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Shortability and Asset Pricing Model: Evidence from The Hong Kong Stock Market

Min Bai[*] Xiao-Ming Li[†] Yafeng Qin[‡]

Abstract

This study explores how the violation of free short selling assumption affects the performance of CAPM and the Fama-French three-factor model, as existing studies show that short-sales constraints affect asset pricing of the stocks. Using data from the Hong Kong Stock Market which has unique regulations on short selling, we conduct both time-series and cross-sectional regression analyses to evaluate the performance of the two models under the short-sales-constraints and the no-constraints market environment. The two models perform much worse in the former environment than in the latter, indicating a significant impact of the short sales constraints on the explanatory power of the models. We then augment the two models with a shortability-mimicking factor. Our results show that the factor has a significant power in explaining both time-series and cross-sectional variation in the size-B/M portfolio returns. The addition of the factor to the two models considerably increases their overall performance.

Keywords: Asset pricing models; Short-sales constraints; Shortability factor

JEL: G

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This study explores how the violation of free short selling assumption affects the performance of CAPM and the Fama-French three-factor model, as existing studies show that short-sales constraints affect asset pricing of the stocks. Using data from the Hong Kong Stock Market which has unique regulations on short selling, we conduct both time-series and cross-sectional regression analyses to evaluate the performance of the two models under the short-sales-constraints and the no-constraints market environment. The two models perform much worse in the former environment than in the latter, indicating a significant impact of the short sales constraints on the explanatory power of the models. We then augment the two models with a shortability-mimicking factor. Our results show that the factor has a significant power in explaining both time-series and cross-sectional variation in the size-B/M portfolio returns. The addition of the factor to the two models considerably increases their overall performance.

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1. Introduction

Many studies have shown that short-sales constraints affect asset pricing, such as causing overvaluation by preventing the stocks from incorporating negative information or pessimistic opinions into the prices (Miller, 1977; Chang, Cheng and Yu, 2007; Berkman et al., 2009; Diether et al., 2009; Boehmer and Wu, 2009), reducing the speed of price discovery by preventing informed investors from trading on bad news (Diamond and Verrecchia, 1987; Fung and Draper, 1999; Reed, 2007; Bris, Goetzmann, and Zhu, 2007; Chen and Rhee, 2010; Mashruwala and Mashruwala, 2014), and generating significant bubbles accompanied by large trading volumes and high price volatility (Scheinkman and Xiong 2003). However, despite the ample evidence on the impact of short-sales constraints on asset prices, it has never been incorporated in the typical asset pricing tests.

The CAPM has been the most widely-employed model [1]. Its underlying four assumptions of perfection in competitive markets[2] simplify the building of the model and permit one to consider only the mean and variance of the returns. It has been shown that the homogeneous-expectations assumption does not significantly affect the validity of the CAPM (Lintner, 1969). The normality and risk-averse-investor assumptions are generally regarded as an acceptable approximation to

[1]According to Welch (2008), about 75% of finance professors recommended using the CAPM. Graham and Harvey (2001) surveyed 392 CFOs within the US firms and find that 73.5% of the surveyed firms had always or almost always relied on the CAPM in estimating the cost of equity capital. The Wall Street Prep course in their training manual asserts that among several competing asset-pricing models, “The most popular and commonly used in practice is the capital asset pricing model (CAPM).” (p. 86).

[2]The four assumptions are: (1) homogeneous expectations from investors; (2) normal distribution of asset returns; (3) risk averse of individual investors who maximize the expected utility of their end of period wealth; and (4) absence of short-sales restrictions on any assets including risk-free asset.

reality (Black, 1972). However, Black (1972) argues that, among the assumptions, the absence of short-sales constraints is the most restrictive one. Regarding the FF three-factor model, an empirical extension of the CAPM and now becoming one of the standard benchmarks for performance evaluation (Cremers, Petajisto and Zitzewitz, 2010), it also assumes no short-sales restrictions when constructing the well-known small-minus-big (SMB) and high-minus-low (HML) factor portfolios.

In many markets, however, short-sales restrictions are present. According to Bris, Goetzmann and Zhu (2007), out of their 46 sample countries, 21 do not allow and/or do not practice short sales due to either restrictive regulations or huge costs on shorting stocks[3]. In fact, during the recent financial crisis period from 2007 to 2009, even many of the remaining 25 countries that used to allow short selling imposed short-selling bans on either the entire market or some sectors or individual stocks from time to time, including the US and most European countries (Beber and Pagano, 2013). The point made here is that the assumption of no short-selling restrictions underlying asset pricing models does not apply in many markets and/or at many time points. This poses an interesting question that whether the presence of the short-sales constraints would make much difference in terms of model performance. Surprisingly, no studies have ever formally tested it, which inspires us with the first objective of this study, that is, to investigate the extent to which the short-sales constraints would affect the performance of asset pricing models. In particular, we examine the performance of CAPM and FF three-factor model in two opposite short-selling environments. We find that, both models capture significantly more variation in stock returns when short selling is allowed than when it is banned, in both the time-series and the cross-sectional tests. For example, when we apply CAPM to explain the

[3] See Table 1 in Bris, Goetzmann and Zhu (2007) for detailed descriptions of the 46 countries.

time-series returns of shortable stocks, the average adjusted R^2 increases by more than 50% (from 38.4% to 58.4%) compared with the case when we apply the model to non-shortable stocks. With respect to the FF three-factor model, though the increase (from 61.0% to 65.0%, an increase of 6.56%) is not as dramatic as in the CAPM, it is still statistically significant.

Such finding, while indicating a significant deterioration in the explanatory power of the asset pricing models with the presence of the short-sales constraints, leads to our second objective—to improve the performance of the models with a shortability-mimicking factor in the markets with short-sales constraints/restrictions. This objective is motivated by the various risk factors already proposed in the literature and by their success in improving model performance. We propose a new risk factor (NMS) as the difference between the return on a portfolio of non-shortable stocks and the return on a portfolio of shortable stocks, and coin a term "the shortability factor" to refer to it throughout the paper. We believe that NMS is a risk factor, as non-shortable stocks have higher risk hence higher expected excess returns than shortable stocks, for three reasons detailed below.

The first is related to the well-known over-pricing of the non-shortable stocks and disagreements between investors about the stocks' value. For convenience, we refer to the risk as the "overvaluation risk". Short-sales constraints prevent the stocks from impounding negative information into, or reflecting pessimistic opinions in, their prices, leading to overvaluation. Once the constraints are lifted, their prices will decline, with constraint-induced upward price biases being corrected (Chang, Cheng and Yu, 2007; Berkman *et al*, 2009; Diether *et al*, 2009; and Boehmer and Wu, 2009). If there is overcorrection, the price drops would be even greater, overshooting the fundamental value. The higher the overvaluation, the worse will be the situation.

Thus, the uncertainty in the short-selling status of already constrained stocks is a risk for investors (whether informed or uninformed) holding them, relative to those investing in shortable stocks without significant and persistent overvaluation.

The second reason has to do with the liquidity of non-shortable stocks being low relative to that of shortable stocks. In other words, this liquidity risk is induced by short-sales constraints, and we refer to it as “the constraint-induced liquidity risk”. A short-selling ban reduces the speed of price discovery by preventing informed investors to trade on bad news, thereby increasing the information asymmetry component of bid-ask spread and reducing the liquidity of non-shortable stocks (Diamond and Verrecchia, 1987). A number of empirical studies have provided evidence in support of the theory (See, for example, Kolasinksi, Reed and Thornock, 2010; Boehmer, Jones and Zhang, 2013; and Bai and Qin, 2014). A drop in liquidity could be particularly detrimental to investors during a crisis when investors are in great need of liquidity. Thus, investors would require higher returns as compensation for taking on the risk of losses resulting from the lower liquidity caused by short-selling restrictions.

The third reason concerns what we call the “constraint-induced information risk”. Theory predicts that short-sales constraints lower the speed of price discovery for constrained stocks (Bai, Chang and Wang, 2006), and investors will view such a speed slowdown as loss of information efficiency. That is, a decline in the speed of price discovery entails not just liquidity risk but also information risk. Investors will therefore require higher returns on constrained stocks. The empirical literature provides evidence that non-shortable stocks do have a lower price discovery/adjustment speed than shortable stocks (Bris, Goetzmann and Zhu, 2007; Chen and Rhee, 2010; and Saffi and Sigurdsson, 2011).

Based on the above considerations, we augment the CAPM and the FF three-factor model with the shortability factor, and conjecture that the factor is priced. Following Fama and French (1993) who treat respectively the size factor and the value factor as a whole, we take the shortability factor as synthesizing the above-discussed "overvaluation risk", "constraint-induced liquidity risk" and "constraint-induced information risk". If a risk premium is detected for the factor, this implies that investors require compensation for bearing the synthesised risk embodied in the factor. Our empirical results confirm our conjecture. For example, the time series tests show that for both CAPM and FF three-factor models, the augmented models with NMS factor produce significantly higher adjusted R^2 than the standard models without the factor; and the cross-sectional tests indicate that the risk premium for NMS is more significant than those for the market, size and book-to-market risk factors, both economically and statistically.

Our study contributes to the asset pricing literature in two aspects. First, it provides empirical evidence that the presence of short-sales constraints would lead to considerable decline in the performance of the CAPM and the FF three-factor model when applied to markets where shorting restrictions are present. That is, the two models are "confined" by the assumption to work within the environment of no shorting restrictions. Nevertheless, by allowing for an additional factor related to short-sales constraints, the augmented models now work well in the environment with short-selling restrictions. Moreover, the augmented models also nest the standard models, in that, where short sales are allowed and practiced, the former would collapse to the latter.

Second, this study expands the extant set of risk factors with a new one that mimics short-sales constraints. Creating the new factor has three implications. First, it enables one to address the question of how to allow for the presence of short-sales constraints and how to modify asset pricing models accordingly. The second is related to the persistently higher returns on non-shortable stocks than on shortable stocks. Prior work fails to provide explanations, but our proposed new factor can offer one: The return difference could be due to a risk premium required by investors holding non-shortable stocks hence bearing some undiversifiable risk (such as the overvaluation risk, the constraint-induced liquidity risk and the constraint-induced information risk, as noted above). The third implication is that, when it comes to markets where short sales are not allowed, or even for the same markets during the periods of time when short selling is banned, there is an additional pattern in average returns that all the existing factor models cannot explain. This implication suggests that the presence of short-sales constraints could be one of the factors that contribute to the variation in the performance of asset pricing models across different countries and/or over time.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 introduces our methodology. In Section 4, we compare the performance of the CAPM between short-sales-constrained and short-sales-unconstrained stocks, and do the same to the FF three-factor model. In Section 5, we evaluate the shortability-augmented CAPM relative to the standard CAPM, and the shortability-augmented FF three-factor model relative to the standard FF three-factor model. We conclude our study in Section 6.

2. Data and factor construction

The uniqueness of Hong Kong's regulations on short sales provides an ideal laboratory for exploring the relative performance of an asset pricing model in opposite short-selling regimes (the ban and the no-ban regime), and enables us to construct the shortability risk factor. According to Table 1, at a point in time, a stock stays either on the official designated short-selling list or off the list. We therefore differentiate individual stocks into two groups: If a stock is on the list, we refer to it as “shortable”; and if a stock is not on the list, we call it “non-shortable”.

