Suggested Solutions to Project II (FIN 3080)

Spring 2022 CUHKSZ

Case 1

1. Recently your boss heard about the CAPM model in a meeting. Since he wants to know whether CAPM really can explain the return in the Chinese stock market, he asks you to test it during the weekend. Although you studied CAPM in many classes, you never tested it using real-world data. So, you first search the academic journals and find two papers about empirically testing CAPM in the Chinese stock market and the US stock market. After studying these two papers, you decide to use the weekly returns of all stocks listed on both Shenzhen and Shanghai Main Board (including small and medium-sized boards) from January 4, 2017, to December 31, 2020, for CAPM testing. You need to carefully write down the steps and explain each step (and of course the results) to your boss, who is smart and picky. Your boss might prefer intuitive graphical results, but you also want to show the rigorous quantitative results. Please report your main findings in both tables and graphs.

   Solution. We may refer to Chen et al. (2019) for a three-step methodology to test the applicability of the CAPM model in China's main board market from 2017 to 2020. In step zero, we may collect (readily-available) weekly individual stock return data, shibor rate data and market return data from CSMAR as we did in homework 2. Merging the three data sets together yields a firm-week panel with 553,293 observations. Note that testing the CAPM model requires three disjoint yet consecutive sample periods so that we may evenly split the whole period into $[2017w1, 2018w17]$, $[2018w18, 2019w36]$ and $[2019w37, 2020w52]$, in which w denotes the week number.

   In the first step, we restrict sample period to $[2017w1, 2018w18]$ and run the following time-series regression for each individual stock:

   $$r_{i,t} = \alpha_i + \beta_i \cdot r_{m,t} + \epsilon_i, \tag{1.1}$$

   where i, t index the firm and week number; $r_{i,t}$ is company i's stock return at week t and $r_{m,t}$ is the market return at week t. The regression results of eq. (1.1) for a random sample of ten firms are summarized in table 1 and most firms therein deliever significant and positive betas ranging from 0.7 to 1.5.

   In the second step, we sort and divide individual stocks into 10 groups based on their betas estimated from eq. (1.1) with first-period samples, i.e., stocks with betas lying in the p-th quantile are put into the p-th group ($p \in \{1, 2, 3, \cdots, 10\}$). Then we may switch the sample period to $[2018w18, 2019w36]$ and run the following time-series regression for each group:

   $$r_{p,t} - r_{f,t} = \alpha_p + \beta_p \cdot (r_{m,t} - r_{f,t}) + \epsilon_{i,t}, \tag{1.2}$$

where p, t index the group and week number; $r_{p,t}$ is the mean of stock return within group p at week t and $r_{m,t}$ is the market return at week t. The results of eq. (1.2) are presented in table 2. Most groups have a significant beta greater than 1, implying that market returns on average have non-trivial effects on individual stock returns. Since only one group (the top-10% group) has an alpha significantly different from zero, we cannot reject that the null hypothesis that $E(\epsilon) = 0$. Finally, there is no clear monotonicity between R^2 and β_p, suggesting that stock returns also expose to risks other than market conditions.

In the last step, we carry forward the grouping fashion from eq. (1.1) and leverage the third episode of stock return data as well as the β_p estimated from eq. (1.2) to test whether market risks positively relate to expected rates of return. Specificlly, we consider the following group-aggregated cross-sectional regression:

$$\overline{r_{p,t} - r_{f,t}} = \gamma_0 + \gamma_1 \cdot \beta_p + \epsilon_p, \tag{1.3}$$

where p indexes the group, $\overline{r_{p,t} - r_{f,t}}$ is the within-group average stock return (over the last sample period), β_p is group p's coefficient estiamted from eq. (1.2). If γ_1 is significantly greater than zero, then stock returns positively relate to market risks; if γ_0 significantly differs from zero, then there exist unconsidered risks that affect individual stock returns. The regression results for eq. (1.3) are given by table 3 and fig. 1, both of which suggest that CAPM model does to some extent explain stock return heterogenities but does not fully apply to China's A-share markets. □

Remark. *The empirical strategies in Fama and MacBeth (1973) and Chen et al. (2019) are slightly different and it is good enough to apply either of them in our setting. The implementation may be tricky and complex. It is because the method is proposed in absence of advanced econometric tools to track temporal correlations. Thanks to the great influence of Fama and MacBeth (1973), however, this method has subsisted ever since.*

