JÖNKÖPING INTERNATIONAL BUSINESS SCHOOL

Jönköping International Business School

Jönköping University

Short Sale Constraints: Effects on Crashes, Price Discovery, and Market Volatility

Alexander Ivan Soffronow Pagonidis

Bachelor Thesis in Economics

May 26th 2009

Head Supervisor: Åke Andersson
Deputy Supervisor: Pär Sjölander

Table of Contents

Abstract

The recent SEC ban on short selling has presented an unrivaled opportunity to explore the effects of short selling constraints on crashes, market efficiency, and volatility. In this paper I carry out two groups of empirical tests on the individual banned stocks and a series of portfolios created from them: the first tests the hypothesis that short sale constraints increase the frequency and magnitude of crashes, by testing Hong & Stein's (2003) model of market crashes. The second tests the hypothesis that short sale constraints reduce market efficiency, by testing Miller's (1977) model in which stocks that are hard (or impossible) to short tend to exhibit overpricing. In regards to the first group of tests, the results are ambiguous: the frequency and magnitude of crashes increased during the ban period, while the skewness of the returns distribution of the portfolios became more negative, as expected, but these changes hold for the market as a whole, as well. On the other hand, the skewness of the returns distribution of the individual banned stocks became more positive. The second group of tests provides ample support for Miller's model, as the results coincide with the models predictions: banning short selling leads to positive abnormal returns (overpricing) in the affected stocks. The ban is also related with a decrease in volatility relative to the market, an important result from a policy perspective.

JEL Classification: G12, G14, G18
Keywords: short-selling, market efficiency, regulation, valuation, crashes

1 Introduction

On September 19th 2009, as a consequence of the turmoil in financial markets, and especially financial stocks, the Securities and Exchange Commission (SEC) decided to ban short selling for 800 stocks. The consequences of short selling constraints regarding market efficiency, crashes, and volatility are a hotly debated topic in the literature, and this paper attempts to shed some light on the effects of the ban on short selling.

1.1 Background

1.1.1 Short selling

A short sale is the sale of a security that the investor does not own. Short selling can be used in a speculative fashion if the investor believes the price of a stock will fall. It can also be used for hedging risk, for example as part of the trading strategies of convertible arbitrage funds or index arbitrageurs; it might also be part of the regular buffering activities of market makers (Boehmer et al. 2008).

Despite these legitimate uses, short selling has attracted a large amount of criticism due to their potential for abuse in "short and distort" manipulations: an investor short sells a stock, and then attempts to drive its price downwards, for example by spreading false negative information. Other critics accuse short sellers of driving prices below their fundamental values, increasing the volatility of stock markets, or initiating crashes. The first such scandal happened in 1609 when a group of Dutch businessmen shorted stocks of the East India Company (Arturo Bris et al. 2007).

1.1.2 Recent developments and a short history of regulations

In recent years, short sellers have often been the target of criticism, for example during Japan's 1998 dip in economic activity and Australia's 2008 slump (Santini 2008). The latest bout of criticism came in the midst of the 2008 financial crisis, during which short sellers were accused of exaggerating or even generating the large negative returns in financial sector stocks. Short sellers were likened to "bank robbers" (Machintosh 2008). Citing a "potential of sudden and excessive fluctuations of securities prices" and to prevent a "substantial disruption in the securities markets" and to "protect fair and orderly markets (Securities and Exchange Commission 2008) the SEC responded by banning short selling in some 800 stocks for almost three weeks, from September 19th to October 8th. This resulted in an outcry from financial industry professionals and economists who stressed the negative effects of short sale constraints.

Taking a short position has almost always been more heavily regulated than taking a long position. In the U.S.A., short-selling was banned from 1812 to the 1850s, but the ban was not strictly enforced, so that in practice short selling was still taking place (Taulli 2004).

Afterwards, the ban on short selling was lifted and an active short-selling market emerged. The next large wave of regulation came in 1934, as a response to the depression (early regulation often came as a response to busts on the stock market). The 'plus tick rule' was part of this regulation, specifying that an investor can sell a stock short only at a price higher than the price of the last trade, or if the last trade increased the stock price. Recently, the SEC (Securities and Exchange Commission) has put forth propositions to repeal the tick rule, and to ban or increase regulation of 'naked short selling' (selling short without locating an investor from whom the stocks will be borrowed).

1.2 Research Problem

What are the effects of the SEC ban on short selling from September 19th to October 8th 2009 on market volatility, the frequency and severity of crashes, and the efficient pricing of securities?

1.3 Literature Review

The most important article in the literature, Miller's *Risk, Uncertainty, and Divergence of Opinion* (1977), formed an initial theoretical basis for research in the field, and showed that in a market where there is divergence of opinion (i.e. there are heterogeneous beliefs), and where short sales are restricted, the optimists (the investors with relatively high estimates of value) will buy a security while the pessimists will do nothing. The price of the stock will reflect the opinion of the most optimistic investors, thus leading to overpricing and a violation of the efficient markets hypothesis[1]. The greater the divergence of opinion, which usually goes together with high risk ("uncertainty, divergence of opinion about a security's return, and risk go together" (Miller 1977)), the greater this overpricing effect will be.

Jarrow (1980) and Figlewski (1981) modeled Miller's ideas within a CAPM framework, with the latter showing that when investors with negative information cannot sell short, there is excess demand for the stock, resulting in a price exceeding the price that would prevail in a market without short sale restrictions. Wang, Chang & Bai (2006), Abreu & Brunnermeier (2002, 2003), and Duffie, Gârleanu & Pedersen (2002) also present models in which short sale restrictions have negative effects on market efficiency.

Diamond & Verrecchia (1987) developed a model in which short sale restrictions do not result in overpricing, but reduce the adjustment speed of prices to information, especially bad information, due to certain informative trades not being made, which reduces informational efficiency. More recent theoretical advancements in the area include Hong & Stein's (2003) model of market crashes which suggests that under short selling constraints, when a market is falling, the private information of bearish investors who initially stayed out of the market due to the constraint is more likely to be flushed out. An implication of this is that short sale constraints could lead to a higher frequency of extreme negative returns; however, Chang et al. (2007) fail to find any support for the model. Scheinkman & Xiong (2003) and Abreu & Brunnermeier (2002, 2003) develop models in which short sale constraints can cause excess volatility and bubbles.

Empirical evidence generally supports the theoretical position that short sale restrictions reduce market efficiency. Diether, Malloy & Scherbina (2002) and Boehme, Danielsen & Sorescu (2006) make use of various measures of divergence of opinion; their findings support Miller's (1977) theory. Saffi & Sigurdsson's (2007) corroborate those results, as do Curtis & Fargher (2008), who find that "short-sellers do not amplify unwarranted price declines, but instead play an important role in aligning price with

[1] Boehme et al. (2006) argue that these overpricing effects cannot be "arbitraged away" due to a variety of practical reasons: borrowing and transaction fees must be covered, there are fixed costs to operating a hedge fund, and the returns might be too volatile to be attractive.

fundamental value”. Miller (1977) also predicted that short sale restrictions would have adverse effects on efficient option price discovery. Klemkosky & Resnick (1979) find that roughly 55% of all put-call parity violations are due to short sale constrains; Ofek et al. (2004) come to similar conclusions.

Jones & Lamont (2002), using data from 1926 to 1933, show that stocks that are expensive to short subsequently underperform. Asquith et al. (2005) and Desai et al. (2002) corroborate this result. Ofek & Richardson (2003) link short sale restrictions in the form of post-IPO lockups[2] to the bursting of the Dot-Com bubble: after the restrictions were relaxed, these stocks showed very large negative abnormal returns.

Figlewski & Webb (1993) and Brent et al. (1990) find no strong and regular relation between short interest and subsequent returns. The first paper to find such a connection was Asquith & Meulbroek (1995). Following them, Aitken et al. (1998) and Danielsen & Sorescu (2001) investigate the relaxation of short sale constraints through option listings, changes in short interest, and short sale regulations and find it is associated with negative future returns, suggesting that negative information is incorporated more slowly into prices when short sales are restricted. Mayhew & Mihov (2005), criticizing the inflexibility to assumption changes of previous research, contradict it and show that option listings do not constitute a relaxation of short sale constraints.

Arturo Bris, William N. Goetzmann & Ning Zhu (2007) carried out a large study using data from 46 markets; their conclusions support Diamond & Verrecchia's (1987) hypothesis that prices incorporate negative information slower in markets with restricted short sales. They found that short sale constraints have no significant effect on the frequency of extremely negative returns, contrary to the Hong & Stein (2003) model, but that when they do occur, they are less severe. In addition, they found that in markets where short selling is prohibited, market returns display less negative skewness, although they find little evidence that “short sales constraints prevent or mitigate severe price declines at the individual stock level”. Reed (2002) also supports the Diamond & Verrecchia (1987) hypothesis, finding that stocks in which short selling is expensive have large reactions to earnings announcements, particularly negative ones. Diether et al. (2008) find that short sellers trade mostly “on short-term overreaction of stock prices”, and that such a strategy generates significant positive returns, since the traders correctly predict subsequent negative returns. In a similar vein, Dechow et al. (2001) find that short sellers position themselves in firms “with low ratios of fundamentals (such as earning and book values) to market values”.

While most of the literature is focused on the adverse effects of short sale constraints on markets, Bernardo & Welch (2004) create a model showing how the fear of a financial crisis and not a true liquidity crisis, is the true cause of financial crises, implying that if short sale constraints can stop front-runners in a crisis, they may prevent them altogether; this is because front-runners create a “snowball” effect, which eventually results in a market-wide crisis. Lending empirical credence to this model, Allen & Gale (1991) show that short selling can be a destabilizing element in the economy and Wang, Chang & Bai (2006) show how short selling can increase volatility.