Constrained by data availability for constructing NMS, our *effective* sample period for sorting portfolios starts from January 1997 (instead of January 1994) and ends at February 2012. As of February 29, 2012, the designated short-selling list had been successively revised 102 times (since January 1994), and out of 1,498 common stocks traded on the Hong Kong Stock Exchange (HKSE), 1,081 were allowed to be sold short. To construct risk factors[4] and form portfolios, we collect the following data for each individual stock traded on the HKSE: closing prices, market value (ME), book value (BE) and the number of shares outstanding. We also obtain monthly Hong Kong 3-month Treasury bill rate (T-bill) as a proxy for risk-free rate. All these data come from the Datastream database.

As a usual practice, we proxy the market factor by excess market returns denoted as R_m- R_f. R_m is the return on the value-weighted portfolio of all shares traded on the HKSE, and R_f is the Hong Kong 3-month T-bill rate.

In constructing the size and book-to-market risk factors, we follow Fama and French (1992, 1993, 1996). Specifically, at the end of June of each year *t*, we sort all the stocks listed on the HKSE based on their market value (ME) and classify them into each of the two size groups: Stocks with ME above (below) the cross-sectional

[4] Risk factors for the Hong Kong stock market are not available from the Data Library website of Professor Kenneth French. So, we construct all of them, adopting the approach proposed by Fama and French (1992, 1993).

median are classified as big (small) stocks and denoted as B (S). Meanwhile, we rank all the stocks based on their book-to-market ratios (BM) and classify them into one of the three BM groups: Stocks with the highest (lowest) 30% BM are classified as high (low) book-to-market stocks and denoted as H (L), and the rest 40% are classified as medium book-to-market stocks and denoted as M. These independent 2×3 sorts allow us to construct six size and book-to-market portfolios (S/L, S/M, S/H, B/L, B/M and B/H) form the intersections of the two size and the three book-to-market groups. For example, the S/L portfolio contains stocks that are simultaneously in the small-size and the low book-to-market group, and the B/H portfolio contains big-size stocks that also have high book-to-market ratios. We calculate monthly value-weighted returns on the six portfolios from July of year *t* to June of year *t+1* (i.e., the six portfolios are formed/re-formed at June of each year *t* and held for 12 months).

The size factor (SMB: "Small Minus Big") is represented by the portfolio returns meant to mimic the risk related to size. The SMB returns are calculated as the difference, each month, between the simple average of returns on the three small-stock portfolios (S/L, S/M, and S/H) and the simple average of returns on the three big-stock portfolios (B/L, B/M, and B/H):

$$SMB = \frac{(S/L - B/L) + (S/M - B/M) + (S/H - B/H)}{3}$$

This difference is largely free of the influence of BE/ME, focusing instead on the different return behaviours of small and big stocks.

The BE/ME factor (HML: "High Minus Low") is represented by the portfolio returns meant to mimic the risk related to book-to-market equity. The HML returns are calculated as the difference, each month, between the simple average of returns on the two high-BE/ME portfolios (S/H and B/H) and the simple average of returns on the two low-BE/ME (S/L and B/L) portfolios:

$$HML = \frac{(S/H - S/L) + (B/H - B/L)}{2}$$

HML is largely free of the size effect, and focuses on the different return behaviours of high-BE/ME and low-BE/ME stocks.

The shortability factor NMS is meant to mimic the risk related to short-sales constraints (i.e., the synthesised risk discussed in Introduction). In constructing this factor, within each of the six size and book-to-market portfolios, we separate the stocks based on their shortability statuses and form the shortable and non-shortable portfolios. The NMS returns are the difference, each month, between the simple average of returns on the six non-shortable portfolios (S/H^N, B/H^N, S/M^N, B/M^N, S/L^N, and B/L^N) and the simple average returns of the six shortable portfolios (S/H^S, B/H^S, S/M^S, B/M^S, S/L^S, and B/L^S), where the superscript *N* denotes the non-shortable portfolios and the superscript *S* denotes the shortable portfolios. Formally,

$$NMS = \frac{1}{6}\big((S/H^N - S/H^S) + (B/H^N - B/H^S) + (S/M^N - S/M^S) + (B/M^N - B/M^S) + (S/L^N - S/L^S) + (B/L^N - B/L^S)\big)$$

Thus, *NMS* is the difference in returns between the non-shortable and shortable stocks with about the same weighted-average size and book-to-market ratios. This difference should be largely free of the influence of Size and B/M, focusing instead on the different return behaviours caused by short selling restrictions[5].

True mimicking portfolios for common risk factors in returns will minimize the variance of firm-specific factors. The six Size–B/M portfolios (S/L, S/M, S/H,

[5] We also explore several other measures of NMS: the difference between non-shortable SMB and shortable SMB (NMS_{smb} alone); the difference between non-shortable HML and shortable HML (NMS_{hml} alone); both NMS_{smb} and NMS_{hml}; and the average of NMS_{smb} and NMS_{hml} ((NMS_{smb} + NMS_{hml})/2). Their results are qualitatively similar and are available upon requests.

B/L, B/M and B/H) as well as the twelve shortable and non-shortable size-B/M portfolios are all value weighted, in the spirit of minimizing variance and reducing estimation bias[6]. More importantly, use of value-weighted components results in mimicking portfolios that capture the different return behaviours of small and big stocks, high-BE/ME and low-BE/ME stocks, or shortable and non-shortable stocks, in a practical way.

Table 2 presents the descriptive statistics about the four risk factors: market (R_m- R_f), size (*SMB*), book-to-market (*HML*) and shortability (*NMS*). Averaging over the sample period from January 1997 through to February 2012, the market portfolio underperforms risk-free assets, so we see a negative excess market return of -2.2%. Small stocks outperform big stocks, resulting in a statistically significant average return of 1.3% on the size portfolio (t-statistic = 2.23). Stocks with high book-to-market ratios generate higher returns than stocks with low book-to-market ratios. Hence, there is a statistically significant average return on the value portfolio of 1.1% (t-statistic = 2.40). Finally, stocks with a short-selling ban generate a significantly higher return than stocks without the ban. So, there is an average return on the NMS portfolio of 3.0% (t-statistic = 3.70).

3. Methodology

The primary empirical method we employ is the Fama-MacBeth (1973) two-pass regressions.

The first pass runs the time-series (across t = 1, 2,…, *T*) regression as follows:

$$R_t = A + BF_t + e_t \tag{1}$$

[6]Asparouhova, Bessembinder and Kalcheva (2013) point out that equally weighted returns of portfolios constructed based on firm characteristics could produce estimation bias.

where R_t is an $N\times1$ vector of excess returns on N test portfolios (in excess of the risk-free rate) at t; F_t is a $K\times1$ vector of K factors at t; B is an $N\times K$ matrix of the test portfolios' loadings on factors; A is an $N\times1$ vector of abnormal returns (or alphas) on the N test portfolios; and e_t denotes an $N\times1$ vector of mean-zero residuals at t. Using the FF three-factor model as a specific example, we have:

$$R_t = \begin{bmatrix} R_{1t}^{ex} \\ \vdots \\ R_{pt}^{ex} \\ \vdots \\ R_{25t}^{ex} \end{bmatrix},\ A = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_p \\ \vdots \\ \alpha_{25} \end{bmatrix}, B = \begin{bmatrix} b_1 & s_1 & h_1 \\ \vdots & \vdots & \vdots \\ b_p & s_p & h_p \\ \vdots & \vdots & \vdots \\ b_{25} & s_{25} & h_{25} \end{bmatrix}, F_t = \begin{bmatrix} R_{mt} - R_{ft} \\ SMB_t \\ HML_t \end{bmatrix} \text{ and } e_t = \begin{bmatrix} e_{1t} \\ \vdots \\ e_{pt} \\ \vdots \\ e_{25t} \end{bmatrix}$$

where $R_{pt}^{ex} = R_{pt} - R_{ft}$ is the return on a size-B/M portfolio p (R_{pt}) *in* excess of the risk-free rate (R_{ft}) at t; R_{mt} - R_{ft} the excess return on the market portfolio at t; SMB_t the size factor at t; HML_t the value (book-to-market) factor at t; α_p is the intercept measuring the abnormal return; and b_p, s_p and h_p are the slope coefficients measuring the sensitivity of the excess return on a size-B/M portfolio p to, respectively, the three factors.

Evaluating the relative time-series performance of an asset pricing model for shortable vis-a-vis non-shortable size-B/M portfolios, we rely on the intercept α_p, the R^2 and the adjusted R^2, and the GRS F-statistic (Gibbons, Ross and Shanken, 1989) and its unexplained Sharpe ratio ($\theta_z(\alpha)$), all estimated/obtained from the time-series regression in equation (1).

The second pass runs the cross-sectional (across p = 1, 2, …, N) regression as follows:

$$\mathrm{E}(R) = zl + B\lambda + \varepsilon \qquad (2)$$

where E(R) is an $N\times1$ vector of the expected values of R; z is the cross-sectional intercept (a scalar); l is an $N\times1$ vector of ones; λ is a $K\times1$ vector of regression slopes (also known as risk premiums) on factor loadings B; and ε is an $N\times1$ vector of pricing errors. Using again the FF three-factor model as a specific example, we have:

$$E(R)=\begin{bmatrix}\bar{R}_1^{ex}\\ \vdots\\ \bar{R}_p^{ex}\\ \vdots\\ \bar{R}_{25}^{ex}\end{bmatrix},\ \lambda=\begin{bmatrix}\lambda_b\\ \lambda_s\\ \lambda_h\end{bmatrix}\ \text{and}\ \varepsilon=\begin{bmatrix}\varepsilon_1\\ \vdots\\ \varepsilon_p\\ \vdots\\ \varepsilon_{25}\end{bmatrix}$$

where $\bar{R}_p^{ex}$ is the time-series average of R_{pt}^{ex} over t = 1, 2, …, T. That is, one regresses E(R), which has 25 observations, against b, s and h each having 25 observations, to obtain one estimate of z, of λ_b, of λ_s, and of λ_h, but 25 estimates of ε.

Undertaking the cross-sectional asset pricing tests, we follow the approach proposed by Lewellen, Nagel and Shanken (henceforth LNS) (2010). The authors show that none of the five published multifactor asset pricing models pass the stringent LNS tests. Given the rigorous hurdles set in the LNS approach, it seems too hard to find a model that can meet them. Thus, our criterion is to see which model is *closer* to meeting the hurdles: the closer, the better. Briefly, we resort to the following elements embraced in the LNS approach. First, we expand the 25 size-B/M portfolios to include other portfolios such as industry portfolios which do not correlate strongly with SMB and HML. This is to tackle the problem of the strong covariance structure of the 25 size-B/M portfolios. Second, we report the GLS R^2 from a GLS cross-sectional regression. An additional benefit of the GLS R^2 over the OLS R^2 is that it has a useful economic interpretation in terms of relative mean-variance efficiency of a model's factor mimicking portfolios. Third, we use confidence intervals of the OLS and the GLS R^2 and the quadratic q in Shanken's (1985) T^2 statistic, and do not rely just on their point estimates and p-values. According to LNS, confidence intervals can reveal the often high sampling errors in the statistics in a way that is more direct and transparent than p-values or standard errors, and show the range of true parameters that are consistent with the data without taking a stand on the right null hypothesis. The cross-sectional T^2 statistic tests the null hypothesis that pricing errors (ε in equation (2)) are zero, and is a function of q[7]. The quadratic q measures the distance between the maximum generalized squared Sharpe ratio on any portfolio and that attainable from K portfolios formed from the test assets that are maximally correlated with the factors. Thus, we refer to q as the "T^2-related unexplained Sharpe ratio": If the model fully explains the cross-section of expected returns, then q is zero. We obtain the various confidence intervals via simulations with 40,000 replications in each case, following the procedures detailed in LNS (2010).