Case 2

1. You are an intern in a quantitative hedge fund. Your boss heard a good strategy about trading small-capitalization stocks in a meeting. He wants to see if this is the case. He asks you to test whether the small-cap stocks have an average return higher than large market capitalization stocks. You decide to use all stocks listed on the Shanghai and Shenzhen mainboards (including the small and medium-sized boards) for the test. Your boss prefers to test using portfolio construction methodology as we have discussed in the class. Please construct 10 different portfolios based on the firm size every month and compare the average returns of the 10 portfolios. Please build up a long-short strategy based on your findings and our lecture note. Calculate the average return of the strategy and the alpha of the CAPM model (Please use monthly stock return data starting from 2006) (Please use the monthly stock return data since 2006).

Solution. Similarly, we may first manually collect monthly individual stock return data, shibor rate data and market return data from CSMAR and then merge them together to obtain a firm-month panel spannning 419,261 observations. Different from the situation in Case 1, however, firm grouping now becomes dynamic - for each month, we need to sort firms based on their market value (i.e., market capitalization) in **last month** and assign them into proper groups, namely $Q1, Q2, \cdots Q10$, given their market value quantiles. Holding these firms and rebalancing the position every month equip us with ten portfolios and monthly returns for these portfolios are visualized by fig. 2.

One may tell from fig. 2 that $Q10$ generates higher returns than $Q1$ under both equal-weighted and valued-weighted methods. Intuitively, longing $Q1$ and shorting $Q10$ can produce significant profits. To formally test this intuition, we may estimate the CAPM model based on the returns induced by $Q1$, $Q10$ and $Q1 - Q10$ respectively, and then determine whether alphas are significantly different from zero. Table 4 reports the regression results. It is clear that (i) results are consistent either when weights are assigned equally or according to firm values; (ii) $Q1$'s alpha is much higher than $Q10$'s alpha; (iii) alpha spread (across $Q1$ and $Q10$) is significantly positive. Hence, we may conclude that taking a long position in a quantile portfolio with lowest firm size and a short position in a qunatile portfolio with highest firm size generates a 0.324% annualized risk-adjusted return in China's main board market. □

2. Since you want to take the opportunity to impress your boss, you will explore other market rumors that may generate high returns. For example, you have heard that there is a strategy of chasing ups and downs in the stock market. More specifically, one first calculates the realized return in the past 1 month or 3 months for each stock and divides them into 10 portfolios based on the past return. Then hold the stocks in each portfolio for 1 month. Repeat the same procedure and reallocate stocks into each portfolio every month. Examine whether the past winners would generate a higher return than past losers? Please build up a long-short strategy based on your findings and our lecture note. Calculate the average return of the strategy and the alpha of the CAPM model (Please use monthly stock return data starting from 2006).

   Solution. To impress our boss with a market-performance-based strategy, it suffices to set the grouping criterion to stock return in **last month** and replicate the steps in the previous question. In so doing, we may arrive at fig. 3 and table 5. The results suggest that, contradicted with common perception, there are short-term reversals in stock returns - firms with good past performance tend to perform worse in the future; longing firms with lowest past return and shorting firms with highest past return may equip us with a 0.204% annualized risk-adjusted return. It is also noteworthy that profits mostly arise from shorting firms with best past performance. □

3. Finally, you heard that Buffett likes to buy cheap stocks, such as stocks with low P/B ratios. Can you use the sorting and portfolio construction method to test whether stocks with low P/B ratios would generate higher returns in the future? Please construct a long-short strategy based on your finding. Calculate the average return of the strategy and the alpha of the CAPM model (Please use monthly stock return data starting from 2006).

Solution. Again, the main framework is identical with those discussed above. By merging past P/B ratios with stock returns, we may obtain fig. 4 and table 6. Figure 4 suggests that stocks with low P/B ratios on average have higher returns in the future and table 6 further highlights that the scale of alpha is comparable with that of stocks with low past stock returns. We can likewise construct a long-short portfolio based on P/B ratios to generate a 0.084% annualized return and interestingly, such portfolio only works if firms within each group are assigned with equal weights. □

4. Please try to propose and test another strategy.

Solution. This is an open question and there are hunderds (if not thousands) potential factors can be used to construct theoretically profitable strategies. You may develop ideas from corporate governance or take a pure asset pricing perspective, i.e., focusing on factors that incorporate secondary market trading patterns (e.g., past stock returns). Here we consider the illiquidity in the past month as a potential factor. The idea is that illiquid stocks are more diffcult to sell - it is hard to find a trading counterpart. Hence, investors are less likely to pay any high prices for illiquid stocks, which equip illiquid stocks with higher expected returns. Intuitively, taking a long position in the least liquid stocks and a short position in the most liquid stocks may generate significant profits.