[2] Underwriters typically ban insiders from trading the stock for several months after the initial public offering.

2 Theoretical Framework

2.1 Theoretical Background

Why do short sales happen at all? Given the low cost of put options, combined with their low potential loss in relation to short selling, along with the need to find a lender, post a margin, and obey the 'tick plus' rule, it seems strange that investors short sell at all. One explanation could be that the costs associated with short selling (primarily the margin) are relatively low compared to option prices, and justify the increased risk for some investors. Most of the literature suggests that options can partially relax short sale constraints, but recent research (Mayhew & Mihov (2005), Blau (2008)) suggests that options are not a substitute for short selling at all. This may partially explain why investors short sell, given the existence of options.

In fact, there is circumstantial evidence that short selling and options are complementary to a certain extent: market makers need to be able to sell short to operate efficiently. While market makers were excluded from the ban on short selling, more stringent requirements were introduced for them. This made locating stocks to borrow more difficult, thus increasing the costs of market makers. The result was higher bid-ask spreads (because markets makers had to cover increased costs) and a sharp drop in options trading volume: on September 17th and 18th (the two days before the ban,) record trading volumes were recorded on the Chicago Board Options Exchange. The average daily trading volume for September before the ban was roughly 20 million options; for the rest of September (during the ban), it was roughly 14 million options (The Options Insider 2008).

2.1.1 Crashes

A common reason cited by regulators for introducing short sale constraints is that they reduce big market swings. Even though short selling and restrictions of it are quite old, there is still considerable debate on whether these restrictions stabilize or destabilize markets.

Hong & Stein (2003) create a model of market crashes resulting from short selling constraints, based on heterogeneous beliefs and a lack of informational efficiency. They start by defining a crash as an event encompassing three elements, all based on empirical facts: "1) A crash is an unusually large movement in stock prices that occurs without a correspondingly large public news event; 2) moreover, this large price change is negative; and 3) a crash is a "contagious" market wide phenomenon. That is, it involves not just an abrupt decline in the price of a single stock, but rather a highly correlated drop in the prices of an entire class of stocks".

The first element is based on the observation that many of the biggest negative movements in stock market history have not been caused by some specific news event (Cutler et al. 1989). The second is based on the widely documented fact that stock returns exhibit negative skewness, or in other words that volatility is asymmetric: it is inversely related with returns (see, for example, Bekaert & Wu (2000)). The third element is based on the empirical observation that crashes tend to be market-wide: correlation of individual stock returns tends to increase in a falling market (Duffee 2001).

The model contains two investors, A and B. Heterogeneous opinions are modeled by each investor receiving a private signal about a stock's terminal payoff; each investor only takes into account his own signal. There is also a class of fully rational, risk-neutral arbitrageurs, who know they can obtain the best estimate of the stock's true payoff by averaging A and B's signals. However, due to short sale constraints, A and B can only take long positions and so the arbitrageurs may not always be able to observe both signals.

If at time 1 B gets a pessimistic signal, which results in a lower valuation that A's, he simply will not invest. The arbitrageurs will trade with A, and deduce that B's valuation is lower than A's, but they cannot know how much lower. Thus, the price at 1 will not fully reflect all the available information. If at time 2 A receives a new positive signal, it will again be incorporated into the price, while B will still remain out of the market and his information hidden.

If A gets a bad signal at time 2 though, there is a possibility that B's information will be revealed: as A leaves the market. The point at which B steps in and starts buying will provide the arbitrageurs with information. If there is only a small drop in price before B begins buying, then A's time 1 estimate will not have been very far off the mark. If, however, there is a large drop (a crash) before B starts buying, then B's time 1 signal is worse than the arbitrageurs previously thought, and is thus an additional piece of bad news. The crash is thus aggravated. The model can easily be extended with multiple stocks: a crash in one stock may release information that is relevant to other stocks as well.

The model catches all three elements of crashes, as defined above: the movement can be out of proportion with the news event, due to the release of B's previously hidden signal. If A gets a good signal, it is simply incorporated in the price. If he gets a bad signal, though, then B's information may also be revealed; as such, more information is released when markets are falling. The release of information relevant for many stocks, even when only one of them is falling, results in a high correlation of returns in falling markets.

Hong & Stein's (2003) model thus predicts an increased frequency of extreme negative returns and a more negatively skewed (or less positively skewed) returns distribution when short sales are constrained. Negative skewness implies that the left tail of the returns distribution is fatter. Extreme negative returns are defined as returns that are two standard deviations below the mean (as per Arturo Bris et al. (2007), Chang, Cheng & Yu (2007) and others). A coefficient of skewness will be calculated (equation (1)), following Chang, Cheng & Yu (2007), by dividing the third moment of daily returns by their standard deviation raised to the third power.

(1) Coefficient of skewness = $$\frac{n(n-1)^{3/2}\sum R_{it}^{3}}{(n-1)(n-2)(\sum R_{it}^{2})^{3/2}}$$

Where n is the size of the sample, and R_{it} is the return of stock i on day t.

2.1.2 Market efficiency

Within the CAPM, short selling restrictions result in a loss of the property that combinations of efficient portfolios are also efficient portfolios. Thus, the aggregate market index (a combination of the efficient portfolios of all investors) cannot be efficient under short selling constraints (Haugen 2000).

Outside the CAPM, Miller (1977) develops a model in which a high divergence of opinion coupled with restrictions on short selling can result in overpricing and subsequent underperformance. He proposed a two-period model with one-year government bonds, and a single company taking on a project. At the end of the year the company is liquidated and the assets divided among the investors. Investors seek to maximize the present value of their investment; they make estimates about the return on the stock, and if it exceeds the return on government bonds, they purchase one share in the company (this assumption can be justified by limited funds, for example). There is uncertainty about the true return on the stock, so investors make different estimates.

Figure 1 below illustrates this principle; it is a graph of cumulative distribution of the number of investors with estimates above a certain value. The shape of the curve is derived from the fact that the extremes of the estimate distribution are thinner than the center: therefore the absolute value of the slope is higher the further it goes from the 50^{th} percentile. There are N shares available, so (given the assumption that each investor can only purchase one share) the price is determined by the intersection of ABC and N, i.e. R. The price is thus determined by the N most optimistic investors; if the price were any lower, more than N investors would want to hold the stock as they would believe it to be undervalued; its price would be bid up to R. If it were higher, some investors holding it would believe it to be overvalued and would sell it, driving the price down to R. As long as the whole supply can be absorbed by an optimistic minority, which is usually the case, since the number of investors holding a stock is much smaller than the total number of potential investors, the market clearing price will stay above the mean valuation of all investors, or the fundamental value.

The curve FBJ represents a greater divergence of opinion, and as can be seen, it results in a higher equilibrium price than ABC, and vice versa for the curve DBE. The shape of the curve changes to reflect that greater divergence of opinion means higher estimates of value for the optimists, and lower estimates for the pessimists. The higher equilibrium results because the greater divergence of opinion means that the optimists make relatively higher estimates of value, and the optimists are the only ones that matter in determining the price, due to the limited supply. The case of no divergence of opinion (every investor makes the same estimate) is the straight line GBH, which results in a price of G.

As Miller (1977) notes, if potential investors make unbiased estimates of returns distributions, and make investment decisions "in accordance with […] standard portfolio theory", the price prevailing in the market can be above the price that an investor with perfect information about the returns would be willing to pay. Thus, markets may not produce Pareto optimal results. If firms try to maximize the market value of their stocks, there will be overinvestment in sectors and specific firms in which divergence of opinion is highest.

Short selling allows the investor to create stock in a company, by paying an owner of an existing stock any dividends, and to return the borrowed shares upon demand. From the point of view of the holder of the borrowed stock, it is equal in almost all ways (except for voting power). The result of a short sale is an increase in the supply of stock on the market. On Figure 1, this would correspond to a shift of N towards the right, with a corresponding drop in price. If sufficiently many stocks are sold short, the price could even drop below the mean estimate, and the price would be determined by the pessimists. However, this is highly improbable since short selling is only profitable for securities that decline in price, at a rate sufficient to cover interest and dividends. The reason for this is that the short seller cannot use the proceeds from the short sale, but instead has to deposit them with the lender. A simple subnormal return is not enough if it is still positive. One implication of this, if combined with the existence of badly informed investors, is that it "destroys the theoretical case for the random walk hypothesis" (Miller 1977). As short selling is usually allowed and widely practiced, N is generally much higher than the number of stocks that have been issued. A ban on short selling would thus reduce N drastically, and result in an increase in overvaluation of the security.

Miller's model disregards the signaling effects of short selling: a short sale provides information about the estimate of the investor; other investors can use this and adjust their own estimates downwards.