In the cross-sectional regression, our test assets are always the FF 25 size-B/M portfolios formed respectively on shortable and non-shortable stocks (Section 4) or formed on all stocks (Section 5). But, we will also consider expanding the 25 test portfolios to include N_n *non-test* industry portfolios *as per* the LNS approach discussed above. These imply four versions of the time-series regression model (1):

$$R_{shortable,t} = A + BF_t + e_t \tag{1a}$$

$$R_{nonshortable,t} = A + BF_t + e_t \tag{1b}$$

$$R_{shortable+ind,t} = A + BF_t + e_t \tag{1c}$$

$$R_{nonshortable+ind,t} = A + BF_t + e_t \tag{1d}$$

$R_{shortable,t}$($R_{nonshortable,t}$) contains 25 shortable (non-shortable) size-B/M portfolios only. $R_{shortable+ind,t}$($R_{nonshortable+ind,t}$) includes 25 shortable (non-shortable) size-B/M portfolios

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[7] Appendix A in LNS (2010) shows that $T^2 = q\left[T/\left(\lambda'\Sigma_F^{-1}\lambda\right)\right]$, where $q \equiv \varepsilon'\left(y\Sigma y\right)^{+}\varepsilon$ with $y \equiv I - x\left(x'x\right)^{-1}x'$, $x \equiv \left[l \quad B\right]$, Σ being the covariance matrix of R and "+" denoting "pseudo inverse". T is the number of time-series observations and Σ_F^{-1} is the inverse of the covariance matrix of F.

plus a common set of industry portfolios. In (1c) and (1d), A becomes an $(N+N_n)\times 1$ vector of alphas, $R_{shortable+ind,t}(R_{nonshortable+ind,t})$ becomes an $(N+N_n)\times 1$ vector of excess returns, and B *is* an $(N+N_n)\times K$ matrix of the test portfolios' loadings on factors. It then follows that the cross-sectional regression model (2) will also have four versions corresponding to (1a) – (1d):

$$\mathrm{E}(R_{shortable,t}) = zl + B\lambda + \varepsilon \tag{2a}$$

$$\mathrm{E}(R_{nonshortable,t}) = zl + B\lambda + \varepsilon \tag{2b}$$

$$\mathrm{E}(R_{shortable+ind,t}) = zl + B\lambda + \varepsilon \tag{2c}$$

$$\mathrm{E}(R_{nonshortable+ind,t}) = zl + B\lambda + \varepsilon \tag{2d}$$

Note that, across (1a) – (1d) and across (2a) – (2d), the left-hand-side (LHS) vector of test assets R_t differs, but the factors F_t and the factor loadings B remain unchanged. This indicates an important difference between our analysis and a common practice in the asset pricing literature. The latter keeps R_t unchanged but changes F_t hence B, to generate and compare different models (e.g., the CAPM if $F_t = R_{mt} - R_{ft}$ and the FF three-factor model if $F_t = [R_{mt} - R_{ft};\ SMB_t;\ HML_t]'$) in terms of their cross-sectional explanatory powers for the same R_t ($\mathrm{E}(R_t)$). That is, they address this question: Does the proposed model perform well? We keep F_t hence B unchanged but change R_t, to compare the different cross-sectional explanatory powers of the *same* model (e.g., the CAPM *or* the FF three-factor model) for different R_t (e.g., $R_{shortable,t}$ and $R_{nonshortable,t}$) due to different short-selling statuses of the stocks. That is, we address this question: In which short-selling environment, will the *given* model perform better? To this end, we compare (2a) with (2b), and (2c) with (2d), for the CAPM, and then do the same for the FF three-factor model, adopting the LNS cross-sectional test approach.

4. Short-selling restriction and relative performance of asset pricing models

4.1 Time-series regression analysis

Before carrying out time-series analysis, let us take a look at some descriptive statistics relevant to the analysis in this section. Table 3 reports the means and standard deviations of the 25 shortable and 25 non-shortable size-B/M portfolio returns. Panel A indicates that, among the shortable stocks, there seems to be a book-to-market effect (i.e., value stocks generally outperform growth stocks) among small to medium sized stocks, but no size effect (i.e., small stocks do not outperform large stocks within each BE/ME quintile). Panel B shows that, for non-shortable stocks, there is a significant size effect (i.e., all small stocks outperform large stocks) within each BE/ME quintile) and a book-to-market effect within each size quintile, but the latter is weaker than the former. Comparing the mean returns of the two sets of 25 portfolios, Panel C exhibits that the shortable stocks underperform the non-shortable stocks, in that the former's mean returns are significantly lower than the latter's. This is consistent with Miller's (1977) overpricing theory and other empirical evidence that short-sales constraints/bans can lead to overvaluation. Regarding the volatility of portfolio returns, one can see that while the non-shortable portfolios with lower B/M tend to have slightly higher standard deviations than the shortable portfolios, on average, these two groups of stocks do not show significant differences. The average standard deviation of the shortable portfolios is 0.136 and that of the non-shortable portfolios is 0.145 (See Panels A and B).

Since our interest is particularly in the performance difference of an asset pricing model between shortable and non-shortable assets, and also to preserve space, we only report the *differences* in the time-series regression results[8]. Table 4 uses the coefficient estimates on the dummy variable ss_p (equals 1 for shortable, and 0 for non-shortable stocks) and on the interaction term to show the difference in the CAPM regression loading (the market beta) between the 25 size-B/M shortable portfolios and their 25 non-shortable counterparts. We also present the R^2 and the adjusted R^2 of the regressions. The dummy variable ss_p has significantly negative coefficients for micro stocks, while most of the coefficient estimates on the interaction terms are insignificant. These results suggest that, *ceteris paribus*, small shortable stocks tend to underperform small non-shortable stocks, but this is rarely the case for the medium or large stocks. Also, the sum of the α_p and α'_p coefficient estimates in each of the 25 cases makes abnormal returns closer to zero, meaning that the CAPM captures the time-series variation in the returns of the 25 shortable portfolios better than the 25 non-shortable portfolios. Another observation is that shortable and non-shortable stocks in general do not differ significantly in the market beta, as the 25 b'_p coefficient estimates are mostly insignificant.

Table 5 pertains to the FF three-factor model. With regard to the size effect, shortable and non-shortable stocks show significant difference in their sensitivity to the SMB risk factor. The s'_p coefficient estimates are significantly negative. This implies that, given the s_p coefficient estimates for non-shortable being all positive (not reported), shortable stocks are significantly less sensitive to the SMB risk factor than non-shortable stocks. However, the two types of stocks do not have the same degree of systematic difference in their sensitivity to the HML risk factor, as the h'_p coefficient estimates are less statistically and economically significant than the s'_p

[8] The time-series regression results of an asset pricing model for, respectively, shortable and non-shortable assets are available from us upon requests.

coefficient estimates. As far as the α'_p coefficient estimates are concerned, the evidence is visually less clear-cut than that in Table 4, regarding whether the FF 3-fractor model works better for shortable than non-shortable stocks.

To have a formal way of making judgements on the FF three-factor model as well as the CAPM discussed above, we resort to the GRS F-test. Table 6 sets out the GRS F-statistics and their p-values for each of the one-factor and the three-factor model with, respectively, the shortable and non-shortable size-B/M portfolios. Consider the one-factor CAPM model first. Shortable portfolios have a GRS F-statistic of 1.668 whereas non-shortable portfolios have a GRS F-statistic of 2.256. The much greater GRS F-statistic with non-shortable portfolios rejects the null hypothesis that the 25 alphas are jointly equal to zero more strongly than that with shortable portfolios. This suggests that the CAPM model works better in the shortable environment than in the non-shortable environment, even though in both cases the model fails to pass the GRS F test.

Turning to the FF three-factor model, shortable size-B/M portfolios have a GRS F-statistic of 1.310, whereas non-shortable size-B/M portfolios have a GRS F-statistic of 1.713. More importantly, while we can reject the null hypothesis that all the 25 alphas are jointly zero for the non-shortable portfolios (p-value of the GRS F-statistic is 0.029), we fail to do so for the shortable portfolios (p-value of the GRS F-statistic is 0.163). This result suggests that the FF three-factor model performs much better in the shortable market than in the non-shortable market.

Comparing the absolute values of alphas is also informative. Table 6 demonstrates that, for each of the two asset pricing models, the absolute value of alpha is much smaller when the 25 size-B/M portfolios are shortable than when they are non-shortable: 0.007< 0.018 and 0.006< 0.009, respectively for CAPM and FF three-factor model. This provides evidence that the two models work better in capturing the time-series variation in the returns on shortable stocks than on non-shortable stocks.

With regard to the unexplained Sharpe ratio $\theta_z(\alpha)$[9],we can see from Table 6 that the CAPM with shortable portfolios has it equal to 0.538, smaller than 0.695 for the CAPM with non-shortable portfolios. Similar observations can also be made for the FF three-factor model: The unexplained Sharpe Ratio of the shortable portfolios is 0.497, smaller than 0.631 from non-shortable portfolios. That is, the one-factor model and the three-factor model all explain a greater portion the Sharpe ratio for shortable than non-shortable stock returns.

Finally, let us compare the average R^2 and the average adjusted R^2 across the two opposite short-selling statuses, for each of the two asset pricing models. Table 6 reveals that the two models have much greater explanatory powers for shortable portfolio returns than for non-shortable portfolio returns. Consider the CAPM first. The average R^2 increases from 38.7% in the non-shortable case to 58.7% in the shortable case. Such an improvement in the explanatory of the model is significant not only statistically (paired-wise t-statistic of 7.50) but also economically (an overall increase of more than 51%). The average adjusted R^2 increases with similar magnitude, from 38.4% to 58.4%. Pertaining to the FF three-factor model, the differences in the explanatory power of the model are also statistically significant, though not as strong as those with the CAPM model. Specifically, the average R^2

[9] $\theta_z(\alpha)$ is the core component of the GRS F-statistic: $\theta_z^2 = \alpha'\Sigma^{-1}\alpha$, where α is a vector of the time-series intercepts and Σ^{-1} is the inverse of the covariance matrix of e_t in equation (1). LNS (2010, page 186) interpret $\theta_z^2(\alpha)$ as the evaluated model's unexplained squared Sharpe ratio. Thus, the smaller the $\theta_z(\alpha)$ statistic, the better the time-series performance of the tested model.

increases by 6.48% (from 61.7% to 65.7%), and the average adjusted R^2rises by 6.56% (from 61.0% to 65.0%), switching from the non-shortable to the shortable case.

Based on the above time-series regression analyses, we conclude that the two asset pricing models fare much better in capturing the time-series variation of returns on the shortable than the non-shortable stocks, and the differences are too statistically and economically significant to overlook.