Amihud (2002) provide a good annual proxy for illiquidity and CSMAR extends Amihud's insights and make available the following monthly illiquidity measure:

$$Illiquidity_{i,t} = \frac{1}{Days_{i,t}} \sum_{d=1}^{Days_{i,t}} \frac{|R^d_{i,t} \cdot M^d_{i,t}|}{V_{i,t}}, \tag{4.1}$$

in which $illiquidity_{i,t}$ denote firm i's illiquidity measure at month t, $Days_{i,t}$ is the number of trading days for firm i in month t, $R^d_{i,t}$ is the daily stock return of firm i in day d of month t, $M^d_{i,t}$ is the market capitalization for firm i in day d of month t, and $V_{i,t}$ denotes firm i's total trading volumes in month t.

The measure raised by eq. (4.1) may be interpreted as the stock price's sensitivity to trading volumes on dollar basis , or put in plain English, how much trading volume, on average, does the stock take to deviate from a certain price level. In this sense, given identical trading volumes in a specific period, one may expect illiquid stocks to fluctuate more pronouncedly than liquid stocks do. Empirically, merging CSMAR's illiquidity measures and replicating the standard procedures yield table 7, which validates our intuition.

□

Remark. *Finance people have identified a host of factors and anomalies with prediction power on stock returns over past decades, and now we have a 'zoo of factors' (Cochrane 2011). Given so many factors, however, one may natually doubt whether these factors are profitable in reality. The choice of liquidity in this solution is intended to inspire your skepticism - stocks in the* $Q10$ *portfolios are illiquid per se, how could one always rebalance the portfolios at fair prices every month? Indeed, the effect of many* *factors significantly weakens when trading costs are taken into consideration. A classic example is the 'PEAD' effect and you may refer to Bernard and Thomas (1989) and Ng, Rusticus, and Verdi (2008) for a rigorous discussion.*

References

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Ng, Jeffrey, Tjomme O Rusticus, and Rodrigo S Verdi (2008). "Implications of transaction costs for the post–earnings announcement drift". In: *Journal of Accounting Research* 46.3, pp. 661–696.

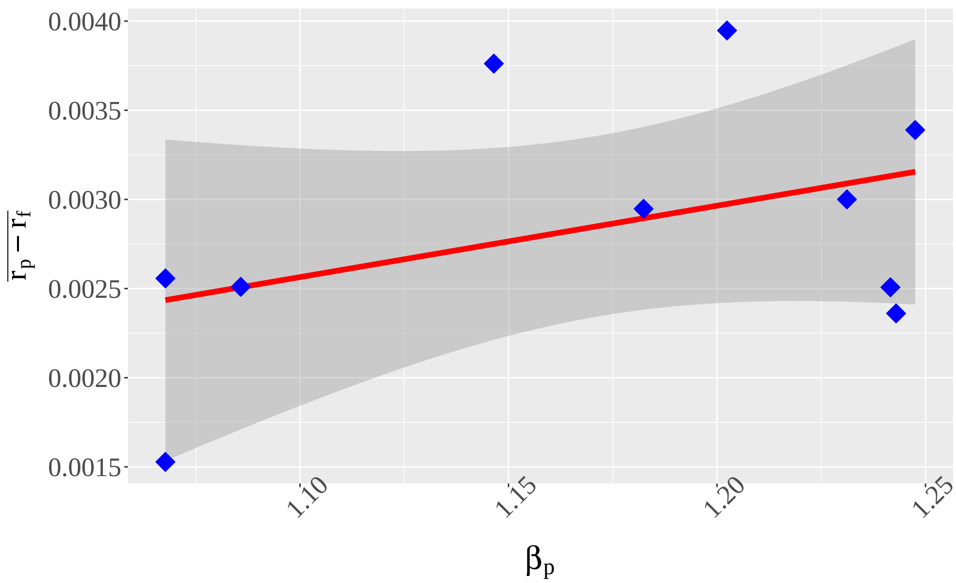

Figure 1: Regression scatter plot (Case 1)

Figure 1 shows the regression results of eq. (1.3): $\overline{r_{p,t} - r_{f,t}} = \gamma_0 + \gamma_1 \cdot \beta_p + \epsilon_p$. Typically, red line shows the fitted linear model and blue points display the real observations. All data are sourced from CSMAR's *Stock Trading* and *Shibor Rate* tables.