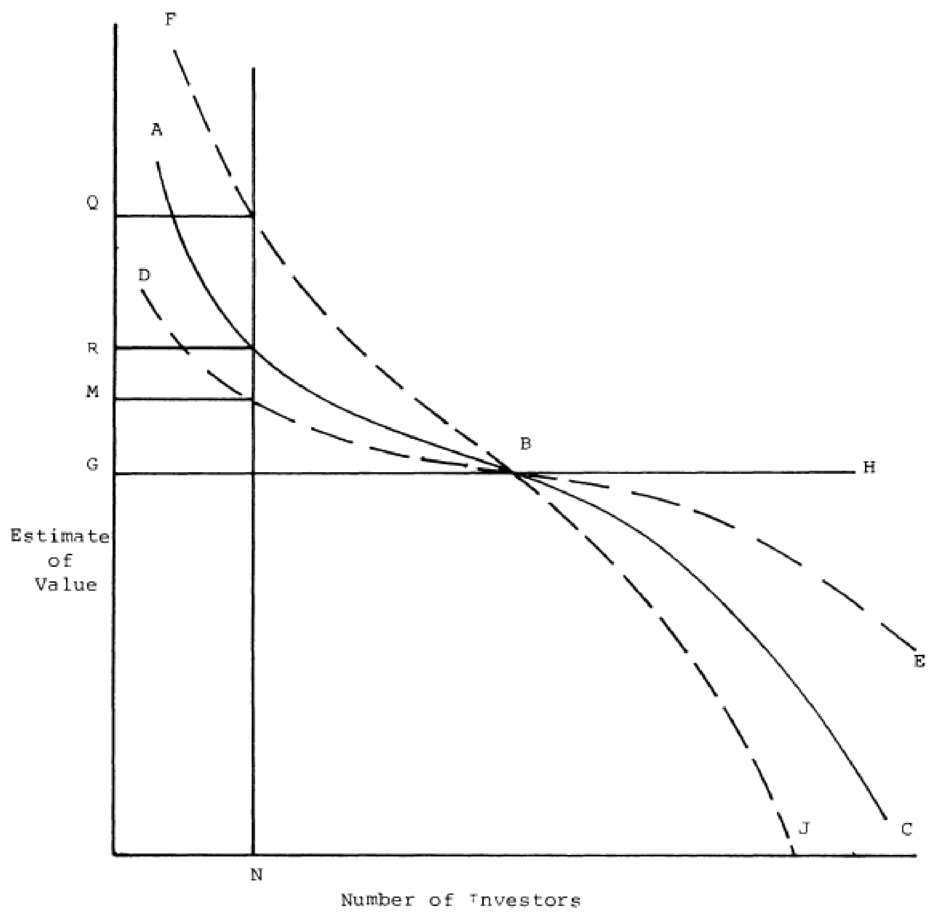


Figure 1 - Estimate of value versus cumulative number of investors
Source: Miller (1977)

Variables that can proxy for dispersion of opinion include: standard deviation of daily raw returns, standard deviation of error terms of the market model, and turnover (Harris and Raviv (1993) and Shalen (1993)). Due to the very high risk environment prevailing during the period under consideration (resulting, for example, in a high standard deviation of daily returns) the high divergence of opinion prerequisite for overpricing is assumed to hold true.

The short time period of the sample, along with the absolute nature of the short selling constraints (it was banned altogether) presents a situation which warrants a new approach to cumulative abnormal returns. If short selling constraints are indeed associated with an overvaluation, it "should disappear through time, either because the dispersion of beliefs is subsequently diminished […], or because the short-sale constraints are subsequently reduced" (Boehme et al. 2006). Thus, stocks that are subject to short-selling constraints are expected to produce negative abnormal returns as the overvaluation disappears. The source, however, of the negative abnormal returns is the relaxation of short selling constraints or a decrease in the dispersion of beliefs. Since the ban is absolute (there was no reduction in constraints until they were removed completely), and there is no reason to doubt there was a significant change in dispersion of beliefs, the abnormal returns during the ban are expected to be positive: the securities become overvalued. Since the removal of the restrictions is complete and instant, the overvaluation should disappear quickly after it: the banned stocks are expected to show significant negative abnormal returns the day the ban is lifted. Setting aside the issues of short interest, restrictions on institutional investors, and other assorted short sale constraints, I assume that short selling stocks that were not on the ban list was completely unrestricted during the period under consideration.

Eight price-weighted portfolios each containing a random selection of the banned stocks will be constructed. The stocks on the banned list will be divided into 8 portfolios, and their abnormal returns will be evaluated. Two models will be used to measure abnormal returns, (a) a returns model simply based on the capital asset pricing model (CAPM) shown in equation (2), and (b) a four-factor (F-F) regression model based on the Fama-French three factor model (Fama & French 1993) combined with Carhart's (1997) momentum factor added to account for momentum bias, shown in equation (3). I will also calculate cumulative abnormal returns (CAR) over the period during which short sales were prohibited (equations (4) and (5)).

$$(2)\quad AR_{CAPM,i,t} = \alpha_{it} = R_{it} - R_{ft} - \beta_i (R_{mt} - R_{ft})$$

$$(3)\quad AR_{F-F,i,t} = \alpha_{it} = R_{it} - R_{ft} - \beta_i (R_{mt} - R_{ft}) - s_i SMB_t - h_i HML - u_i UMD$$

$$(4)\quad CAR_{CAPM,i,t_1,t_2} = \sum_{t=t_1}^{t_2} AR_{CAPM,i,t}$$

$$(5)\quad CAR_{F-F,i,t_1,t_2} = \sum_{t=t_1}^{t_2} AR_{F-F,i,t}$$

In both models, the value of α_{it} is interpreted as the abnormal return earned by security i at time t. CAR(t_1,t_2) is the cumulative abnormal return between times t_1 and t_2. The factors of the four-factor model are calculated from the relative performances of different portfolios consisting of shares of companies with specific properties such as size and book to market ratios. SMB is the size factor, and is equal to the average return on three portfolios comprised of small companies, minus the average return on three portfolios comprised of large companies. HML is the growth factor and is equal to the average return on two "value" portfolios minus the average return on two "growth" portfolios[3]. Finally, UMD is the momentum factor, calculated as "the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios" (French n.d.).

2.2 Hypotheses

From the above theoretical analysis of Hong & Stein's (2003) model of crashes due to short sale constraints and Miller's (1977) model of overvaluation due to short sale restrictions, I extract the following hypotheses:

Hypothesis 1: *short sale constraints (a) increase the negative skewness of the returns distribution, and (b) increase the frequency and magnitude of extreme negative returns.*

Hypothesis 2: *short sale constraints lead to overvaluation of the affected securities, i.e. positive abnormal returns during the ban period, and negative abnormal returns when the ban is lifted.*

Due to its significance on regulatory matters, and because it is an often cited reason for the introduction of short sale constraints, I also construct a hypothesis to test the effects of short sale constraints on market volatility:

Hypothesis 3: *short sale constraints decrease the variance of the returns distributions of the affected securities.*

[3] "Value" portfolios are those comprised of companies with high book-to-price ratios, while "growth" portfolios are those comprised of companies with low book-to-price ratios.

3 Data

3.1 Sample

The recent restrictions on short selling provide a new and quite interesting, albeit temporally limited, dataset which is used in this paper. A usual problem in previous literature is finding a suitable proxy for the relative level of constraints (short interest is a widely used proxy). This is not an issue in this case because of the outright ban on shorting some stocks.

After discarding stocks for which data is not available for the whole period under examination, 758 are left out of the original 799. These will comprise the sample of banned stocks. Two sets of panel data of the 758 remaining securities that are subject to short selling restrictions are used. The first, from August 7, 2007 (the day the ECB and the Fed injected $90bn into the financial system; this date will be used as the beginning of the liquidity crisis) to September 18, 2008 (thus covering 283 trading days), a period during which short selling was allowed, and widely practiced (this will be called the pre-ban period). The second is from September 19, 2008 to October 9, 2008 (a period containing 15 trading days); this is the period during which the restrictions were in place.

Selection bias is a significant problem with the data: the securities were selected because short selling "may be causing sudden and excessive fluctuation" (SEC 2008) of their prices, and they all had ties to the financial sector, which was experiencing significant turmoil during the relevant periods. Another reason cited by the SEC is the potential for "short and distort" tactics; however, these are always possible and by themselves are not enough to warrant a ban. This selection bias is even more troubling because it is not possible to overcome: it arises from the SEC's subjective choice of securities to ban short selling in. Thus, the returns of the selected securities are expected to show relatively high volatility, and have relatively highly correlated returns due to financial industry-specific shocks; these issues can weaken the significance of the results. However, the banned stocks are not all strictly confined to the financial sector: even corporations with very weak ties to financial services were on the list, thus somewhat decreasing the effects of selection bias.

Values of the Standard & Poor's 500 index, as well as the returns, an approximation for the market as a whole, from the same time periods will be used as a benchmark, and to control for market-wide effects. There is no overlap between the securities in the S&P 500 index and the ones on the banning list. For the individual stocks on the S&P 500, 400 stocks are used as an approximation, all of which have full data available for the period under consideration.

The daily data for the four-factor model has been taken and is available from Kenneth French's web page. The effect of liquidity constraints on the part of institutional investors might create a problem: even the most optimistic investors might not be able to invest in the securities they want because of liquidity issues.

3.2 Descriptive Statistics

Table 10 in Appendix 1 contains descriptive statistics on the returns of the banned stocks, individual S&P 500 stocks, the S&P 500 index, and the averages for the portfolios constructed from the banned stocks. These statistics are presented separately for the two periods.

3.3 Statistical Method

The skewness coefficient of the returns distributions of the portfolios, the individual stocks, the S&P 500, and the individual stocks from the S&P 500 will be calculated as per equation (1). The frequency and magnitude of extreme returns (defined as returns below two standard deviations below the mean) will be calculated for the individual stocks affected by the ban, individual S&P 500 stocks, and the portfolios.

Ordinary least squares regressions will be run to fit the CAPM and the F-F model on the returns of the eight portfolios. The resulting coefficients will be used to calculate abnormal returns during the two periods under consideration, according to equations (2)-(5). The daily and cumulative abnormal returns will then be tested for significance.