4.2 Cross-sectional regression analysis

The time-series regression for an asset pricing model, as the first pass (equation (1)), yields factor loadings *B* (e.g., 25 *b's*, 25 *s's* and 25 *h's* in the FF three-factor model). The loadings are then used as regressors in the second pass (equation (2)), namely the cross-sectional regression, to evaluate the model based on how well its generated factor loadings explain average returns on its LHS portfolios (such as 25 size-B/M portfolios). This is known as the cross-sectional asset pricing test. According to the discussion in Section 3, we report the test results in Table 7.

Table 7 reports the results of cross-sectional regressions in equations (2a) through (2d) for, respectively, the CAPM and the FF three-factor model. At first glance, the GLS R^2 is greater with non-shortable-asset pricing models than with shortable-asset pricing models: 0.017> 0.014, 0.005> 0.002, 0.153> 0.029, and 0.127> 0.022. However, this does *not* mean that a given model (either the CAMP or the FF three-factor model) performs better for non-shortable stocks than for shortable stocks. In fact, when comparing the same model (with the same F_t), cross different short-selling regimes (i.e., across $R_{shortable,t}$ and $R_{nonshortable,t}$ or across $R_{shortable+ind,t}$ and $R_{nonshortable+ind,t}$) via the cross-sectional regression, the GLS R^2 statistic becomes uninformative in the economic sense[10]. Only the q (unexplained squared Sharpe ratio) and the T^2 statistic are relevant where one wants to judge on the relative performance of a given model in different short-selling regimes (i.e., with different LHS assets).

Consider the CAPM first. From both Panels A and B, the two T^2 statistics and the two corresponding q statistics rise when the LHS size-B/M portfolios turn from being shortable to being non-shortable. It is true that the four p-values allow one to reject the CAPM in both short-selling regimes, but the magnitudes of the rises, from 0.385 to 0.801 and from 1.348 to 2.416, in the two T^2 statistics still indicate the relatively much better performance of the CAPM in the markets where short sales are allowed. Perhaps more economically meaningful evidence comes from the q statistics. The unexplained squared Sharpe ratio of the CAPM for non-shortable size-B/M portfolios is 2.081 (= 0.801/0.385) times as large as for shortable ones. After adding 33 industry portfolios to the 25 test size-B/M portfolios, this figure becomes 1.792 (= 2.416/1.348), still economically significant.

While a sample q provides some useful information, its confidence intervals add more. From Panels A through D in Table 7, confidence intervals for the true q are

[10] The definition GLS $R^2 \equiv 1 - q/Q$(see Appendix A in LNS, 2010) indicates that GLS R^2 depends on both q and Q. While q has an economic interpretation for judging a model's performance, Q does not. Q changes only if R_t changes, thereby impairing the important information conveyed by changes in q. Thus, the CAPM and the FF three-factor will have the same Q under the same short-selling regime (i.e. with the same R_t on the left-hand side), but different Q under different regimes (i.e., with different R_t). The latter fact makes the GLS R^2 incomparable between a model for shortable stocks and the same model for non-shortable stocks (e.g, between $R_{shortable,t}$ and $R_{nonshortable,t}$). But, the GLS R^2 is comparable between the CAPM and the FF three-factor model if they have the same LHS R_t. For instance, the FF three-factor model performs better than the CAPM under the same circumstances: 0.029 > 0.014 where both have $R_t = R_{shortable,t}$, 0.153 > 0.017 where both have $R_t = R_{nonshortable,t}$, 0.022 > 0.002 where both have $R_t = R_{shortable+ind,t}$, and 0.127 > 0.005 where both have $R_t = R_{nonshortable+ind,t}$.

larger and at higher levels when the test portfolios are non-shortable, and this is true whether or not 33 industry portfolios are included in R_t (E(R_t)). Specifically, Panel A shows that, without 33 industry portfolios, we cannot reject that q is between 0.127 and 0.390 for shortable stocks, and we cannot reject that q is between 0.825 and 1.681 for non-shortable stocks. Panel B suggests that, with 33 industry portfolios added, there is a 95% chance that shortable stocks' q will fall between 0.996 and 1.482, while non-shortable stocks' q will fall between 2.664 and 3.798.

Next, consider the FF three-factor model covered by Panels C and D of Table 7. The two T^2 statistics and the two corresponding q statistics also move up as the test assets switch from shortable size-B/M portfolios to non-shortable ones. Again, the four p-values suggest rejecting the FF three-factor model in explaining the cross-section of either shortable or non-shortable stock returns. However, from a comparative perspective, the rises in the two T^2 statistics from 28.91 to 39.22 and from 125.06 to 168.89 suggest that the FF three-factor model is more workable without short-sale bans in presence than with. This statistical evidence is reinforced by economic evidence. Without adding 33 industry portfolios, the unexplained squared Sharpe ratio q of the FF three-factor model in the test with the non-shortable size-B/M portfolios is 1.841 (= 0.626/0.340) times as great as for the shortable ones. Expanding the test assets to 58 (= 25 + 33), this percentage becomes 1.585 (= 2.217/1.399), still economically significant.

To conclude, the time-series and cross-sectional regression analyses conducted in sections 4.1 and 4.2 have yielded unambiguous evidence that the performance of the CAPM and the FF three-factor model deteriorates in the markets where short sales are constrained/banned. This finding highlights the importance of the no-shorting-constraint assumption underlying asset pricing models, an assumption largely ignored in empirical asset pricing tests so far. The finding therefore also calls for research endeavours to find a way that takes the importance into account and so makes asset pricing models more applicable in the markets with short-selling restrictions.

5. A shortability-augmented asset pricing model

As a response to the "call" made at the end of Section 4, we conceive a new factor – the shortability factor, and explore it in this section. To implement the idea, we change the models described in Section 3 by simply adding NMS_t to F_t in equation (1). This will lead to an additional factor loading in B and one more risk premium in λ. As in Section 4, we conduct successively time-series and cross-sectional analyses, and report their results in two subsections below.

5.1 Time-series regression analysis

Unlike in Section 4, we sort 25 size-B/M portfolios using *all* stocks without differentiating between their short-selling status. That is, we take the shortability factor as a systematic risk factor affecting all stocks albeit with different size and value characteristics.

Table 8 presents the means and standard deviations of raw and excess returns on the 25 size-B/M portfolios sorted using all stocks. The summary statistics indicate that small firms have higher returns than large firms, and high book-to-market stocks have higher returns than low book-to-market stocks. Specifically, firms with the smallest size and the highest B/M ratios have the largest return: 5.5% per month for the raw return and 2.8% for the excess return. Firms with the second biggest size and the lowest B/M ratio have the lowest return: 0.1% per month for the raw return and -2.7% for the excess return. Furthermore, the stock returns of small firms generally have higher standard deviations than the stock returns of large firms, consistent with the notion that small firms are riskier than large firms and hence investors demand a higher rate of return from the former as compensation for bearing extra risk.

Now we are ready to carry out a time series analysis, to see how much the shortability factor can improve the performances of the CAPM and the FF three-factor model in the Hong Kong market where short-sales constraints are present. In so doing, we begin with the two models without the shortability factor, and then augment each of them with the factor. All the time-series regression results are presented in Tables 9 through 12.

Table 9 reports the results of time-series regressions of the 25 size-B/M portfolio returns on the market factor, while Table 10 presents the regression results with the NMS factor added to the CAPM. Comparing the regression results in the two tables, we can make the following observations. (1) After adding NMS to the CAPM, 20 out of the 25 alphas get closer to zero, in terms of both economic magnitude and statistical significance. In particular, among all the 20 reduced t-statistics of alphas, 10 drop from the 90% significance level or higher to being insignificant. (2) 21 out of the 25 loadings on NMS are positive and statistically significant, ranging from 0.183 to 1.399. (3) All of the 25 adjusted R^2s increase significantly, and some of them are more than doubled. (4) The increased explanatory power as reflected by the increased adjusted R^2 could come from two sources. One is the explanatory power added by NMS *per se*. The other is the enhanced explanatory power of the market factor owing to the addition of NMS: After NMS is added to the model, all the 25 t-statistics of the b_p coefficients are increased. To sum up, augmenting the CAPM with the shortability factor significantly increases the ability of the model to explain the time-series variation in size-B/M portfolio returns.

Similar results appear in Tables 11 and 12, where comparison is made between the standard FF three-factor model and its extension with the NMS factor added. Again, the model augmented with NMS produces higher adjusted R^2s in 23 out of 25 regressions than its standard version (with only two fall slightly from 64.5% to 64.4%, and from 49.2% to 49.0%, respectively). Among the 25 coefficients (n_p) on NMS, 23 are positive with 15 being significant at a higher than 99% level. Also, the addition of the NMS factor enhances the explanatory power of the market factor, with 22 out of 25 t-statistics of the b_p coefficients increased.

To sum up, the above tests verify that the shortability factor has strong power in explaining the time-series variations in the test portfolio returns, and also enhances the importance of the market factor in the two asset pricing models.

5.2 Cross-sectional regression analysis

The next question we want to address is whether NMS as a shortability-mimicking portfolio can help better explain the cross-section of average size-B/M portfolio returns. The results are presented in Table 13.

We compare the standard with the augmented CAPM, and compare the standard with the augmented FF three-factor model, considering either just 25 size-B/M portfolios or 25 size-B/M + 33 industry portfolios in R_t (E(R_t)). The most striking observation from Table 13 is that the coefficient estimates of the NMS factor (0.031, 0.035, 0.030 and 0.033) all have a positive sign, are all highly statistically significant (at a higher than the 1% level), and all demonstrate much greater magnitudes and statistical significance than other factor loadings (the market beta, the SMB beta and the HML beta). These results are robust regardless of whether 33 industry portfolios are added to the LHS assets. So, the risk involved in the shortability factor is priced and receives a significant premium.

The second key result is embodied in the GLS R^2. Unlike the asset pricing tests in Section 4, the GLS R^2 now is a meaningful yardstick[11]. Adding NMS to factor portfolios F_t dramatically increases the GLS R^2 for the standard (from 0.005 to 0.193) and the expanded CAPM (from 0.001 to 0.009), and the increases are even more dramatic for the standard (from 0.103 to 0.401) and the expanded FF three-factor model (from 0.021 to 0.128). The OLS R^2, though not relevant for the question of how well a model explains the risk-return opportunities available in the market, can still be useful in addressing whether a model's predictions of expected returns are accurate for a given set of assets (LNS, 2010). It also shows considerable increases for the standard (from -0.043 to 0.616) and the expanded CAPM (from 0.001 to 0.249), and for the standard (from 0.529 to 0.710) and the expanded FF three-factor model (from 0.242 to 0.354). Further, confidence intervals of the GLS R^2 and OLS R^2 all move up to higher levels in the cross-section regressions with the shortability factor added.

The third key result pertains to the T^2 and q statistics, and the shortability factor plays a significant role in reducing both. With the factor added, the T^2 statistic drops from 99.82 to 61.43 for the standard CAPM, from 211.30 to 149.81 for the

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[11]Refer back to note 10 for the definition GLS $R^2 \equiv 1 - q/Q$. If two models have the same test assets in R_t, Q will remain unchanged across them. And if the two models have different factors in F_t, q will be different across them. Then, the GLS R^2 differs only because q changes: A higher/lower q leads to a lower/higher GLS R^2. For example, the two CAPM models with the same 25 size-B/M portfolios in R_t but different factors in F_t, in rows 3 and 4 of Table 13, will have a different GLS R^2 only attributed to a different q. Since q can be interpreted as the unexplained squared Sharpe ratio, changes in the GLS R^2 due only to changes in q will have both statistical and economic meanings.

expanded CAPM, from 69.53 to 39.48 for the standard FF three-factor model, and from 182.91 to 130.23 for the expanded FF three-factor model. Meanwhile, the sample q suggests similar conclusions to the GLS R^2, as the former is closely related to the latter (given the same R_t ($E(R_t)$)). Specifically, after we include the shortability factor in factor portfolios F_t, q falls from 0.701 to 0.455 for the standard CAPM, from 1.428 to 1.163 for the expanded CAPM, from 0.603 to 0.354 for the standard FF three-factor model, and from 1.225 to 1.003 for the expanded FF three-factor model.