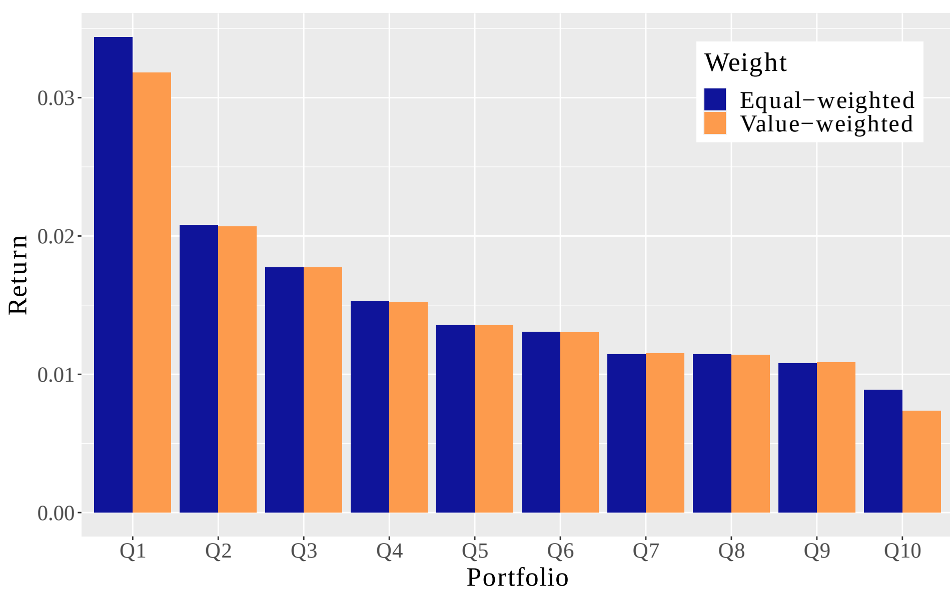

Figure 2: Monthly average returns for size-based portfolios (Case 2.1)

Figure 2 shows the monthly average returns for ten size-based portfolios; monthly portfolios are constructed as follows: for each month, we sort firms based on their market values in the last month and assign firms with i-th quantile market values into portfolio Qi, i.e., $Q1$ ($Q10$) is consisted of firms with the lowest (highest) market values over the time. The blue (orange) bar shows the equal-weighted (value-weighted) portfolio returns. All data are sourced from CSMAR's *Stock Trading* and *Shibor Rate* tables.

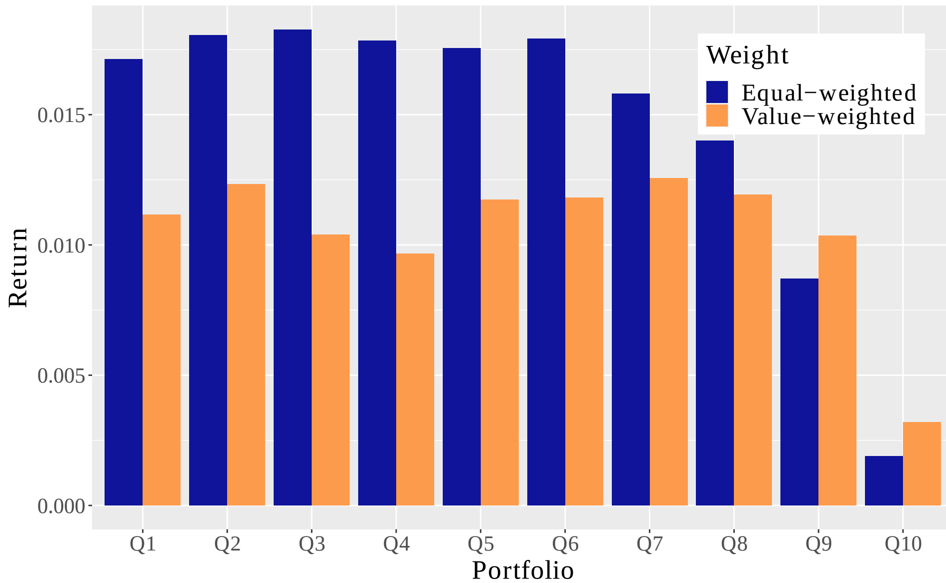

Figure 3: Monthly average returns for return-based portfolios (Case 2.2)

Figure 3 shows the monthly average returns for ten return-based portfolios; monthly portfolios are constructed as follows: for each month, we sort firms based on their stock returns in the last month and assign firms with i-th quantile returns into portfolio Qi, i.e., $Q1$ ($Q10$) is consisted of firms with the lowest (highest) stock returns over the time. The blue (orange) bar shows the equal-weighted (value-weighted) portfolio returns. All data are sourced from CSMAR's *Stock Trading* and *Shibor Rate* tables.