This methodology is problematic in that the banned securities are compared either with themselves (pre-ban and during the ban), or they are compared with the S&P 500 index. The former might underestimate the significance of the observed effects, and the results do not contain any information about the actual size of the loss due to the decreased market efficiency. The latter is largely ineffective: the index and the banned stocks are affected in different ways by external events. In order to properly assess the effect of the ban on short selling (that is, the size of the deadweight loss due to decreased efficiency), the development of the affected stocks **had the ban not happened** must be calculated through the use of a control group, and then compared with their actual returns. Otherwise, it would not be possible to determine the size or existence of the short-sale ban effect, as the results could simply be effects of other, external variables. However, to do this would require methods (the use of difference-in-differences, and the creation of “twin” securities) that are unsuitable for a bachelor thesis. Despite its faults, the methodology described above is employed. It can still yield an estimate and allow the effects of the ban to be analysed and conclusions to be drawn.

4 Results and Analysis

4.1 Crashes

4.1.1 Skewness

To test part a of the first hypothesis, I calculate the coefficient of skewness for the returns distributions of individual banned stocks, the portfolios, the S&P 500 index, and individual stocks on the S&P 500 index. As can be seen in Table 1, the coefficient of skewness of the distribution of returns on individual stocks on the ban list became more positive during the ban, from 3.508868 during the pre-ban period, to 5.00391 during the period of the ban; a result contrary to my expectations. The skewness of the S&P 500 returns distribution also fell during the same period, from -0.3263471 to -1.274880. The coefficient of skewness of the distribution of the returns on the portfolios became more negative, as expected, a change significant at the 1% level (t-value: 18.624). It is interesting to note that the coefficient of skewness is positive for both individual stocks and the portfolios before the ban: Hong & Stein (2003) speculate that this is due to information flows from the listed companies: managers prefer to reveal negative information piecemeal, but reveal positive information all at once.

In the case of portfolio returns, these results are consistent with the predictions of Hong & Stein's (2003) model: the left tail of the returns distribution becomes relatively fatter when short selling is disallowed; I can not reject the hypothesis that short selling constraints make returns distributions more negatively skewed. These results do not hold on the individual stock level, though, where the hypothesis is rejected.

Table 1 - Coefficient of skewness

	Before Ban	*During Ban*
Individual banned stocks	3.508868	5.003910
S&P 500	-0.326347	-1.274880
Individual S&P 500 stocks	-3.648752	-1.978450
Portfolio 1	0.649218	-1.394974
Portfolio 2	0.285370	-1.303080
Portfolio 3	0.209648	-1.882976
Portfolio 4	0.194499	-1.625577
Portfolio 5	0.221512	-2.206513
Portfolio 6	0.279929	-1.467512
Portfolio 7	0.172863	-1.516616
Portfolio 8	0.263778	-2.014266

4.1.2 Extreme Returns

In order to test part b of hypothesis 1, I have calculated the frequency and size of extreme negative returns (defined as any returns below two standard deviations below the mean) before and during the ban period, but using the same cut-off point for both periods. As can be seen in Table 2, there is an increase across the board in the frequency of crashes. This increase is in line with the expectations from the Hong & Stein (2003) model, but given the increase in crashes in the market as a whole during that period, the effects of the ban and market-wide shocks would have to be disentangled and separated. It is nonetheless interesting to note that the frequency increased the most (more than the S&P 500 stocks) for the portfolios, while it increased the least (less than the S&P 500 stocks) for individual banned stocks. This result echoes the outcome of the skewness test, above, in which the Hong & Stein (2003) predictions seemed to apply to the portfolios but not the individual stocks.

The size of the crashes increased (a change significant at the 1% level) during the ban period, but this increase was across the board, and extracting the effect of the ban from the data would, like in the case of the frequencies above, require advanced econometric techniques not suitable for a bachelor thesis.

Table 2 – Frequency and magnitude of extreme returns

	Frequency of extreme negative returns			***Average size of negative extreme returns***	
	Before ban period	**During ban period**	**% Difference**	**Before ban period**	**During ban period (Z-value)**
Individual banned stocks	1.8796%	13.0146%	692%	-12.1048%	-13.3094%*** (-4.640)
Individual S&P 500 stocks	1.4002%	20.1500%	1439%	-9.8399%	-10.9463%*** (-7.031)
Portfolios	1.1042%	22.3214%	2021%	-4.5455%	-5.9681%*** (-3.457)

*,**,***: change between the periods significant at 10%, 5%, 1% significance level, Mann-Whitney test.

4.2 Market Efficiency

4.2.1 CAPM

The regression results of the CAPM model on the 8 portfolios are summarized in Table 3 (the full results can be found in Appendix 2). Autocorrelation of the residuals is not an issue, as the Durbin-Watson statistic did not take any values indicative of a problem. As can be seen from the adjusted R^2 values, the CAPM model is a relatively good fit to the data. The F-values, as well as the t-values, indicate that β is non-zero and related to portfolio returns.

Table 3 - CAPM regression results, dependent variable: portfolio returns

Portfolio	*β (t-value)*	*F-value*	R^2
Portfolio 1	1.156 (34.003)	1156.199	0.796
Portfolio 2	1.086 (28.304)	801.106	0.730
Portfolio 3	0.746 (23.361)	545.749	0.648
Portfolio 4	1.026 (32.369)	1047.736	0.780
Portfolio 5	0.714 (27.364)	748.812	0.717
Portfolio 6	1.020 (26.448)	699.495	0.703
Portfolio 7	0.998 (27.508)	765.673	0.719
Portfolio 8	1.353 (23.265)	541.269	0.646

The CAPM results regarding daily and cumulative abnormal returns for the two periods under consideration are tabulated in Table 7. The daily abnormal returns of the portfolios increased on average during the ban period compared to the period before the ban, as was expected; the change is significant at the 1% level (t-value: -5.411, 2 sample t-test; Z: -4.825 Mann-Whitney test). The daily abnormal returns were not significantly different from zero for any of the portfolios before the ban and only significant for two of the portfolios during the ban.

The cumulative abnormal returns during the pre-ban period are not significantly different from zero (none of the daily abnormal returns are significantly different from zero, either). On the other hand, the cumulative abnormal returns for the period of the ban are positive (with daily abnormal returns for 6 out of the 8 portfolios not being significantly different from 0), and significantly different from 0 at the 1% level, as was expected.

The abnormal returns for the portfolios on September 19th and October 9 (the day the ban begun, and the day it ended) are shown in Table 4: as expected, there are positive abnormal returns on the 19th, significantly different from 0 at the 1% level. On October 9th they are negative; they are significantly different from 0 at the 5% level.

These results are perfectly in line with the predictions of Miller's model: securities are overvalued in the absence of short selling, thus leading to positive abnormal returns. When the restrictions are lifted, the overvaluation starts to disappear, leading to negative abnormal returns.

Table 4 - Abnormal returns (CAPM)

Portfolio	*Abnormal returns September 19th*	*Abnormal returns October 9th*
Portfolio 1	0.0140892	-0.014434
Portfolio 2	0.027702	-0.02221
Portfolio 3	0.041041	-0.01561
Portfolio 4	0.038539	-0.03026
Portfolio 5	0.019192	-0.036145
Portfolio 6	0.035765	-0.01959
Portfolio 7	0.01466	-0.0187
Portfolio 8	0.034776	-0.09053
Average	0.028221*** (7.304)	-0.030935** (3.474)

*,**,***: significantly different from 0 at 10%, 5%, 1% significance level, one-sample t-test.

4.2.2 Four-Factor Market Model

The results of the regressions are summarized in Table 5 (the full results are presented in Appendix 3). The adjusted R^2 is higher than in the CAPM regressions in all cases, indicating that the model is a better fit to the data. Multicollinearity was not an issue with the data; again, the residuals did not present any worrying levels of autocorrelation. Heteroscedasticity was not as issue either; Graphs 3-5 in Appendix 4 contain residual plots and histograms for portfolio 7. The F-values indicate that at least one of the parameters is non-zero and thus related to the portfolio returns. The t-values for each parameter and in each regression indicate that they are significantly different from 0 at the 1% level of significance.

Table 5 - F-F model regression results, dependent variable: portfolio returns

Portfolio	*β (t-value)*	*h (t-value)*	*s (t-value)*	*u (t-value)*	*F-value*	*R^2*
Portfolio 1	0.879 (39.841)	0.003 (10.559)	0.006 (5.172)	-0.004 (-11.140)	1168.615	0.941
Portfolio 2	0.821 (26.172)	0.003 (7.482)	0.006 (4.327)	-0.003 (-7.368)	518.655	0.876
Portfolio 3	0.577 (20.033)	0.004 (4.986)	0.003 (6.187)	-0.002 (-5.983)	300.077	0.804
Portfolio 4	0.864 (33.315)	0.006 (6.866)	0.004 (9.553)	-0.002 (-5.582)	650.733	0.899
Portfolio 5	0.581 (26.014)	0.004 (7.076)	0.004 (8.338)	-0.001 (-4.714)	441.785	0.858
Portfolio 6	0.766 (26.580)	0.005 (6.798)	0.005 (7.777)	-0.004 (-9.211)	568.113	0.886
Portfolio 7	0.767 (29.743)	0.006 (7.290)	0.005 (9.723)	-0.003 (-9.444)	677.589	0.902
Portfolio 8	0.940 (20.784)	0.005 (8.152)	0.009 (5.058)	-0.005 (-7.954)	425.333	0.853

Table 8 contains daily and cumulative abnormal returns resulting from the F-F model. The daily abnormal returns of the portfolios increased during the ban period compared to the pre-ban period, as was expected, the change being significant at the 1% level (t-value: -6.911 2 sample t-test; Z: -6.482 Mann-Whitney test). The daily abnormal returns of only one portfolio were significantly different from zero during the pre-ban period, while there were four portfolios with significantly non-zero daily abnormal returns during the ban. Contrary to the results of the CAPM model, in the F-F model the cumulative abnormal returns during the pre-ban period are significantly different from zero (at the 5% level) and negative. On the other hand, the cumulative abnormal returns for the period of the ban are positive and significantly different from 0 at the 1% level, pointing towards an overvaluation effect, as was expected.