Focusing on the sample q is perhaps too narrow, and its confidence intervals should shed more light on the issue of model performance. From Table 13, we cannot reject that q is between 0.000 and 0.432 for the CAPM augmented with the shortability factor, but when the factor is not included, the range for q where we cannot reject rises to [0.071, 0.732]. Take the expanded FF three-factor model as another example, the inclusion of the factor makes the confidence intervals of the true q fall significantly, from [0.299, 1.210] to [0.009, 0.974]. In other words, allowing for the factor, the FF three-factor model will have a 95% chance for q to take a value between 0.009 and 0.974, while excluding the factor the model will have a 95% chance for q to equal anything between 0.299 and 1.210.

To conclude, the time-series and cross-sectional regression analyses conducted in sections 5.1 and 5.2 provide strong evidence that augmenting the CAPM and the FF three-factor model with the shortability-mimicking factor will significantly improve their applicability in the markets where short sales are constrained/banned.

6. Conclusion

Asset pricing models assume that asset markets are free of arbitrage-related frictions and participants can short sell their assets freely. The problem is not so much with the assumption being unrealistic, but with the fact that researchers and practitioners have simply applied the models to circumstances where the assumption does not hold as if this would not matter much. Two premises are needed to justify that one need not be worried too much about the impracticableness of the assumption. One is that short-sales constraints occur occasionally and/or in a negligible number of markets/circumstances. However, this is certainly not the case. Most security markets have constantly imposed restrictions on short selling, though the constraints could vary from time to time and/or in the degree of severity. Even if in some market regulators do not officially prohibit short selling, the costs incurred in short selling can be high enough to deter many, if not all, short sellers, rendering a large number of assets not being practiced with short selling.

The other premise is that the violation of free short selling assumption does not significantly affect the performance of the existing factor models. This study attempts to explore how the presence of short-sales constraints affects the explanatory power of two most important asset pricing models: the CAPM and the FF three-factor model. We find that both models perform much worse when short selling is banned.

We then go further to examine the question of how to improve the performance of the two models in the markets where short sales are restricted. In doing so, we propose a shortability-mimicking factor and augment the models with the factor. Our results show that the factor, constructed using the short-selling status of stocks, has a significant power in explaining both time-series and cross-sectional variations in the FF 25 size-B/M portfolio returns. The addition of the shortability factor to the two models considerably increases their overall performance, as evidenced by the following facts. First, most of the adjusted R^2's from time-series regressions rise significantly, and in some cases are even more than doubled. Second, the shortability factor itself has a significant loading, suggesting that it has strong power in explaining stock returns. Third, adding the factor into the two asset pricing models greatly raises the cross-sectional OLS R^2 and GLS R^2, considerably reduces the cross-sectional T^2 statistic, and significantly narrows/lowers the confidence intervals of the unexplained squared Sharpe ratio *q*.

Our study is carried out using the data from the Hong Kong stock market, as its unique designated short-selling list makes it possible for us to construct various test portfolios and factor portfolios needed for exploring our research questions. However, we believe that the findings of this study have implications beyond the Hong Kong market, and can be readily applied to all the other markets that have different levels/degrees of short-sales constraints.

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Table 1: Changes in the Official Short-Selling List

This table provides information on changes in the official short-selling list of the HKSE from January 1994 to February 2012, including the effective date on which a change took place ("Change date"), the numbers of stocks added to ("Addition") and deleted from ("Deletion") the list, and the total number of stocks appearing on the list ("No. of on-list stocks").

Change	Addition	Deletion	No. of on-list	Change	Addition	Deletion	No. of on-list	Change	Addition	Deletion	No. of on-list
3/01/1994	17	0	17	8/07/2005	1	0	265	14/11/2008	6	144	366
25/03/1996	96	0	113	15/07/2005	1	0	266	12/02/2009	25	27	364
1/05/1997	129	1	241	15/08/2005	14	12	268	14/05/2009	13	22	355
12/01/1998	69	0	310	5/09/2005	1	0	269	10/07/2009	1	0	356
16/03/1998	15	0	325	28/10/2005	1	0	270	5/08/2009	49	16	389
9/11/1998	19	149	195	18/11/2005	11	7	274	5/11/2009	58	11	436
1/03/1999	7	7	195	20/02/2006	10	8	276	18/11/2009	1	0	437
20/09/1999	3	17	181	1/03/2006	2	0	278	3/12/2009	1	0	438
12/11/1999	1	0	182	29/05/2006	23	17	284	15/12/2009	1	0	439
28/02/2000	24	12	194	2/06/2006	1	0	285	24/12/2009	1	0	440
31/05/2000	7	0	201	2/06/2006	1	0	286	1/02/2010	65	8	497
28/08/2000	32	16	217	25/08/2006	38	10	314	1/03/2010	1	0	498
12/02/2001	15	11	221	1/09/2006	1	0	315	10/03/2010	1	0	499
14/05/2001	6	0	227	23/10/2006	1	0	316	25/03/2010	1	0	500
20/08/2001	9	11	225	27/10/2006	1	0	317	10/05/2010	59	12	547
3/12/2001	17	85	157	1/12/2006	55	9	363	16/07/2010	1	0	548
25/02/2002	7	14	150	5/03/2007	30	24	369	4/08/2010	40	19	569
21/05/2002	11	6	155	14/03/2007	1	0	370	30/08/2010	1	0	570
29/07/2002	24	5	174	19/04/2007	5	0	375	29/10/2010	47	18	599
29/11/2002	6	15	165	26/04/2007	4	0	379	15/11/2010	1	0	600
27/01/2003	5	7	163	21/05/2007	29	14	394	22/11/2010	2	0	602
19/05/2003	18	7	174	21/05/2007	1	0	395	20/12/2010	1	0	603
21/07/2003	1	16	159	29/05/2007	1	0	396	30/12/2010	1	0	604
4/08/2003	0	1	158	4/07/2007	1	0	397	28/01/2011	1	0	605
3/11/2003	36	5	189	17/07/2007	1	0	398	1/02/2011	1	0	606
6/01/2004	1	0	190	13/08/2007	137	9	526	25/02/2011	70	17	659
10/02/2004	29	3	216	27/08/2007	1	0	527	24/05/2011	65	18	706
7/04/2004	1	0	217	26/11/2007	64	23	568	9/06/2011	1	0	707
27/04/2004	26	4	239	14/12/2007	2	0	570	12/07/2011	2	0	709
1/07/2004	1	0	240	14/12/2007	1	0	571	12/08/2011	24	50	683
9/07/2004	1	0	241	18/02/2008	33	41	563	6/09/2011	1	0	684
2/08/2004	8	21	228	13/03/2008	1	0	564	3/11/2011	18	97	605
8/11/2004	9	11	226	13/05/2008	22	47	539	14/11/2011	1	0	606
7/02/2005	15	7	234	15/05/2008	1	0	540	2/02/2012	2	0	608
1/03/2005	2	0	236	3/06/2008	5	0	545	10/02/2012	12	39	581
17/05/2005	37	9	264	7/08/2008	10	51	504	29/02/2012	1	0	582

Table 2: Summary Statistics for Risk Factors

We construct the market risk factor by using all Hong Kong shares and the all-share index is value weighted. SMB and HML are the risk factors associated with firm size and book-to-market ratio respectively.

We break all Hong Kong stock into two size groups based on the breakpoints for the bottom 50% (Small), and top 50% (Big) of the ranked values of ME. We also break all Hong Kong stocks into three book-to-market equity groups based on the breakpoints for the bottom 30%(Low), middle 40% (Medium), and top 30% (High) of the ranked values of BE/ME. Then we construct six portfolios (S/L,S/M,S/H,B/L,B/M,B/H) from the intersections of the two ME and three BE/ME groups. For example, the S/L portfolio contains the stocks in the small-ME group that are also in the low- BE/ME group, and the B/H portfolio contains the big-ME stocks that are also in the low-BE/ME group, and the B/H portfolio contains the big-ME stocks that also have high BE/MEs. Monthly value-weighted returns on the six portfolios are calculated from July of year t to June of t+1 (so the portfolios are formed/re-formed at June of t+1 and held for 12 months). We calculate returns beginning in July of year t to make sure that book equities for year t-1 are known. The size factor (SMB) is the average of the returns on the small-stock portfolios minus the returns on the big-stock portfolios:

$$SMB = \frac{(S/L - B/L) + (S/M - B/M) + (S/H - B/H)}{3}$$

Likewise, the B/M factor (HML) is the average of the returns on the high-B/M portfolios minus the returns on the low-B/M portfolios :

$$HML = \frac{(S/H - S/L) + (B/H - B/L)}{2}$$

The NMS (shortable minus nonshortable) factors are constructed as: Each month, within each of the six Size-B/M portfolios, we calculate the difference in value-weighted returns of nonshortable and shortable portfolios, and then average the diffeences across the six portfolios:

$$NMS = \frac{1}{6}\big((S/H^N - S/H^S) + (B/H^N - B/H^S) + (S/M^N - S/M^S) + (B/M^N - B/M^S) + (S/L^N - S/L^S) + (B/L^N - B/L^S)\big)$$

	R_m - R_f	*SMB*	*HML*	*NMS*
Mean	-0.022	0.013	0.011	0.030
t-value for mean	-3.54	2.23	2.40	3.70
Median	-0.015	0.005	0.007	0.011
Maximum	0.215	0.504	0.543	0.746
Minimum	-0.440	-0.214	-0.122	-0.254
Standard Deviations	0.084	0.080	0.062	0.107
No. Obs	182	182	182	182

Table 3: Summary Statistics of Monthly Excess Returns for 25 Shortable and 25 Non-shortable Size-B/M Portfolios

At the end of June of each year, we construct 25 shortable size-B/M portfolios. The size breakpoints are the 20th, 40th, 60th, 80th percentiles of market capitalization. The B/M quintile breakpoints are 20th, 40th, 60th, 80th percentiles of the book-to-market ratio. The intersections of 5×5 independent size and B/M sorts for those shortable stocks produce 25 value-weighted size-B/M shortable portfolios. In the same way, we construct 25 non-shortable size-B/M portfolios. Sample period: January 1997 to February 2012 (with 182 monthly observations).