Figure 4: Monthly average returns for PB-based portfolios (Case 2.3)

Figure 4 shows the monthly average returns for ten PB-based portfolios; monthly portfolios are constructed as follows: for each month, we sort firms based on their P/B ratios in the last month and assign firms with i-th quantile ratios into portfolio Qi, i.e., $Q1$ ($Q10$) is consisted of firms with the lowest (highest) P/B ratios over the time. The blue (orange) bar shows the equal-weighted (value-weighted) portfolio returns. The blue (orange) bar shows the equal-weighted (value-weighted) portfolio returns. All data are sourced from CSMAR's *Stock Trading* and *Shibor Rate* tables.

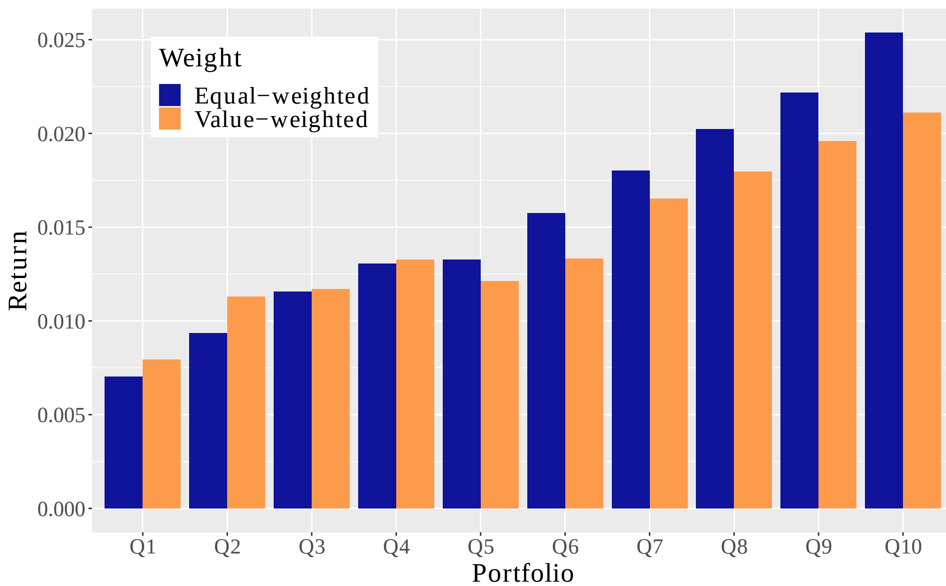

Figure 5: Monthly average returns for illiquidity-based portfolios (Case 2.4)

Figure 5 shows the monthly average returns for ten return-based portfolios; monthly portfolios are constructed as follows: for each month, we sort firms based on their illiquidity measures in the last month and assign firms with i-th quantile illiquidity into portfolio Qi, i.e., $Q1$ ($Q10$) is consisted of firms with the highest (lowest) liquidity over the time. The blue (orange) bar shows the equal-weighted (value-weighted) portfolio returns. The blue (orange) bar shows the equal-weighted (value-weighted) portfolio returns. All data are sourced from CSMAR's *Stock Trading*, *Shibor Rate* and *Stock Market Derivative Index* tables.

Table 1: Time-series regression results of the first period of random sample stocks (Case 1)

Table 1 summarizes the regression results of eq. (1.1): $r_{i,t} = \alpha_i + \beta_i \cdot r_{m,t} + \epsilon_i$, where monthly stock market data are sourced from CSMAR's *Stock Trading* table and market return data are collected from CSMAR's *Shibor Rate* tables; samples are restricted to firms listed on China's main board during 2017 to 2021. The dependent variable is individual stock return and the independent variable is market return r_m. Columns (1)-(10) report the results for a random sample of ten listed firms; t-statistics are in parentheses; $^{*}p < 0.05, ^{**} p < 0.01, ^{***} p < 0.001$.