The abnormal returns for the portfolios on September 19th and October 9 (the day the ban begun, and the day it ended) are shown in Table 6: again as expected, there are positive abnormal returns on the 19th, significantly different from 0 at the 1% level. On October 9th they are negative; they are significantly different from 0 at the 5% level. As was the case with the CAPM, the negative abnormal returns on September 19th do not correspond to the cumulative abnormal returns during the ban period (except in the case of portfolio 8): the overvaluation does not completely disappear.

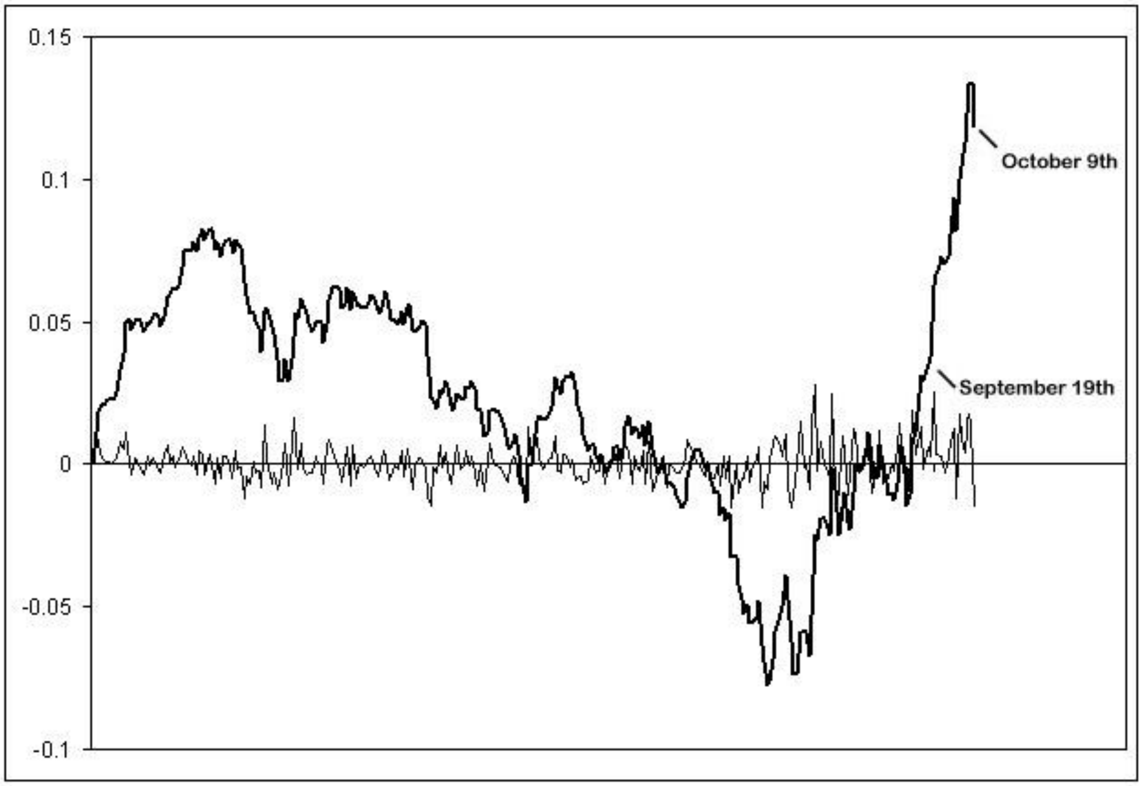
Table 6 - Abnormal returns (F-F model)

Portfolio	*Abnormal returns September 19th*	*Abnormal returns October 9th*
Portfolio 1	0.01580	-0.01907
Portfolio 2	0.02803	-0.02512
Portfolio 3	0.03256	-0.01117
Portfolio 4	0.02726	-0.02169
Portfolio 5	0.01252	-0.03053
Portfolio 6	0.02511	-0.01539
Portfolio 7	0.00168	-0.01195
Portfolio 8	0.034056	-0.09395
Average	0.022127*** (5.608)	-0.02860875** (-2.974)

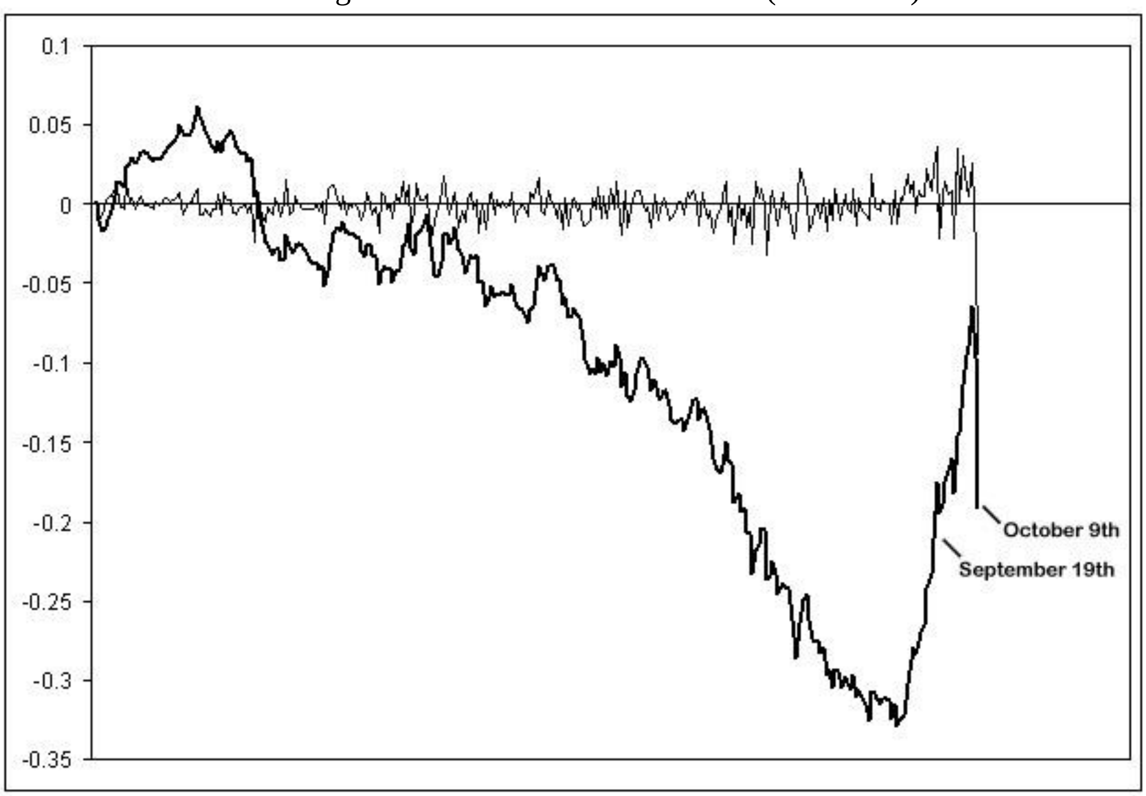
*,**,***: significantly different from 0 at 10%, 5%, 1% significance level, one-sample t-test.

Graphs 1 and 2 are graphs of daily and cumulative abnormal returns using the F-F model, for portfolios 7 and 8 respectively, with the x-axis representing time, and the y-axis representing abnormal returns. The fat line represents cumulative abnormal returns since the start of the sample, while the thin line represents daily abnormal returns. They illustrate the change during the ban period: the cumulative abnormal returns increase, an effect of positive daily abnormal returns, indicative of the stock being overpriced. Additionally, the negative abnormal returns on October 9th, the last data point, can easily be seen, and are especially prominent in the case of portfolio 8.

Like the CAPM results, the F-F model results are in line with the predictions of Miller's model, showing a tendency towards overvaluation during the ban period. None of the results from any of the two models offers any reason to reject the hypothesis that short selling constraints lead to overpricing.



Graph 1 – Daily (thin line) & cumulative (thick line) abnormal returns of portfolio 7, from August 7th 2007 to October 9th 2008 (F-F model)



Graph 2 – Daily (thin line) & cumulative (thick line) abnormal returns of portfolio 8, from August 7th 2007 to October 9th 2008 (F-F model)

Table 7 - Abnormal returns (CAPM)

Portfolio	*Before Ban* Average Daily Abnormal Returns (t-value)	*Before Ban* Cumulative Abnormal Returns	*During Ban* Average Daily Abnormal Returns (t-value)	*During Ban* Cumulative Abnormal Returns
Portfolio 1	-0.00026 (-0.482)	-0.07365	0.00351 (0.885)	0.04917
Portfolio 2	-0.00027 (-0.461)	-0.07555	0.01144** (2.263)	0.16019
Portfolio 3	-0.00039 (-0.795)	-0.11033	0.00640 (1.494)	0.08960
Portfolio 4	0.00000 (0.006)	0.00086	0.00379 (0.797)	0.05306
Portfolio 5	-0.00032 (-0.831)	-0.09111	0.00141 (0.396)	0.01976
Portfolio 6	0.00025 (0.407)	0.07141	0.00568 (1.495)	0.07949
Portfolio 7	0.00032 (0.544)	0.09105	0.00578* (2.039)	0.08091
Portfolio 8	-0.00050 (-0.574)	-0.14210	0.00697 (1.079)	0.09754
Averages	-0.00015	-0.04118 (-1.356)	0.00562	0.07872*** (5.350)

*,**,***: significantly different from 0 at 10%, 5%, 1% significance level, one-sample t-test.