	Book-to-Market Equity (BE/ME) Quintiles										
Size	Low	2	3	4	High	Size	Low	2	3	4	High
	Panel A: Summary statistics for 25 shortable size-B/M portfolios										
	Mean						Standard deviation				
Small	-0.045	-0.045	-0.018	-0.017	-0.022	Small	0.170	0.166	0.170	0.153	0.169
2	-0.035	-0.024	-0.020	-0.022	-0.018	2	0.247	0.127	0.130	0.139	0.143
3	-0.032	-0.024	-0.013	-0.023	-0.012	3	0.140	0.119	0.124	0.133	0.145
4	-0.019	-0.017	-0.020	-0.023	-0.020	4	0.099	0.106	0.127	0.119	0.138
Big	-0.020	-0.019	-0.024	-0.020	-0.020	Big	0.087	0.094	0.107	0.108	0.134
	Panel B: Summary statistics for 25 non-shortable size-B/M portfolios										
	Mean						Standard deviation				
Small	0.024	0.008	0.003	0.017	0.036	Small	0.188	0.196	0.187	0.169	0.280
2	-0.017	0.009	0.005	0.004	0.001	2	0.185	0.189	0.122	0.144	0.127
3	-0.024	-0.011	-0.013	-0.007	-0.007	3	0.153	0.140	0.112	0.123	0.119
4	-0.031	-0.016	-0.019	-0.014	-0.016	4	0.138	0.106	0.126	0.100	0.127
Big	-0.027	-0.016	-0.007	-0.015	-0.010	Big	0.143	0.103	0.130	0.095	0.121

Panel C: Difference in the mean of returns between 25 shortable and 25 non-shortable size-B/M portfolios

	25 shortable size-B/M portfolios		25 non-shortable size-B/M portfolios
Mean	-0.023		-0.006
Differences		-0.0171	
t - differences		-4.33	

Table 4: Difference in CAMP Regressions between Shortable and Non-shortable Portfolios

This table only reports the differences in the estimated time-series coefficients between the model with 25 shortable size-B/M portfolios and the model with 25 non-shortable portfolios. ss_p = 1 indicates that portfolio *p* is formed using shortable stocks, while ss_p = 0 indicates that portfolio *p* is formed using non-shortable stocks. α_p measures the abnormal return. α'_p measures the difference in the abnormal return. b'_p measures the difference in the beta of the market factor. Sample period: January 1997 to February 2012 (with 182 monthly observations).

Time-series regression: $R_p - R_f = \alpha_p + \alpha'_p{*}ss_p + b_p{*}(R_m - R_f) + b'_p{*}ss_p{*}(R_m - R_f) + e_p$

Book-to-Market Equity (BE/ME) Quintiles

Size	Low	2	3	4	High	Size	Low	2	3	4	High
		α_p						t(α_p)			
Small	0.045	0.034	0.031	0.038	0.063	Small	3.778	2.865	2.830	3.759	3.950
2	0.010	0.036	0.024	0.024	0.024	2	0.695	3.808	3.282	2.938	3.248
3	0.003	0.011	0.006	0.014	0.014	3	0.398	1.553	1.021	1.971	1.927
4	-0.010	0.006	0.007	0.005	0.009	4	-1.407	1.090	1.087	1.003	1.322
Big	0.001	0.006	0.016	0.003	0.008	Big	0.210	1.382	2.681	0.626	1.171
		α'_p						t(α'_p)			
Small	-0.059	-0.052	-0.020	-0.026	-0.054	Small	-3.420	-3.027	-1.287	-1.841	-2.382
2	-0.017	-0.032	-0.018	-0.019	-0.014	2	-0.791	-2.413	-1.768	-1.593	-1.325
3	-0.006	-0.009	0.006	-0.009	0.002	3	-0.514	-0.914	0.650	-0.963	0.231
4	0.012	-0.001	0.001	-0.003	-0.001	4	1.275	-0.167	0.145	-0.351	-0.132
Big	0.000	-0.003	-0.016	-0.001	-0.001	Big	-0.047	-0.462	-1.892	-0.149	-0.085
		b'_p						t(b'_p)			
Small	0.246	0.077	0.073	0.327	0.206	Small	1.233	0.392	0.408	0.998	0.798
2	-0.072	-0.014	0.302	0.319	0.258	2	-0.290	-0.093	1.557	1.369	1.156
3	0.051	0.144	0.236	0.321	0.321	3	0.386	1.243	1.300	1.837	1.723
4	0.017	0.005	0.101	0.294	0.141	4	0.150	0.057	0.023	1.344	1.284
Big	-0.324	0.028	0.015	0.205	0.396	Big	-3.571	0.420	0.156	1.431	2.332
		R^2						adj R^2			
Small	0.284	0.326	0.375	0.353	0.232	Small	0.278	0.320	0.370	0.348	0.226
2	0.212	0.423	0.450	0.435	0.509	2	0.205	0.418	0.445	0.430	0.505
3	0.503	0.499	0.521	0.509	0.503	3	0.499	0.494	0.516	0.505	0.498
4	0.466	0.582	0.616	0.598	0.570	4	0.462	0.578	0.613	0.594	0.567
Big	0.629	0.707	0.566	0.569	0.483	Big	0.626	0.704	0.562	0.566	0.478

Table 5: Difference in the FF Three-Factor Regressions between Shortable and Non-shortable Portfolios

This table only reports the differences in the estimated time-series coefficients between the model with 25 shortable size-B/M portfolios and the model with non-shortable portfolios. ss_p = 1 indicates that portfolio p is formed using shortable stocks, while ss_p = 0 indicates that portfolio p is formed using non-shortable stocks. α_p measures the abnormal return. α'_p measures the difference in the abnormal return. b'_p measures the difference in the beta of the market factor. s'_p measures the difference in the beta of the size factor. h'_p measures the difference in the beta of the value factor. Sample period: January 1997 to February 2012 (with 182 monthly observations).

Time-series regression:

$$R_p - R_f = \alpha_p + \alpha'_p * ss_p + b_p*(R_m - R_f) + b'_p*ss_p*(R_m - R_f) + s_p*SMB + s'_p*ss_p*SMB + h_p*HML + h'_p*ss_p*HML + e_p$$

Book-to-Market Equity (BE/ME) Quintiles

Size	Low	2	3	4	High	Size	Low	2	3	4	High
		α_p						$t(\alpha_p)$			
Small	0.034	0.017	0.017	0.017	0.007	Small	3.146	1.627	1.744	1.942	0.666
2	-0.012	0.016	0.013	0.005	0.010	2	-0.877	1.869	1.908	0.815	1.701
3	-0.006	-0.002	-0.005	-0.002	-0.003	3	-0.761	-0.364	-0.853	-0.401	-0.555
4	-0.020	-0.004	-0.003	-0.006	-0.005	4	-3.383	-0.845	-0.562	-1.301	-0.851
Big	-0.006	-0.001	0.007	-0.004	-0.004	Big	-1.161	-0.315	1.235	-0.737	-0.676
		α'_p						$t(\alpha'_p)$			
Small	-0.058	-0.052	-0.021	-0.015	-0.012	Small	-3.629	-3.378	-1.514	-1.249	-0.753
2	-0.013	-0.016	-0.016	-0.009	-0.013	2	-0.652	-1.373	-1.699	-0.927	-1.489
3	0.001	0.000	0.010	-0.001	0.000	3	0.085	-0.056	1.270	-0.168	-0.023
4	0.022	0.008	0.009	0.006	0.007	4	2.578	1.219	1.168	0.822	0.834
Big	0.010	0.006	-0.008	0.005	0.003	Big	1.339	1.133	-0.983	0.674	0.370
		β'_p						$t(b'_p)$			
Small	0.188	-0.016	-0.019	0.323	0.511	Small	1.047	-0.093	-0.123	2.365	2.844
2	-0.103	0.024	0.270	0.343	0.249	2	-0.470	0.182	2.556	3.196	2.560
3	0.008	0.099	0.224	0.338	0.233	3	0.065	1.104	2.509	3.731	2.882
4	0.005	0.005	0.104	0.306	0.137	4	0.055	0.059	1.138	3.885	1.399
Big	-0.325	0.054	0.035	0.185	0.340	Big	-3.877	0.852	0.369	2.317	3.256
		s'_p						$t(s'_p)$			
Small	-0.376	-0.539	-0.529	-0.729	-0.725	Small	-2.030	-2.707	-3.309	-5.147	-3.884
2	-0.447	-0.784	-0.351	-0.471	-0.119	2	-1.978	-5.645	-3.211	-4.232	-1.175
3	-0.589	-0.838	-0.341	-0.415	-0.387	3	-4.532	-8.997	-3.682	-4.430	-4.615
4	-0.694	-0.601	-0.498	-0.454	-0.558	4	-6.883	-7.598	-5.239	-5.565	-5.504
Big	-0.656	-0.410	-0.385	-0.493	-0.683	Big	-7.555	-6.235	-3.900	-5.954	-5.763
		h'_p						$t(h'_p)$			
Small	0.261	0.771	0.508	-0.137	-2.263	Small	1.086	2.738	2.431	-0.740	-9.289
2	0.176	-0.440	0.143	-0.273	0.033	2	0.597	-2.425	1.000	-1.878	0.253
3	0.044	0.122	0.006	-0.203	0.513	3	0.236	1.002	0.051	-1.658	4.681
4	-0.077	-0.131	-0.134	-0.185	-0.099	4	-0.584	-1.268	-1.076	-1.732	-0.744
Big	-0.139	-0.269	-0.221	0.025	0.461	Big	-1.224	-3.125	-1.714	0.233	2.754
		R^2						adj R^2			
Small	0.445	0.493	0.561	0.572	0.648	Small	0.434	0.482	0.552	0.564	0.641
2	0.407	0.589	0.583	0.659	0.691	2	0.395	0.580	0.575	0.652	0.685
3	0.627	0.715	0.656	0.703	0.777	3	0.619	0.709	0.649	0.697	0.773
4	0.608	0.690	0.686	0.694	0.674	4	0.600	0.684	0.680	0.687	0.668
Big	0.700	0.752	0.619	0.633	0.622	Big	0.694	0.747	0.611	0.625	0.614

Table 6: Summary statistics for the time-series regressions of the CAPM and Fama-French three-factor models to explain monthly excess returns on, respectively, shortable and non-shortable size-B/M portfolios.

The GRS F-statistic tests whether all the 25 intercepts in each of the four time-series regressions are jointly zero. $|\alpha|$ is the average absolute intercept. Avr R^2 is the average R^2. Avr $\bar{R}^2$ is the average adjusted R^2. We save 25 R-squares of shortable portfolios and 25 R-squares of non-shortable portfolios, and then use paired difference test to examine differences. We save 25 adjusted R-squares of shortable portfolios and 25 adjusted R-squares of non-shortable portfolios, and then use paired difference test to examine differences. The unexplained Sharpe ratio, $\theta_z(\alpha)$, is the core component of the GRS F-statistic (the square root of the unexplained squared Sharpe ratio, θ_z^2). Sample period: January 1997 to February 2012 (with 182 monthly observations).