Dependent Variable	Individual stock return									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	002767	002371	000717	601390	600497	600223	002522	000607	600353	601021
α	-0.012*	0.011	0.005	-0.003	-0.001	-0.007**	-0.006	-0.012**	-0.006	-0.001
	(-1.74)	(1.26)	(0.57)	(-0.93)	(-0.18)	(-2.35)	(-0.91)	(-2.51)	(-0.76)	(-0.31)
β	1.311***	1.019**	1.488***	0.753***	1.403***	1.105***	1.460***	1.274***	1.591***	1.005***
	(3.65)	(2.23)	(3.06)	(5.14)	(4.74)	(7.23)	(4.36)	(5.12)	(4.55)	(4.63)
R^2	0.168	0.070	0.124	0.286	0.257	0.442	0.224	0.284	0.289	0.245
Observations	68	68	68	68	67	68	68	68	53	68

Table 2: Time-series regression results of the second period of ten portfolios (Case 1)

Table 2 summarizes the regression results of eq. (1.2): $r_{p,t} - r_{f,t} = \alpha_p + \beta_p \cdot (r_{m,t} - r_{f,t}) + \epsilon_{i,t}$, where weekly stock market data are sourced from CSMAR's *Stock Trading* table and market return data are provided by *Shibor Rate* table; samples are restricted to firms listed on China's main board during 2017 to 2021. The dependent variable is portfolio stock return and the independent variable is the difference between market return r_m and risk-free rate r_f. The portfolios are constructed as follows: we first sort firms based on their betas estimated from the first period using eq. (1.1) ($r_{i,t} = \alpha_i + \beta_i \cdot r_{m,t} + \epsilon_i$) and then assign firms with i-th quantile betas into portfolio Qi, i.e., $Q1$ ($Q10$) is consisted of firms with the lowest (highest). t-statistics are in parentheses; $^{*}p < 0.05, ^{**} p < 0.01, ^{***} p < 0.001$.

Dependent Variable	Stock portfolio return									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$Q1$	$Q2$	$Q3$	$Q4$	$Q5$	$Q6$	$Q7$	$Q8$	$Q9$	$Q10$
α	-0.003*	-0.001	-0.001	-0.000	-0.001	-0.001	-0.000	-0.001	-0.001	-0.002
	(-1.78)	(-0.88)	(-0.42)	(-0.27)	(-0.38)	(-0.32)	(-0.21)	(-0.28)	(-0.36)	(-0.77)
β	1.068***	1.068***	1.086***	1.146***	1.202***	1.182***	1.243***	1.231***	1.242***	1.248***
	(16.85)	(19.64)	(17.65)	(18.77)	(17.82)	(17.07)	(17.46)	(17.60)	(17.77)	(15.26)
R^2	0.811	0.854	0.825	0.842	0.828	0.815	0.822	0.824	0.827	0.779
Observations	68	68	68	68	68	68	68	68	68	68

Table 3: Cross-sectional regression results of the third period of ten portfolios (Case 1)

Table 3 summarizes the regression results of eq. (1.3): $\overline{r_{p,t} - r_{f,t}} = \gamma_0 + \gamma_1 \cdot \beta_p + \epsilon_p$, where weekly stock market data are sourced from CSMAR's *Stock Trading* table and market return data are provided by *Shibor Rate* table; samples are restricted to firms listed on China's main board during 2017 to 2021. The dependent variable is weekly average portfolio stock return and the independent variable is β estimated from table 2. t-statistics are in parentheses; $^{*}p < 0.05, ^{**} p < 0.01, ^{***} p < 0.001$.

	γ_0	γ_1	R^2	F-statistics	P-value
Coefficient	-0.002	0.004	0.1716	1.66	0.23
t-value	(-0.50)	(1.29)			

Table 4: Time-series regression results of the CAPM model with size-based portfolios (Case 2.1)

Table 4 summarizes the regression results of the CAPM model with ten size-based portfolios and monthly portfolios are constructed as follows: for each month, we first sort firms based on their market values in the last month and then assign firms with i-th quantile market values into portfolio Qi, i.e., $Q1$ ($Q10$) is consisted of firms with the lowest (highest) market values over the time. Typically, monthly stock market data are sourced from CSMAR's *Stock Trading* table and market return data are provided by *Shibor Rate* table; samples are restricted to firms listed on China's main board from 2006 to 2021. The dependent variable is monthly portfolio stock return and the independent variable is monthly market return. Columns (1)-(10) report the results for equal-weighted returns for portfolios $Q1, Q2, \cdots, Q10$, respectively; columns (11) uses the difference betweem monthly returns of $Q1$ and $Q10$ portfolios as dependent variables; t-statistics are in parentheses; $^{*}p < 0.05, ^{**} p < 0.01, ^{***} p < 0.001$.

