp.	SLG
Ashford Hospitality Trust Inco	AHT	Equity Residential	EQR	LTC Properties Inc	LTC	Sovran Self Storage Inc	SSS
Associated Estates Realty Corp.	AEC	Essex Property Trust Inc	ESS	Mack Cali Realty Corp.	CLI	Strategic Hotels and Resorts Inc	BEE
Avalonbay Communities Inc	AVB	Extra Space Storage Inc	EXR	Maguire Properties Inc	MPG	Sun Communities Inc	SUI
Biomed Realty Trust Inc	BMR	Federal Realty Investment Trust	FRT	Medical Properties Trust Inc	MPW	Sunstone Hotel Investors Inc	SHO
Boston Properties Inc	BXP	Felcor Lodging Trust Inc	FCH	MFA Financial Inc	MFA	Supertel Hospitality Inc	PPR
Brandywine Realty Trust	BDN	First Industrial Realty Trust Inc	FR	Mid America Apartment Communities	MAA	Tanger Factory Outlet Centers	SKT
BRE Properties Inc	BRE	First Potomac Realty Trust	FPO	Mission West Properties Inc	SW	Taubman Centers Inc	TCO
BRT Realty Trust	BRT	Franklin Street Properties Corp.	FSP	National Health Investors Inc	NHI	The Hallwood Group Inc	HWG
Camden Property Trust	CPT	Friedman Billings Ramsey Group	FBR	National Retail Properties Inc	NNN	The Macerich Company	MAC
Capital Source	CHR	General Growth Properties Inc	GWP	Nationwide Health Properties Inc	NHP	UMH Properties Inc	UMH
Caplease Inc	LSE	Getty Realty Corp.	GTY	Newcastle Investment Corp.	NCT	U-Store-It Trust	YSI
Capstead Mortgage Corp.	CMO	Gladstone Commercial Corp.	OOD	Northstar Realty Finance Corp.	NRF	UDR Inc	UDR
Care Investment Trust	CRE	Glimcher Realty Trust	GRT	Omega Healthcare Investors Inc	OHI	Universal Health Realty Income Trust	UHT
CBL and Associates Properties Inc	CBL	HCP Inc	HCP	One Liberty Properties Inc	OLP	Urstadt Biddle Properties Inc	UBP
Cedar Shopping Centers Inc	CDR	Health Care Reit Inc	HCN	Pasific Office Properties	PCE	Ventas Inc	VTR
Chimera Investment Corp.	CIM	Healthcare Realty Trust Inc	HR	Parkway Properties Inc	PKY	Vestin Realty Mortgage I Inc	RTA
Cogdell Spencer Inc	CSA	Hersha Hospitality Trust	HT	Pennsylvania Real Estate Investment Trus	PEI	Vornado Realty Trust	VNO
Colonial Properties Trust	CLP	Highwoods Properties Inc	HIW	PMC Commercial Trust	PCC	Washington Real Estate Investment Trust	WRE
Corporate Office Properties Trust	OFC	Home Properties Inc	HME	Post Properties Inc	PPS	Weingarten Realty Investors	WRI
Cousins Properties Inc	CUZ	Hospitality Properties Trust	HPT	Potlatch Corp.	PCH	Winthrop Realty Trust	FUR
DCT Industrial Trust Inc	DCT	Host Hotels and Resorts Inc	HST	Prologis	PLD		
Deerfield Capital	DFR	Hrpt Properties Trust	HRP	PS Business Parks Inc	PSB		

B.2 Summary statistics of fraction of ”attackers”

Tables B.3 and B.4 present summary statistics for conditional and unconditional $\alpha(t)_k$ respectively.

Table B.3: Summary statistics of fraction of ”attackers” within stock-investory-type groups

	$\alpha(t)_k$, Conditional							
	Median	Mean	Std. Dev.	Min.	Max.	Skeweness	Kurtosis	Obs.
1998Q2-1999Q1	0.051	0.056	0.033	0.013	0.200	1.419	5.580	222
1999Q2-2000Q1	0.036	0.046	0.032	0.007	0.188	1.613	6.039	183
2000Q2-2001Q1	0.039	0.050	0.035	0.008	0.190	1.419	5.403	295
2001Q2-2002Q1	0.043	0.052	0.035	0.008	0.273	1.875	9.589	317
2002Q2-2003Q1	0.037	0.049	0.040	0.005	0.333	2.679	15.035	346
2003Q2-2004Q1	0.032	0.044	0.037	0.007	0.250	2.234	9.546	296
2004Q2-2005Q1	0.031	0.044	0.037	0.005	0.250	1.918	8.410	394
2005Q2-2006Q1	0.033	0.046	0.040	0.005	0.231	1.813	6.946	406
2006Q2-2007Q1	0.826	0.819	0.094	0.300	1.000	-0.885	5.396	920
2007Q2-2008Q1	0.034	0.042	0.030	0.004	0.214	1.624	7.034	549

The table presents the summary statistics for conditional $\alpha(t)_k$ where t denotes the time period (*i.e.* quarter or year while k denotes stock-investor-type group). $\alpha(t)_k$ denotes the proportion of attackers for each quarter. Each $\alpha(t)_k$ is a group of institutional investors (divided by institutional investor type as in Table B.1 above) holding the same REIT.

Table B.4: Summary statistics of fraction of "attackers" within stock-investor-type groups

	$\alpha(t)_k$, Unconditional							
	Median	Mean	Std. Dev.	Min.	Max.	Skeweness	Kurtosis	Obs.
1998Q2-1999Q1	0.000	0.019	0.033	0.000	0.200	1.963	7.156	640
1999Q2-2000Q1	0.000	0.016	0.029	0.000	0.188	2.296	9.040	531
2000Q2-2001Q1	0.020	0.031	0.036	0.000	0.190	1.475	5.425	486
2001Q2-2002Q1	0.000	0.026	0.036	0.000	0.273	1.909	8.525	662
2002Q2-2003Q1	0.000	0.024	0.037	0.000	0.333	2.777	15.913	699
2003Q2-2004Q1	0.000	0.018	0.032	0.000	0 .250	2.881	14.132	730
2004Q2-2005Q1	0.000	0.022	0.034	0.000	0.250	2.343	10.495	807
2005Q2-2006Q1	0.006	0.024	0.037	0.000	0.231	2.293	9.416	801
2006Q2-2007Q1	0.826	0.819	0.094	0.300	1.000	-0.885	5.396	920
2007Q2-2008Q1	0.015	0.024	0.031	0.000	0.214	1.697	6.865	957

The table presents the summary statistics for conditional $\alpha(t)_k$ where t denotes the time period (*i.e.* quarter or year while k denotes stock-investor-type group). $\alpha(t)_k$ denotes the proportion of attackers for each quarter. Each $\alpha(t)_k$ is a group of institutional investors (divided by institutional investor type as in Table B.1 above) holding the same REIT.

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