	Shortable portfolios						Non-shortable portfolios						Difference in Avr R^2 and Avr $\bar{R}^2$			
	GRS F	p-value	$|\alpha|$	$\theta_z(\alpha)$	Avr R^2	Avr $\bar{R}^2$	GRS F	p-value	$|\alpha|$	$\theta_z(\alpha)$	Avr R^2	Avr $\bar{R}^2$	R^2	t-value	Avr $\bar{R}^2$	t-value
CAPM	1.668	0.032	0.007	0.538	0.587	0.584	2.256	0.002	0.018	0.695	0.387	0.384	0.200	7.500	0.201	7.500
FF Three-Factor	1.310	0.163	0.006	0.497	0.657	0.650	1.713	0.029	0.009	0.631	0.617	0.610	0.040	2.720	0.040	2.720

Table 7: Cross-sectional regression tests

The table reports the OLS cross-sectional regression results (supplemented by the GLS R^2) with 25 size-B/M portfolios used alone or together with 33 industry portfolios as the LHS variables. The OLS R^2 is an adjusted R^2. The cross-sectional T^2 statistic tests whether pricing errors in a cross-sectional regression are all zero, with simulated p-values in brackets. *q* is the distance between a model's mimicking portfolios and the minimum-variance frontier, measured as the difference between the maximum generalized squared Sharpe ratio and that attainable from the mimicking portfolios. Ninety-five percent confidence intervals for the OLS R^2, the GLS R^2 and the q statistic are reported in brackets below their sample values. Each confidence interval is obtained by simulations with 40,000 replications. Coefficient estimates and their t-values (in parentheses) are computed according to Shanken and Zhou (2007). The sample period used in the first-pass regression is from January 1997 to February 2012, with 182 monthly observations.

Panel A								
CAPM (25)	***Const***	***R_m - R_f***			**OLS R^2**	**GLS R^2**	**T^2**	***q***
Shortable	-0.011	-0.010			-0.022	0.014	39.76	0.385
	-0.670	-0.700			[-0.043, 0.111]	[0.000,0.091]	[p=0.000]	[0.127, 0.390]
Non-shortable	-0.010	0.004			-0.042	0.017	69.33	0.801
	-0.420	0.180			[-0.043, 0.176]	[0.000, 0.096]	[p=0.000]	[0.825, 1.681]
Panel B								
CAPM (25+33)	***Const***	***R_m - R_f***			**OLS R^2**	**GLS R^2**	**T^2**	***q***
Shortable	-0.120	0.079			0.139	0.002	194.66	1.348
	-4.270	3.110			[-0.019,0.441]	[0.000, 0.010]]	[p=0.000]	[0.996, 1.482]
Non-shortable	-0.022	0.009			0.000	0.005	224.73	2.416
	-2.530	1.010			[-0.021,0.227]	[0.000, 0.012]	[p=0.000]	[2.664, 3.798]
Panel C								
FF 3-factor(25)	***Const***	***R_m - R_f***	***SMB***	***HML***	**OLS R^2**	**GLS R^2**	**T^2**	***q***
Shortable	-0.030	0.009	-0.012	0.000	0.042	0.029	28.91	0.340
	-1.440	0.470	-1.770	0.030	[-0.077, 0.595]	[0.004, 0.374]	[p=0.000]	[0.110, 0.348]
Non-shortable	-0.002	-0.029	0.029	0.008	0.474	0.153	39.22	0.626
	-0.100	-1.600	3.390	1.380	[0.096, 0.820]	[0.009, 0.482]	[p=0.000]	[0.209, 0.801]
Panel D								
FF 3-factor (25+33)	***Const***	***R_m - R_f***	***SMB***	***HML***	**OLS R^2**	**GLS R^2**	**T^2**	***q***
Shortable	-0.078	0.039	0.013	0.001	0.004	0.022	125.06	1.399
	-2.280	1.180	0.640	0.070	[-0.050, 0.242]	[0.002, 0.211]	[p=0.000]	[0.565, 1.309]
Non-shortable	-0.023	-0.006	0.018	0.015	0.265	0.127	168.89	2.217
	-3.06	-0.79	2.86	3.21	[0.004, 0.614]	[0.008,0.301]	[p=0.000]	[1.593, 2.510]

Table 8: Summary Statistics of Monthly Raw and Excess Returns on 25 Size-B/M Portfolios Sorted Using All Stocks
At the end of June of each year, we construct 25 size-B/M portfolios. The size breakpoints are the 20th, 40th, 60th, 80th percentiles of market capitalization. The B/M quintile breakpoints are 20th, 40th, 60th, 80th percentiles of book-to-market ratio. The intersections of the 5x5 independent size and B/M sorts for those stocks produce 25 monthly value-weighted size-B/M portfolios. Risk free rate is monthly Hong Kong 3-month Treasury bill rate.

Raw Return											
Size	Low	2	3	4	High	Size	Low	2	3	4	High
		Means						Standard Deviations			
Small	0.051	0.033	0.036	0.044	0.055	Small	0.175	0.153	0.156	0.153	0.224
2	0.011	0.026	0.019	0.023	0.027	2	0.149	0.165	0.107	0.119	0.125
3	0.005	0.013	0.009	0.017	0.016	3	0.151	0.109	0.108	0.122	0.120
4	0.001	0.007	0.015	0.013	0.013	4	0.108	0.102	0.110	0.123	0.112
Big	0.007	0.009	0.004	0.009	0.016	Big	0.083	0.088	0.100	0.103	0.139

Excess Return											
Size	Low	2	3	4	High	Size	Low	2	3	4	High
		Means						Standard Deviations			
Small	0.024	0.005	0.008	0.017	0.028	Small	0.178	0.157	0.159	0.157	0.226
2	-0.017	-0.002	-0.009	-0.005	-0.001	2	0.155	0.170	0.112	0.124	0.130
3	-0.023	-0.015	-0.018	-0.010	-0.012	3	0.154	0.114	0.115	0.128	0.126
4	-0.027	-0.021	-0.013	-0.015	-0.015	4	0.113	0.109	0.117	0.131	0.118
Big	-0.021	-0.019	-0.023	-0.019	-0.012	Big	0.089	0.094	0.107	0.110	0.143

Table 9: Summary Statistics for Time-Series Regressions Based on the CAPM to Explain Monthly Excess Returns on 25 Size-B/M Portfolios

The 25 size-B/M portfolios are constructed using all stocks without differentiating them into the shortable and the non-shortable group. α_p measures the abnormal return. b_p measures the beta of the market factor. The sample period used for regressions is from January 1997 to February 2012, with 182 monthly observations.

Time-series regressions:

$$R_{pt} - R_{ft} = \alpha_p + b_p\left(R_{mt} - R_{ft}\right) + \varepsilon_{pt}$$

Book-to-Market Equity (BE/ME) Quintiles

Size	Low	2	3	4	High	Size	Low	2	3	4	High
			α_p						$t(\alpha_p)$		
Small	0.045	0.024	0.029	0.041	0.054	Small	3.721	2.216	2.759	4.112	3.440
2	0.008	0.026	0.010	0.017	0.025	2	0.850	2.485	1.551	2.351	3.574
3	-0.003	0.008	0.005	0.013	0.013	3	-0.243	1.453	0.906	1.856	1.990
4	-0.004	0.003	0.013	0.012	0.009	4	-0.680	0.669	2.648	1.837	1.543
Big	0.001	0.004	0.001	0.006	0.016	Big	0.178	1.417	0.241	1.412	2.139
			b_p						$t(b_p)$		
Small	0.972	0.842	0.953	1.075	1.187	Small	6.926	6.765	7.817	9.445	6.565
2	1.124	1.241	0.863	0.982	1.132	2	10.279	10.416	11.445	11.892	14.326
3	0.910	1.031	1.053	1.056	1.121	3	7.625	15.695	16.141	12.882	14.958
4	1.036	1.072	1.166	1.189	1.081	4	16.062	19.923	20.722	15.940	16.305
Big	0.950	1.023	1.102	1.120	1.253	Big	28.024	31.025	23.143	22.332	14.492
			R^2						Adj R^2		
Small	0.212	0.205	0.256	0.334	0.195	Small	0.208	0.200	0.251	0.330	0.190
2	0.372	0.379	0.424	0.443	0.536	2	0.369	0.375	0.421	0.440	0.533
3	0.246	0.581	0.594	0.482	0.557	3	0.242	0.578	0.592	0.480	0.554
4	0.592	0.690	0.707	0.588	0.599	4	0.589	0.689	0.705	0.586	0.597
Big	0.815	0.844	0.751	0.737	0.541	Big	0.814	0.843	0.749	0.735	0.539

Table 10: Summary Statistics for Time-Series Regressions Based on the CAPM Augmented with the Shortability Factor to Explain Monthly Excess Returns on 25 Size-B/M Portfolios

The 25 size-B/M portfolios are constructed using all stocks without differentiating them into the shortable and the non-shortable group. α_p measures the abnormal return. b_p measures the beta of the market factor. n_p measures the beta of the shortability factor. The sample period used for regressions is from January 1997 to February 2012, with 182 monthly observations.

Time-series regressions:

$$R_{pt} - R_{ft} = \alpha_p + b_p\left(R_{mt} - R_{ft}\right) + n_p NMS_t + \varepsilon_{pt}$$

Book-to-Market Equity (BE/ME) Quintiles

Size	Low	2	3	4	High	Size	Low	2	3	4	High
			α_p						$t(\alpha_p)$		
Small	0.014	0.003	0.005	0.018	0.013	Small	1.639	0.318	0.589	2.301	1.198
2	-0.002	-0.003	-0.003	-0.001	0.008	2	-1.545	-0.449	-0.578	-0.238	1.586
3	-0.003	-0.003	-0.006	0.002	0.000	3	-2.528	-0.675	-1.131	0.234	0.026
4	-0.005	-0.003	0.007	0.003	0.000	4	-2.974	-0.953	1.481	0.522	0.015
Big	0.002	0.006	0.004	0.008	0.011	Big	0.734	1.909	1.068	1.803	1.406
			b_p						$t(b_p)$		
Small	0.992	0.855	0.968	1.090	1.214	Small	10.227	8.215	10.454	12.667	9.948
2	1.137	1.260	0.872	0.994	1.143	2	13.012	17.108	14.141	17.211	19.368
3	0.923	1.038	1.060	1.064	1.129	3	9.250	19.272	19.222	14.624	18.120
4	1.043	1.076	1.169	1.195	1.087	4	19.195	22.243	22.062	17.260	18.146
Big	0.949	1.022	1.099	1.119	1.257	Big	28.288	31.274	23.705	22.419	14.794
			n_p						$t(n_p)$		
Small	1.063	0.717	0.831	0.782	1.399	Small	13.987	8.791	11.452	11.603	14.634
2	0.691	0.981	0.457	0.619	0.552	2	10.089	17.008	9.457	13.682	11.938
3	0.689	0.395	0.367	0.400	0.438	3	8.812	9.359	8.497	7.014	8.969
4	0.366	0.249	0.201	0.296	0.301	4	8.598	6.557	4.847	5.459	6.419
Big	-0.058	-0.053	-0.118	-0.066	0.183	Big	-2.197	-2.064	-3.249	-1.685	2.743
			R^2						Adj R^2		
Small	0.626	0.446	0.572	0.622	0.636	Small	0.622	0.440	0.568	0.617	0.632
2	0.602	0.764	0.617	0.729	0.743	2	0.597	0.761	0.613	0.726	0.740
3	0.476	0.719	0.712	0.595	0.695	3	0.470	0.716	0.708	0.590	0.692
4	0.712	0.751	0.741	0.647	0.675	4	0.709	0.748	0.738	0.643	0.671
Big	0.820	0.848	0.765	0.741	0.560	Big	0.818	0.846	0.762	0.738	0.555

Table 11: Summary Statistics for Time-Series Regressions Based on the FF Three-Factor Model to Explain Monthly Excess Returns on 25 Size-B/M Portfolios

The 25 size-B/M portfolios are constructed using all stocks without differentiating them into the shortable and the non-shortable group. α_p measures the abnormal return. b_p measures the beta of the market factor. s_p measures the beta of the size factor. h_p measures the beta of the value factor. The sample period used for regressions is from January 1997 to February 2012, with 182 monthly observations.