DV	Equal-weighted portfolio return										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	$Q1$	$Q2$	$Q3$	$Q4$	$Q5$	$Q6$	$Q7$	$Q8$	$Q9$	$Q10$	$Q1-Q10$
Mean return	0.039***	0.025***	0.022***	0.019***	0.017**	0.017**	0.015**	0.015**	0.014**	0.012*	0.027***
	(4.92)	(3.33)	(2.89)	(2.61)	(2.38)	(2.35)	(2.12)	(2.18)	(2.10)	(1.89)	(4.89)
α	0.025***	0.011**	0.007*	0.005	0.003	0.002	0.000	0.000	-0.000	-0.002**	0.027***
	(5.01)	(2.60)	(1.82)	(1.30)	(0.81)	(0.71)	(0.12)	(0.18)	(-0.25)	(-2.11)	(4.82)
β	1.040***	1.067***	1.094***	1.096***	1.086***	1.092***	1.076***	1.076***	1.070***	1.035***	0.005
	(17.71)	(21.61)	(23.37)	(25.58)	(25.68)	(29.18)	(31.63)	(36.53)	(46.53)	(83.27)	(0.08)
R^2	0.619	0.708	0.739	0.772	0.774	0.815	0.838	0.874	0.918	0.973	0.000
Observations	195	195	195	195	195	195	195	195	195	195	195

Table 5: Time-series regression results of the CAPM model with past-return-based portfolios (Case 2.2)

Table 5 summarizes the regression results of the CAPM model with ten return-based portfolios and monthly portfolios are constructed as follows: for each month, we first sort firms based on their stock returns in the last month and then assign firms with i-th quantile returns into portfolio Qi, i.e., $Q1$ ($Q10$) is consisted of firms with the lowest (highest) stock returns over the time. Typically, monthly stock market data are sourced from CSMAR's *Stock Trading* table and market return data are provided by *Shibor Rate* table; samples are restricted to firms listed on China's main board from 2006 to 2021. The dependent variable is monthly portfolio stock return and the independent variable is monthly market return. Columns (1)-(10) report the results for equal-weighted returns for portfolios $Q1, Q2, \cdots Q10$, respectively; columns (11) uses the difference betweem monthly returns of $Q1$ and $Q10$ portfolios as dependent variables; t-statistics are in parentheses; $^{*}p < 0.05, ^{**} p < 0.01, ^{***} p < 0.001$.

DV	Equal-weighted portfolio return										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	$Q1$	$Q2$	$Q3$	$Q4$	$Q5$	$Q6$	$Q7$	$Q8$	$Q9$	$Q10$	$Q1-Q10$
Mean return	0.021***	0.023***	0.022***	0.022***	0.021***	0.022***	0.019***	0.017**	0.012	0.005	0.017***
	(2.88)	(3.12)	(3.17)	(3.11)	(3.03)	(3.06)	(2.70)	(2.45)	(1.65)	(0.66)	(4.11)
α	0.007*	0.009**	0.009***	0.008***	0.007**	0.007**	0.005*	0.003	-0.003	-0.009***	0.017***
	(1.92)	(2.52)	(2.64)	(2.63)	(2.44)	(2.57)	(1.72)	(1.10)	(-0.89)	(-3.01)	(4.13)
β	1.071***	1.079***	1.056***	1.070***	1.077***	1.080***	1.080***	1.069***	1.079***	1.096***	-0.025
	(22.96)	(26.49)	(27.25)	(29.53)	(29.74)	(31.18)	(32.02)	(32.38)	(31.75)	(29.02)	(-0.51)
R^2	0.733	0.785	0.795	0.820	0.822	0.835	0.842	0.845	0.840	0.814	0.001
Observations	194	194	194	194	194	194	194	194	194	194	194

Table 6: Time-series regression results of the CAPM model with PB-based portfolios (Case 2.3)