Table 8 - Abnormal returns (F-F model)

Portfolio	*Before Ban* Average Daily Abnormal Returns (t-value)	*Before Ban* Cumulative Abnormal Returns	*During Ban* Average Daily Abnormal Returns (t-value)	*During Ban* Cumulative Abnormal Returns
Portfolio 1	-0.00037 (-1.207)	-0.10612	0.00411 (1.182)	0.05755
Portfolio 2	-0.00041 (-1.128)	-0.11666	0.01223** (2.585)	0.17115
Portfolio 3	-0.00051 (-1.442)	-0.14387	0.00744* (2.060)	0.10419
Portfolio 4	-0.00023 (-0.715)	-0.06507	0.00543 (1.523)	0.07608
Portfolio 5	-0.00053** (-2.007)	-0.15011	0.00270 (0.989)	0.03783
Portfolio 6	0.00013 (0.356)	0.03761	0.00690** (2.659)	0.09658
Portfolio 7	0.00017 (0.504)	0.04904	0.00722*** (3.163)	0.10106
Portfolio 8	-0.00074 (-1.453)	-0.21046	0.00831 (1.511)	0.11635
Averages	-0.00031	-0.08821** (-2.736)	0.00679	0.09510*** (6.663)

*,**,***: significantly different from 0 at 10%, 5%, 1% significance level, one-sample t-test.

4.3 Volatility

The variances of the returns are tabulated in Table 9, below. There is a clear increase in variance across the board, however when the portfolio variances are corrected for the market variance, it decreases during the ban period compared to the pre-ban period. The average of the raw variances increases during the ban period, from 0.0003039396 to 0.0017257067, a change that is statistically significant at the 1% level (t-value: -4.122). The average of the corrected variances decreases during the ban period: from 1.5567 to 1.1826. This change is also significant at the 1% level (t-value: 4.079). With reference to the raw volatility, I cannot reject the third hypothesis (that short sale restrictions increase market volatility). However, with reference to the market-corrected volatilities, and contrary to the hypothesis, the introduction of a ban on short selling seems to have relatively decreased the volatility of the affected securities, both at the individual stock and at the portfolio levels.

Table 9 - Variance

	Before Ban	***During Ban***	***Before Ban, Corrected***	***During Ban, Corrected***
Individual banned stocks	0.001539361	0.007920846	7.88400	5.42819
S&P 500	0.000195251	0.001459205	N/A	N/A
Portfolio 1	0.000337265	0.002008970	1.72734	1.37676
Portfolio 2	0.000325340	0.002242375	1.66626	1.53671
Portfolio 3	0.000198314	0.000573419	1.01569	0.39297
Portfolio 4	0.000270955	0.001500480	1.38771	1.02829
Portfolio 5	0.000142667	0.000770136	0.73069	0.52778
Portfolio 6	0.000320100	0.001335461	1.63943	0.91520
Portfolio 7	0.000298294	0.001344620	1.52775	0.92147
Portfolio 8	0.000538585	0.004030193	2.75842	2.76191
Portfolio Averages	0.000303940	0.001725707	1.55670	1.18260

5 Conclusions

In this paper I examine a ban on short selling and its effects on crashes, the efficiency of the price discovery mechanism, and market volatility. I posit three hypotheses: (1) a ban on short selling will increase the frequency and magnitude of extreme negative returns, and increase the negative skewness of the returns distribution; (2) a ban on short selling will result in overvaluation of the affected securities; (3) a ban on short selling will decrease the variance of the returns distribution. To test these hypotheses I used data from the recent SEC ban on short selling in the U.S., testing both individual stocks and a series of value-weighted portfolios created from them.

The results regarding the first hypothesis, which is derived from Hong & Stein's (2003) model of market crashes, were ambiguous. Both on the individual security, and the portfolio level, the frequency of crashes increased during the period when short sales were banned. The size of the crashes also increased, but the increase was proportionally smaller than the corresponding increase for the S&P 500 stocks, which also showed an increase in both the frequency and size of crashes.

The coefficient of skewness of the returns of individual banned stocks became more positive, contrary to the hypothesis. On the portfolio level, however, the skewness coefficient of the returns distributions of the portfolios became more negative (in line with expectations from the model), indicating that the left tail of the returns distribution of portfolios became heavier.

Two separate market models were created in order to test the second hypothesis: the capital asset pricing model, and a four-factor model comprised of the three-factor Fama-French model extended with Carhart's (1997) momentum factor. In regards to the efficiency of the pricing mechanism, the results were almost fully in line with the predictions of Miller's (1977) model: portfolios display positive abnormal returns during the ban period, pointing to an overvaluation. The CAPM showed positive cumulative abnormal returns of approximately 7.8% during the ban period, while the four-factor model showed approximately 9.5% positive cumulative abnormal returns during the same period. On October 9th, the day the ban was lifted, all portfolios exhibit significant negative abnormal returns, indicating that the overvaluation recedes.

The raw variance of individual banned stocks and portfolios increased during the ban period. However, after controlling for market volatility, the variance of the returns of both individual stocks and portfolios decreased during the period short selling was banned, thus providing support for the third hypothesis. This result is important from a policy perspective, as many regulators cite the volatility effects of short selling when introducing restrictions against it.

Due to the weakness of the methodology however, it is not possible to separate the effects of market-wide fluctuations from the effects of the ban on short selling. Moreover, comparisons between the securities on the ban list and the S&P 500 are not completely meaningful because different external factors affect the two groups. These methodological limitations thus lessen the meaningfulness of the above results, making it impossible to draw definitive conclusions. Despite this, in light of these results, the Security and Exchange Commission's justification of the ban as protecting "fair and orderly markets" seems out of place.

5.1 Further Remarks

This case of systematic overvaluation of short-sale constrained stocks points to a violation of the efficient markets hypothesis. Given the adverse effects of short selling constraints on the pricing mechanism, the argument for constraints is significantly weakened.

There is no reason to think these results would not apply to situations where the short sale constraints are milder (in the case of high short interest, for example). Market models like the Fama-French model could be extended to include factors such as short interest and dispersion of beliefs to account for the overpricing effect of short sale constraints. Further studies into the effect of short sale constraints on crashes might also want to take trading volume into concern, as the Hong & Stein (2003) model predicts that negative skewness will be most pronounced under high trading volumes. In light of the decreased options volume when the short selling ban went into effect, the relationship between short selling restrictions and options is a topic that deserves further attention. Furthermore, studies of practical trading strategies that take advantage of similar bans could prove to be interesting.

6. References

Abreu, D. & Brunnermeier, M.K., 2003. Bubbles and Crashes. *Econometrica*, 71(1), 173-204.

Abreu, D. & Brunnermeier, M.K., 2002. Synchronization risk and delayed arbitrage. *Journal of Financial Economics*, 66(2-3), 341-360.

Aitken, M.J. et al., 1998. Short Sales Are Almost Instantaneously Bad News: Evidence from the Australian Stock Exchange. *Journal of Finance*, 53(6), 2205-2223.

Allen, F. & Gale, D., 1991. Arbitrage, Short Sales, and Financial Innovation. *Econometrica*, 59(4), 1041-1068.

Arturo Bris, William N. Goetzmann & Ning Zhu, 2007. Efficiency and the Bear: Short Sales and Markets Around the World. *Journal of Finance*, 62(3), 1029-1079.

Asquith, P. & Meulbroek, L., 1995. An empirical investigation of short interest, Working paper.

Asquith, P., Pathak, P.A. & Ritter, J.R., 2005. Short interest, institutional ownership, and stock returns. *Journal of Financial Economics*, 78(2), 243-276.

Bekaert, G. & Wu, G., 2000. Asymmetric Volatility and Risk in Equity Markets. *Review of Financial Studies*, 13(1), 1-42.

Bernardo, A.E. & Welch, I., 2004. Liquidity and Financial Market Runs. *Quarterly Journal of Economics*, 119(1), 135-158.

Blau, B.M., 2008. Short-Sale Constraints, Listing Decisions, and Return Predictability around Option Introductions, Working Paper. Available at: http://ssrn.com/abstract=1260354.

Boehme, R.D., Danielsen, B.R. & Sorescu, S.M., 2006. Short-Sale Constraints, Differences of Opinion, and Overvaluation. *Journal of Financial & Quantitative Analysis*, 41(2), 455-487.

Boehmer, E., Jones, C.M. & Zhang, X., 2008. Which Shorts Are Informed? *The Journal of Finance*, 63(2), 491-527.

Brent, A., Morse, D. & Stice, E.K., 1990. Short Interest: Explanations and Tests. *The Journal of Financial and Quantitative Analysis*, 25(2), 273-289.

Carhart, M.M., 1997. On Persistence in Mutual Fund Performance. *The Journal of Finance*, 52(1), 57-82.

Chang, E.C., Cheng, J.W. & Yu, Y., 2007. Short-Sales Constraints and Price Discovery: Evidence from the Hong Kong Market. *The Journal of Finance*, 62(5), 2097-2121.

Curtis, A. & Fargher, N.L., 2008. Does Short-Selling Amplify Price Declines or Align Stocks with Their Fundamental Values? . Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=817446 [Accessed October 5, 2008].

Cutler, D.M., Poterba, J.M. & Summers, L.H., 1989. What Moves Stock Prices? *Journal of Portfolio Management*, 15(3), 4-12.

Danielsen, B.R. & Sorescu, S.M., 2001. Why Do Option Introductions Depress Stock Prices? A Study of Diminishing Short Sale Constraints. *The Journal of Financial and Quantitative Analysis*, 36(4), 451-484.

Dechow, P.M. et al., 2001. Short-sellers, fundamental analysis, and stock returns. *Journal of Financial Economics*, 61(1), 77-106.