Time-series regressions:

$$R_{pt} - R_{ft} = \alpha_p + b_p\left(R_{mt} - R_{ft}\right) + s_p SMB_t + h_p HML_t + \varepsilon_{pt}$$

Book-to-Market Equity (BE/ME) Quintiles

Size	Low	2	3	4	High	Size	Low	2	3	4	High
			α_p						t(α_p)		
Small	0.030	0.011	0.015	0.022	0.008	Small	3.086	1.113	1.680	2.982	0.900
2	-0.005	0.008	-0.002	0.000	0.009	2	-0.758	1.047	-0.348	0.084	1.929
3	-0.017	-0.001	-0.004	0.001	-0.003	3	-1.977	-0.169	-0.957	0.179	-0.544
4	-0.012	-0.005	0.003	0.001	-0.004	4	-2.673	-1.130	0.699	0.129	-0.876
Big	0.003	0.005	-0.001	0.003	-0.002	Big	1.12733	1.80896	-0.20089	0.71306	-0.449
			b_p						t(b_p)		
Small	1.020	0.842	0.964	1.056	0.954	Small	9.129	7.541	9.358	12.466	9.917
2	1.169	1.253	0.852	0.951	1.095	2	15.186	15.350	14.958	18.642	21.043
3	0.912	1.038	1.048	1.036	1.061	3	9.142	20.954	20.436	15.378	20.063
4	1.033	1.049	1.109	1.154	1.014	4	19.535	22.513	23.685	18.016	19.484
Big	0.965	1.021	1.056	1.068	1.069	Big	28.801	30.735	23.429	22.460	19.774
			s_p						t(s_p)		
Small	1.251	0.828	0.959	1.045	1.485	Small	10.809	7.157	8.985	11.915	14.889
2	1.122	1.229	0.683	0.851	0.763	2	14.069	14.525	11.578	16.099	14.151
3	0.951	0.618	0.568	0.640	0.610	3	9.210	12.041	10.688	9.174	11.130
4	0.528	0.351	0.282	0.489	0.398	4	9.632	7.273	5.809	7.363	7.389
Big	-0.087	-0.089	-0.171	-0.125	0.002	Big	-2.510	-2.579	-3.659	-2.527	0.034
			h_p						t(h_p)		
Small	-0.048	0.181	0.132	0.369	1.927	Small	-0.315	1.194	0.948	3.216	14.769
2	-0.063	0.192	0.230	0.402	0.425	2	-0.601	1.732	2.984	5.818	6.020
3	0.199	0.087	0.161	0.286	0.543	3	1.474	1.297	2.312	3.134	7.568
4	0.138	0.232	0.452	0.350	0.548	4	1.932	3.678	7.130	4.031	7.769
Big	-0.118	-0.008	0.274	0.329	1.262	Big	-2.607	-0.179	4.483	5.102	17.223
			R^2						Adj R^2		
Small	0.527	0.392	0.495	0.651	0.784	Small	0.519	0.382	0.487	0.645	0.780
2	0.705	0.724	0.689	0.798	0.809	2	0.700	0.719	0.683	0.795	0.806
3	0.501	0.774	0.762	0.669	0.791	3	0.492	0.770	0.758	0.664	0.787
4	0.740	0.780	0.808	0.712	0.766	4	0.735	0.776	0.804	0.707	0.762
Big	0.829	0.850	0.788	0.776	0.830	Big	0.826	0.847	0.784	0.772	0.827

Table 12: Summary Statistics for Time-Series Regressions Based on the FF Three-Factor Model Augmented with the Shortability Factor to Explain Monthly Excess Returns on 25 Size-B/M portfolios

The 25 size-B/M portfolios are constructed using all stocks without differentiating them into the shortable and the non-shortable group. α_p measures the abnormal return. b_p measures the beta of the market factor. s_p measures the beta of the size factor. h_p measures the beta of the value factor. n_p measures the beta of the shortability factor. The sample period used for regressions is from January 1997 to February 2012, with 182 monthly observations.

Time-series regressions:

$$R_{pt} - R_{ft} = \alpha_p + b_p\left(R_{mt} - R_{ft}\right) + s_p SMB_t + h_p HML_t + n_p NMS_t + \varepsilon_{pt}$$

Book-to-Market Equity (BE/ME) Quintiles

Size	Low	2	3	4	High	Size	Low	2	3	4	High
			α_p						t(α_p)		
Small	0.013	0.000	0.002	0.021	-0.005	Small	1.445	0.019	0.230	2.686	-0.646
2	0.002	-0.002	0.002	0.002	0.011	2	0.224	-0.299	0.369	0.375	2.335
3	-0.018	0.003	-0.001	0.008	0.002	3	-1.990	0.658	-0.117	1.306	0.332
4	-0.011	-0.003	0.007	0.008	-0.001	4	-2.325	-0.664	1.683	1.444	-0.149
Big	0.002	0.004	0.002	0.005	-0.005	Big	0.632	1.482	0.496	1.066	-1.023
			b_p						t(b_p)		
Small	1.041	0.855	0.981	1.057	0.970	Small	10.891	8.044	10.462	12.468	11.150
2	1.161	1.265	0.847	0.949	1.093	2	15.673	16.731	15.165	18.621	21.119
3	0.912	1.034	1.044	1.028	1.056	3	9.125	21.422	20.903	16.046	20.573
4	1.032	1.047	1.104	1.145	1.010	4	19.502	22.580	24.493	19.143	19.781
Big	0.966	1.022	1.053	1.066	1.073	Big	29.037	30.764	23.775	22.485	20.072
			s_p						t(s_p)		
Small	-0.866	-0.452	-0.621	0.866	-0.032	Small	-3.095	-1.452	-2.265	3.489	-0.126
2	1.914	0.088	1.114	1.012	1.019	2	8.826	0.396	6.812	6.787	6.728
3	0.862	1.050	1.019	1.419	1.096	3	2.947	7.431	6.974	7.573	7.293
4	0.678	0.569	0.760	1.338	0.794	4	4.378	4.196	5.762	7.639	5.311
Big	-0.255	-0.186	0.162	0.068	-0.336	Big	-2.619	-1.908	1.250	0.487	-2.146
			h_p						t(h_p)		
Small	-0.444	-0.059	-0.164	0.335	1.642	Small	-3.209	-0.384	-1.207	2.730	13.029
2	0.086	-0.022	0.311	0.432	0.473	2	0.798	-0.203	3.843	5.856	6.305
3	0.183	0.168	0.245	0.432	0.634	3	1.260	2.403	3.391	4.658	8.519
4	0.167	0.273	0.542	0.509	0.622	4	2.174	4.068	8.301	5.873	8.409
Big	-0.150	-0.026	0.336	0.365	1.199	Big	-3.108	-0.544	5.243	5.311	15.486
			n_p						t(n_p)		
Small	1.713	1.036	1.279	0.145	1.228	Small	8.089	4.398	6.161	0.773	6.370
2	0.640	0.923	0.349	0.131	0.207	2	3.902	5.514	2.817	1.159	1.805
3	0.072	0.349	0.365	0.631	0.393	3	0.325	3.265	3.301	4.445	3.457
4	0.121	0.177	0.387	0.687	0.320	4	1.035	1.719	3.877	5.183	2.827
Big	0.136	0.078	-0.269	-0.155	0.273	Big	1.844	1.064	-2.746	-1.480	2.308
			R^2						Adj R^2		
Small	0.656	0.453	0.585	0.652	0.824	Small	0.648	0.440	0.576	0.644	0.820
2	0.729	0.765	0.702	0.800	0.813	2	0.722	0.759	0.695	0.795	0.808
3	0.501	0.787	0.776	0.703	0.804	3	0.490	0.782	0.771	0.696	0.799
4	0.741	0.783	0.823	0.750	0.776	4	0.736	0.778	0.819	0.745	0.771
Big	0.832	0.851	0.797	0.779	0.835	Big	0.829	0.847	0.792	0.774	0.831

Table 13: Cross-sectional regression tests

The table reports the OLS cross-sectional regression results (supplemented by the GLS R^2) with 25 size-B/M portfolios used alone or together with 33 industry portfolios as the LHS variables. The OLS R^2 is an adjusted R^2. The cross-sectional T^2 statistic tests whether pricing errors in a cross-sectional regression are all zero, with simulated p-values in brackets. *q* is the distance that a model's mimicking portfolios are from the minimum-variance frontier, measured as the difference between the maximum generalized squared Sharpe ratio and that attainable from the mimicking portfolios. Ninety-five percent confidence intervals for the OLS R^2, the GLS R^2, and the *q* statistic are reported in bracket below their sample values. Each confidence interval is obtained by simulations with 40,000 replications. Coefficient estimates and their t-values (in parentheses) are computed according to Shanken and Zhou (2007). The sample period used in the first-pass regression is from January 1997 to February 2012, with 182 monthly observations.

CAPM	***Const***	***R_m - R_f***	***NMS***	**OLS R^2**	**GLS R^2**	**T^2**	**q**
FF25	-0.006	-0.002		-0.043	0.005	99.82	0.701
	(-0.20)	(-0.08)		[-0.043, 0.165]	[0.000, 0.210]	[p=0.009]	[0.071, 0.732]
FF25	-0.026	0.002	0.031	0.616	0.193	61.43	0.455
	(-1.30)	(0.12)	(6.36)	[0.297, 0.851]	0.030, 0.296]	[p=0.125]	[0.000, 0.432]
FF25+33ind.	-0.042	0.022		0.001	0.001	211.30	1.428
	(-1.88)	(1.03)		[-0.019, 0.132]	[0.000, 0.011]	[p=0.000]	[0.693, 1.499]
FF25+33ind.	-0.028	-0.001	0.035	0.249	0.009	149.81	1.163
	(-1.38)	(-0.03)	(3.88)	[0.065, 0.534]	[0.002, 0.010]	[p=0.000]	[0.308, 1.098]

FF 3-factor	***Const***	***R_m - R_f***	***SMB***	***HML***	***NMS***	**OLS R^2**	**GLS R^2**	**T^2**	***q***
FF25	-0.004	-0.020	0.021	0.009		0.529	0.103	69.53	0.603
	(-0.16)	(-0.89)	(4.61)	(1.95)		[0.214, 0.826]	[0.030, 0.438]	[p=0.139]	[0.000, 0.510]
FF25	-0.019	-0.002	0.014	0.008	0.030	0.710	0.401	39.48	0.354
	(-0.99)	(-0.09)	(3.47)	(2.05)	(6.88)	[0.424, 0.925]	[0.101, 0.622]	[p=0.593]	[0.000, 0.297]
FF25+33ind.	-0.020	-0.011	0.024	0.012		0.242	0.021	182.91	1.225
	(-0.98)	(-0.55)	(3.45)	(1.25)		[0.049, 0.487]	[0.009, 0.119]	[p=0.000]	[0.299, 1.210]
FF25+33ind.	-0.012	-0.020	0.028	0.012	0.033	0.354	0.128	130.23	1.003
	(-0.63)	(-1.05)	(4.13)	(1.30)	(3.70)	[0.117, 0.628]	[0.030, 0.198]	[p=0.005]	[0.009, 0.974]