Table 6 summarizes the regression results of the CAPM model with ten PB-based portfolios and monthly portfolios are constructed as follows: for each month, we first sort firms based on their P/B ratios in the last month and then assign firms with i-th quantile ratios into portfolio Qi, i.e., $Q1$ ($Q10$) is consisted of firms with the lowest (highest) P/B ratios over the time. Typically, monthly stock market data are sourced from CSMAR's *Stock Trading* table and market return data are provided by *Shibor Rate* table; samples are restricted to firms listed on China's main board from 2006 to 2021. The dependent variable is monthly portfolio stock return and the independent variable is monthly market return. Columns (1)-(10) report the results for equal-weighted returns for portfolios $Q1, Q2, \cdots Q10$, respectively; columns (11) uses the difference betweem monthly returns of $Q1$ and $Q10$ portfolios as dependent variables; t-statistics are in parentheses; ${}^{*}p < 0.05, {}^{**} p < 0.01, {}^{***} p < 0.001$.

DV	Equal-weighted portfolio return										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	$Q1$	$Q2$	$Q3$	$Q4$	$Q5$	$Q6$	$Q7$	$Q8$	$Q9$	$Q10$	$Q1-Q10$
Mean return	0.021***	0.022***	0.023***	0.021***	0.020***	0.019***	0.019***	0.016**	0.016**	0.014*	0.008*
	(3.01)	(3.10)	(3.10)	(2.92)	(2.74)	(2.64)	(2.61)	(2.28)	(2.17)	(1.92)	(1.91)
α	0.006**	0.007**	0.007**	0.006**	0.005	0.004	0.004	0.002	0.001	-0.001	0.007*
	(2.24)	(2.54)	(2.48)	(1.99)	(1.52)	(1.29)	(1.21)	(0.50)	(0.30)	(-0.20)	(1.74)
β	1.071***	1.101***	1.125***	1.094***	1.088***	1.084***	1.076***	1.055***	1.055***	1.020***	0.051
	(31.90)	(33.38)	(31.72)	(30.37)	(29.11)	(27.55)	(28.12)	(26.32)	(25.51)	(24.12)	(1.07)
R^2	0.843	0.855	0.842	0.830	0.818	0.801	0.807	0.786	0.775	0.755	0.006
Observations	191	191	191	191	191	191	191	191	191	191	191

Table 7: Time-series regression results of the CAPM model with illiquidity-based portfolios (Case 2.4)

Table 7 summarizes the regression results of the CAPM model with ten illiquidity-based portfolios and monthly portfolios are constructed as follows: for each month, we first sort firms based on their illiquidity measures in the last month and then assign firms with i-th quantile market values into portfolio Qi, i.e., $Q1$ ($Q10$) is consisted of firms with the highest (lowest) liquidity over the time. Typically, monthly stock market data are sourced from CSMAR's *Stock Trading* table and market return data are provided by *Shibor Rate* table; samples are restricted to firms listed on China's main board from 2006 to 2021. The dependent variable is monthly portfolio stock return and the independent variable is monthly market return. Columns (1)-(10) report the results for equal-weighted returns for portfolios $Q1, Q2, \cdots Q10$, respectively; columns (11) uses the difference betweem monthly returns of $Q10$ and $Q1$ portfolios as dependent variables; t-statistics are in parentheses; ${}^{*}p < 0.05, {}^{**} p < 0.01, {}^{***} p < 0.001$.

DV	Equal-weighted portfolio return										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	$Q1$	$Q2$	$Q3$	$Q4$	$Q5$	$Q6$	$Q7$	$Q8$	$Q9$	$Q10$	$Q10-Q1$
Mean return	0.009	0.012*	0.015**	0.016**	0.016**	0.019***	0.022***	0.024***	0.026***	0.030***	0.020***
	(1.37)	(1.72)	(2.02)	(2.27)	(2.29)	(2.60)	(2.98)	(3.27)	(3.47)	(3.94)	(4.44)
α	-0.006***	-0.003	-0.001	0.001	0.002	0.004	0.007**	0.009**	0.012***	0.015***	0.021***
	(-4.73)	(-1.50)	(-0.26)	(0.47)	(0.56)	(1.26)	(2.02)	(2.58)	(2.87)	(3.59)	(4.60)
β	1.106***	1.120***	1.113***	1.078***	1.068***	1.085***	1.062***	1.057***	1.054***	1.031***	-0.076
	(75.05)	(45.23)	(36.02)	(30.79)	(27.85)	(26.94)	(24.73)	(24.13)	(22.02)	(20.17)	(-1.37)
R^2	0.968	0.916	0.873	0.835	0.805	0.794	0.765	0.756	0.721	0.684	0.010
Observations	190	190	190	190	190	190	190	190	190	190	190