Desai, H. et al., 2002. An Investigation of the Informational Role of Short Interest in the Nasdaq Market. *The Journal of Finance*, 57(5), 2263-2287.

Diamond, D.W. & Verrecchia, R.E., 1987. Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics*, 18(2), 277-311.

Diether, K.B., Lee, K. & Werner, I.M., 2008. Short-Sale Strategies and Return Predictability. *Rev. Financ. Stud.*, hhn047.

Diether, K.B., Malloy, C.J. & Scherbina, A., 2002. Differences of Opinion and the Cross Section of Stock Returns. *The Journal of Finance*, 57(5), 2113-2141.

Duffee, G.R., 2001. Available at: http://www.frbsf.org/econrsrch/workingp/2000/wp00-18bk.pdf.

Duffie, D., Gârleanu, N. & Pedersen, L.H., 2002. Securities lending, shorting, and pricing. *Journal of Financial Economics*, 66(2-3), 307-339.

Fama, E.F. & French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3-56.

Figlewski, S., 1981. The Informational Effects of Restrictions on Short Sales: Some Empirical Evidence. *The Journal of Financial and Quantitative Analysis*, 16(4), 463-476.

Figlewski, S. & Webb, G.P., 1993. Options, Short Sales, and Market Completeness. *The Journal of Finance*, 48(2), 761-777.

French, K.R., Kenneth R. French - Data Library. Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html [Accessed December 24, 2008].

Haugen, R.A., 2000. *Modern Investment Theory (5th Edition)* 5th ed., Prentice Hall.

Hong, H. & Stein, J.C., 2003. Differences of Opinion, Short-Sales Constraints, and Market Crashes. *The Review of Financial Studies*, 16(2), 487-525.

Jarrow, R., 1980. Heterogeneous Expectations, Restrictions on Short Sales, and Equilibrium Asset Prices. *The Journal of Finance*, 35(5), 1105-1113.

Jones, C.M. & Lamont, O.A., 2002. Short-sale constraints and stock returns. *Journal of Financial Economics*, 66(2-3), 207-239.

Klemkosky, R.C. & Resnick, B.G., 1979. Put-call parity and market efficiency. *Journal of Finance*, 34(5), 1141-1155.

Machintosh, J., 2008. Short shrift. *Financial Times*. Available at: http://www.ft.com/cms/s/0/f8328a36-92fc-11dd-98b5-0000779fd18c.html [Accessed October 5, 2008].

Mayhew, S. & Mihov, V.T., 2005. Short Sale Constraints, Overvaluation, and the Introduction of Options. In *AFA 2005 Philadelphia Meetings. Available at SSRN: http://ssrn.com/abstract=544245*.

Miller, E.M., 1977. Risk, Uncertainty, and Divergence of Opinion. *Journal of Finance*, 32(4), 1151-1168.

Ofek, E. & Richardson, M., 2003. DotCom Mania: The Rise and Fall of Internet Stock Prices. *Journal of Finance*, 58(3), 1113-1137.

Ofek, E., Richardson, M. & Whitelaw, R.F., 2004. Limited arbitrage and short sales restrictions: evidence from the options markets. *Journal of Financial Economics*, 74(2), 305-342.

Reed, A.V., 2002. *Costly short-selling and stock price adjustment to earnings announcements*. Master's Dissertation. University of Pennsylvania.

Saffi, P.A.C. & Sigurdsson, K., 2007. Price Efficiency and Short-Selling. In *AFA 2008 New Orleans Meetings Paper. Available at SSRN: http://ssrn.com/abstract=949027*.

Santini, L., 2008. In Australia, Soul-Searching on Short-Selling: Investors turn to a familiar scapegoat as stock slump hits home. *The Wall Street Journal* April 4th.

Scheinkman, J. & Xiong, W., 2003. Overconfidence and Speculative Bubbles. *The Journal of Political Economy*, 111(6), 1183.

Securities and Exchange Commission, 2008. SEC Halts Short Selling of Financial Stocks to Protect Investors and Markets. Available at: http://www.sec.gov/rules/other/2008/34-58592.pdf [Accessed December 24, 2008].

Taulli, T., 2004. *What is short-selling?*, New York, NY: McGraw-Hill.

The Options Insider, 2008. Short Selling Ban Sends Chills Through Options Market. Available at: http://seekingalpha.com/article/99031-short-selling-ban-sends-chills-through-options-market [Accessed January 31, 2009].

Wang, J., Chang, E.C. & Bai, J., 2006. Asset Prices Under Short-Sale Constraints. Available at: http://www.fep.up.pt/investigacao/cempre/actividades/sem_fin/sem_fin_01_05/PAPERS_PDF/paper_sem_fin_23mar06.pdf [Accessed October 5, 2008].

Yahoo! Inc., Yahoo! Finance. Available at: http://finance.yahoo.com/.

7 Appendices

Appendix 1 – Descriptive Statistics

Table 10 - Descriptive Statistics for periods August 7th 2007 – September 18th 2008, and September 19th 2008 – October 8th 2008

	Before ban				*During ban*			
	Mean	**# of observations**	**Std. dev.**	**Skewness**	**Mean**	**# of observations**	**Std. dev.**	**Skewness**
Individual banned stocks returns	-0.00061	214514	0.03923	3.557	-0.00892	11370	0.08899	5.381
Individual S&P 500 stocks returns	-0.00084	113200	0.02897	-3.566	-0.02281	6000	0.06483	-1.258
S&P 500 returns	-0.00069	283	0.01397	-0.178	-0.01449	15	0.03820	-.186
Portfolio returns	-0.00060	2264	0.01684	0.850	-0.00953	120	0.03996	0.418
Portfolio abnormal returns (CAPM)	-0.00015	2264	0.00983	0.964	0.0056	120	0.01639	-0.138
Portfolio abnormal returns (F-F)	-0.00031	2264	0.00608	-0.100	0.0068	120	0.01369	-0.099

Source: Yahoo! Finance

Appendix 2 – Regression Results (CAPM)

Portfolio 1 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.892	.796	.795	.00946	1.652

Portfolio 1 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.103	1	.103	1156.199	.000
	Residual	.026	296	.000		
	Total	.130	297			

Portfolio 1 - Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	-2.879E-5	.001		-.052	.958
MktMinRf	1.156	.034	.892	34.003	.000

Portfolio 2 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.855	.730	.729	.01068	1.685

Portfolio 2 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.091	1	.091	801.106	.000
	Residual	.034	296	.000		
	Total	.125	297			

Portfolio 2 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.000	.001		.501	.617
	MktMinRf	1.086	.038	.855	28.304	.000

Portfolio 3 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.805	.648	.647	.00889	1.507

Portfolio 3 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.043	1	.043	545.749	.000
	Residual	.023	296	.000		
	Total	.066	297			

Portfolio 3 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2.019E-5	.001		-.039	.969
	MktMinRf	.746	.032	.805	23.361	.000

Portfolio 4 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.883	.780	.779	.00882	1.646

Portfolio 4 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.082	1	.082	1047.736	.000
	Residual	.023	296	.000		
	Total	.105	297			

Portfolio 4 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.000	.001		.353	.724
	MktMinRf	1.026	.032	.883	32.369	.000

Portfolio 5 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.847	.717	.716	.00726	1.718

Portfolio 5 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.040	1	.040	748.812	.000
	Residual	.016	296	.000		
	Total	.055	297			

Portfolio 5 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.000	.000		-.613	.541
	MktMinRf	.714	.026	.847	27.364	.000

Portfolio 6 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.838	.703	.702	.01073	1.522

Portfolio 6 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.081	1	.081	699.495	.000
	Residual	.034	296	.000		
	Total	.115	297			

Portfolio 6 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.001	.001		.869	.385
	MktMinRf	1.020	.039	.838	26.448	.000

Portfolio 7 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.848	.719	.718	.01010	1.643

Portfolio 7 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.077	1	.077	756.673	.000
	Residual	.030	296	.000		
	Total	.107	297			

Portfolio 7 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.001	.001		1.049	.295
	MktMinRf	.998	.036	.848	27.508	.000

Portfolio 8 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.804	.646	.645	.01618	1.552

Portfolio 8 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.142	1	.142	541.269	.000
	Residual	.078	296	.000		
	Total	.219	297			

Portfolio 8 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.000	.001		-.373	.709
	MktMinRf	1.353	.058	.804	23.265	.000

Appendix 3 – Regression Results (F-F Model)

Portfolio 1 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.970	.941	.940	.00512	1.784

Portfolio 1 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.122	4	.031	1168.615	.000
	Residual	.008	293	.000		
	Total	.130	297			

Portfolio 1 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.000	.000		-.375	.708		
	MktMinRf	.879	.022	.679	39.841	.000	.693	1.442
	SMB	.003	.001	.079	5.172	.000	.867	1.153
	HML	.006	.001	.221	10.559	.000	.460	2.175
	UMD	-.004	.000	-.244	-11.140	.000	.421	2.376

Portfolio 2 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.936	.876	.875	.00727	1.662

Portfolio 2 -ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.110	4	.027	518.655	.000
	Residual	.015	293	.000		
	Total	.125	297			

Portfolio 2 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.000	.000		.495	.621		
	MktMinRf	.821	.031	.646	26.172	.000	.693	1.442
	SMB	.003	.001	.095	4.327	.000	.867	1.153
	HML	.006	.001	.227	7.482	.000	.460	2.175
	UMD	-.003	.000	-.233	-7.368	.000	.421	2.376

Portfolio 3 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.897	.804	.801	.00667	1.729

Portfolio 3 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.053	4	.013	300.077	.000
	Residual	.013	293	.000		
	Total	.066	297			

Portfolio 3 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-7.238E-5	.000		-.185	.853		
	MktMinRf	.577	.029	.623	20.033	.000	.693	1.442
	SMB	.004	.001	.172	6.187	.000	.867	1.153
	HML	.003	.001	.190	4.986	.000	.460	2.175
	UMD	-.002	.000	-.239	-5.983	.000	.421	2.376

Portfolio 4 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.948	.899	.897	.00601	1.919

Portfolio 4 -ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.094	4	.023	650.733	.000
	Residual	.011	293	.000		
	Total	.105	297			

Portfolio 4 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	5.878E-5	.000		.167	.868		
	MktMinRf	.864	.026	.743	33.315	.000	.693	1.442
	SMB	.006	.001	.191	9.553	.000	.867	1.153
	HML	.004	.001	.188	6.866	.000	.460	2.175
	UMD	-.002	.000	-.160	-5.582	.000	.421	2.376

Portfolio 5 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.926	.858	.856	.00517	1.722

Portfolio 5 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.047	4	.012	441.785	.000
	Residual	.008	293	.000		
	Total	.055	297			

Portfolio 5 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.000	.000		-1.253	.211		
	MktMinRf	.581	.022	.688	26.014	.000	.693	1.442
	SMB	.004	.001	.197	8.338	.000	.867	1.153
	HML	.004	.001	.230	7.076	.000	.460	2.175
	UMD	-.001	.000	-.160	-4.714	.000	.421	2.376

Portfolio 6 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.941	.886	.884	.00668	1.761

Portfolio 6 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.101	4	.025	568.113	.000
	Residual	.013	293	.000		
	Total	.115	297			

Portfolio 6 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.000	.000		1.269	.205		
	MktMinRf	.766	.029	.630	26.580	.000	.693	1.442
	SMB	.005	.001	.165	7.777	.000	.867	1.153
	HML	.005	.001	.198	6.798	.000	.460	2.175
	UMD	-.004	.000	-.280	-9.211	.000	.421	2.376

Portfolio 7 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.950	.902	.901	.00598	1.743

Portfolio 7 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.097	4	.024	677.589	.000
	Residual	.010	293	.000		
	Total	.107	297			

Portfolio 7 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.001	.000		1.594	.112		
	MktMinRf	.767	.026	.652	29.743	.000	.693	1.442
	SMB	.006	.001	.191	9.723	.000	.867	1.153
	HML	.005	.001	.196	7.290	.000	.460	2.175
	UMD	-.003	.000	-.266	-9.444	.000	.421	2.376

Portfolio 8 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.924	.853	.851	.01049	1.655

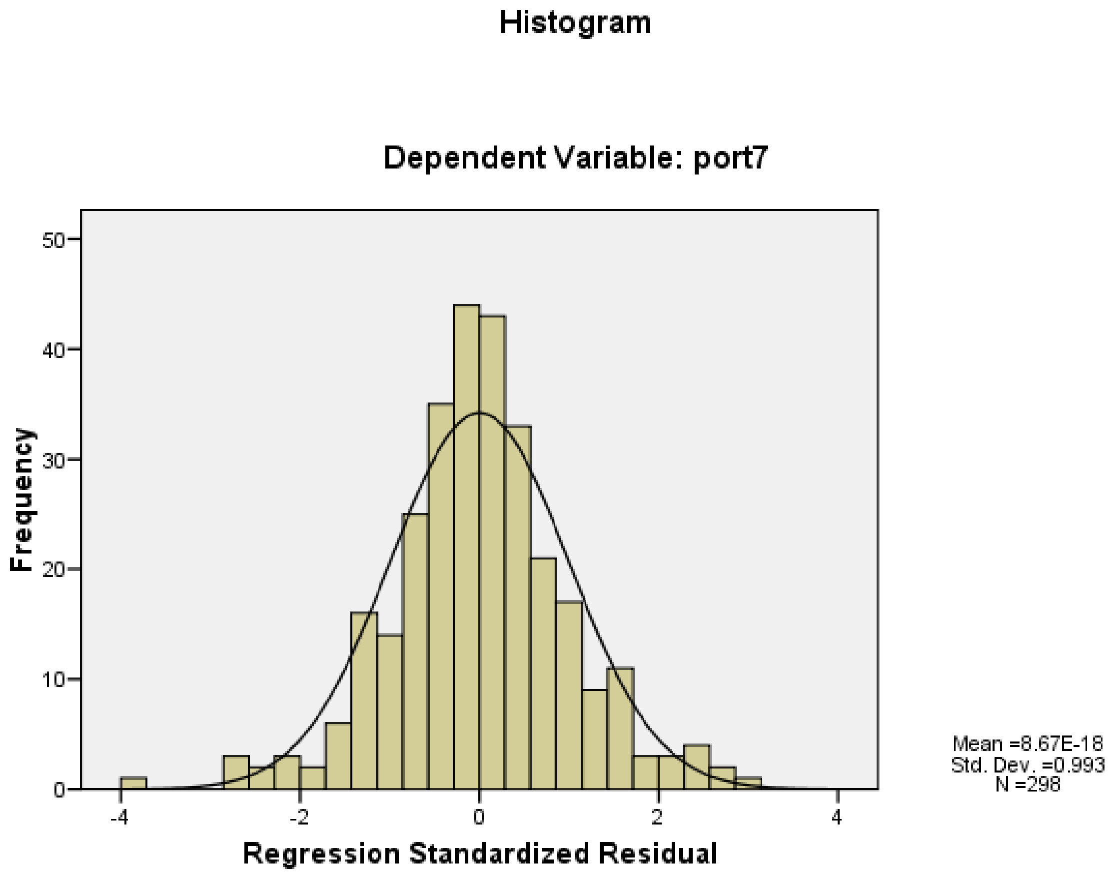
Portfolio 8 - ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.187	4	.047	425.333	.000
	Residual	.032	293	.000		
	Total	.219	297			

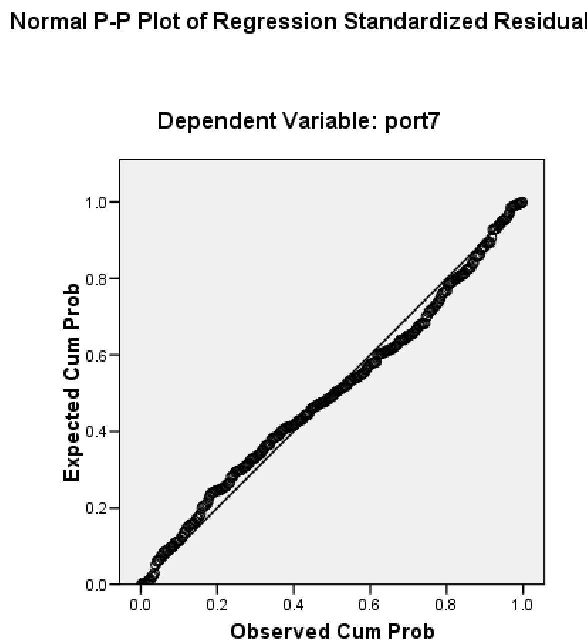
Portfolio 8 - Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.000	.001		-.836	.404		
	MktMinRf	.940	.045	.559	20.784	.000	.693	1.442
	SMB	.005	.001	.122	5.058	.000	.867	1.153
	HML	.009	.001	.269	8.152	.000	.460	2.175
	UMD	-.005	.001	-.275	-7.954	.000	.421	2.376

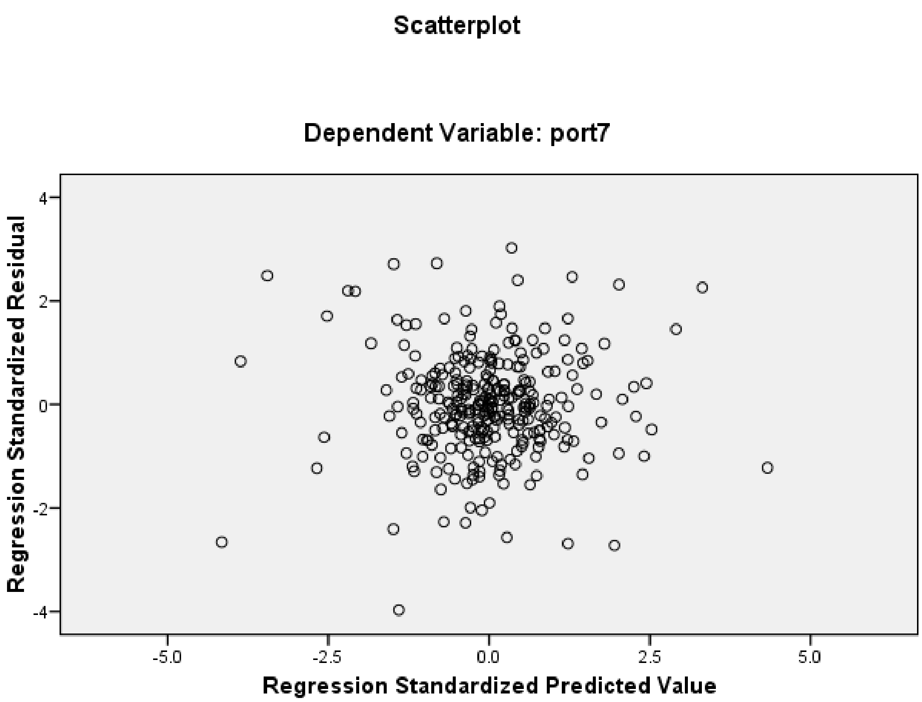
Appendix 4 – Residuals Plots



Graph 3 - Histogram of standardized residuals



Graph 4 – Normal P-P plot of standardized residuals



Graph 5 – Predicted residuals vs obtained values