More powerful tests for anomalies in the China A-share market[1]

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Abstract

Research into asset pricing anomalies in the China A-share market is hampered given the short time series of available returns. Even when average excess returns on candidate factor portfolios are economically sizeable, conventional portfolio sorting methods lack statistical power. We apply an efficient sorting procedure that combines firm characteristics with the covariance matrix. For the China A-share market, we find that the efficient sorting procedure doubles the t-statistics compared to conventional portfolio sorts, leading to nine instead of three significant anomalies over the post-reform period from 2008 to 2020. We find significant size, value, low-risk, and returns-based anomalies. While portfolio characteristics differ between sorting methods, we find that efficient sorting portfolios highly correlate with equally weighted portfolios and capture the same underlying anomaly.

JEL Classification Code: C58, G10, G11, G12, G15, G23, G40

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Conventional asset pricing studies use a benchmark asset pricing model and examine whether the pricing errors of a set of test portfolios are small in a statistical sense. Dating back to at least Fama and French (1993), these test assets are portfolios sorted on a stock characteristic. For example, the sample is divided into 10 decile portfolios formed on the book-to-market ratio, where the top decile contains the stocks with the highest ratio and the bottom decile contains the stocks with the lowest one. If the benchmark asset pricing model, such as the Capital Asset Pricing Model, cannot explain the average returns on these portfolios, this method has produced an anomaly.

Asset pricing studies on US equity markets have time series typically going back to 1963, while for some stock characteristics data can even go back to 1926.[2] The raw data is available to researchers from the Center for Research Security Prices and portfolio returns using this data from the website of Kenneth French. This long sample grants sufficient power to reject the null hypothesis whether economically large asset pricing errors are in the data. For international samples, the time series is typically considerably shorter. For example, Kenneth French's data library contains international characteristic portfolio returns from 1990, reducing the sample length to three decades. Research into asset pricing anomalies in the China A-share market, the world's second-largest stock market, is hampered by even shorter data availability. Although the modern Chinese stock market has data starting from 1990, the cross-section of listed firms and data quality are limited in early years. Therefore, most empirical studies start their sample after 2000, reducing the sample length to only two decades; see, e.g., Liu, Stambaugh, and Yuan (2019).

That said, even this 20-year period may not be representative of today's market. In 2005, the Chinese regulator introduced the Split-Share Structure Reform, which relaxed restrictions on state-owned enterprises and brought a large proportion of formerly non-tradable shares to the market. This reform was executed by 80% of firms at the end of 2007; see Qiao (2019). Carpenter, Lu, and Whitelaw (2021) find that the price informativeness in Chinese equity markets is on par with that in the US after the Split-Share Structure Reform took effect. In addition, investors could make use of accounting statements that more closely adhere to the International Financial Reporting Standards from 2008. For these reasons, Hsu et al. (2018) also have a subsample analysis that starts in 2008. As such, the post-2008 period is characterized by higher liquidity, transparency, and data reliability, which makes it an important breakpoint. However, such considerations further reduce the sample period to only 13 years. This short sample period poses a challenge to asset pricing studies on the A-share market, as Sharpe ratios of test portfolios need to be almost double compared to studies with a 50-year sample period

[2] Baltussen, Van Vliet, and Van Vliet (2021) extend the history of the cross-section of US equity returns back to 1866.

and even triple compared to those with a 100-year sample period, for the null hypothesis of asset pricing model efficiency to be rejected.[3]

Although the non-parametric stock characteristic sorting approach is intuitive and robust, it may not be efficient. For example, the covariance matrix of returns, the cornerstone of Markowitz's (1952) modern portfolio theory, is completely ignored. Because of estimation error in the mean and variance, a strict mean-variance optimization is likely to lead to inefficient portfolios; see, for example, Best and Grauer (1991). Imposing short-sale constraints or using prior information can alleviate these concerns to a large extent; see Jagannathan and Ma (2003) and Ledoit and Wolf (2003, 2004a). Ledoit, Wolf, and Zhao (2019) develop an efficient sorting procedure, which redefines portfolio sorting as a constrained mean-variance optimization problem. These efficient portfolios are optimized to have minimum variance but retain the same average factor characteristic as the conventional portfolio sorts. In doing so, they incorporate information from the covariance matrix of returns into the sorting problem. Assuming that factor characteristics proxy for expected returns, the method aims to keep average portfolio returns unchanged. Since portfolio variance is minimized, the efficient sorting method then results in a higher Sharpe ratio, which in turn leads to a higher test statistic for a given sample size.

The contributions of this paper are twofold. First, by applying the efficient sorting procedure to Chinese A-shares, we are the first to tackle the power challenge related to its relatively short time series. Consequently, we are better-equipped to detect asset pricing anomalies in the Chinese A-share market. The hypothesis that we want to examine is whether using the efficient sorting procedure leads to more rejections of the null hypothesis that there is no alpha relative to the CAPM. This is especially relevant for those characteristics that have economically significant excess returns but would not be statistically significant using conventional methods. For those characteristics that are not associated with positive excess returns, it should not matter whether we use conventional or efficient sorting procedures. Second, we provide an out-of-sample test for Ledoit, Wolf, and Zhao (2019), who find that t-statistics for anomalies in the US stock market on average more than double, representing a power boost equivalent to quadrupling the effective sample period.[4]

Our main findings can be summarized as follows. First, over the post-reform period, only three out of 17 firm characteristics examined by Hsu et al. (2018) are associated with significant excess returns using the conventional sorting method. This triples to nine significant anomalies when applying the efficient sorting method. We find evidence for significant size, value, low-risk, and returns-based anomalies in the A-share market in the post-reform period. The anomalies that are not statistically

[3] Assuming independently and identically distributed samples, the standard error can be estimated as $\widehat{SE} = \frac{\hat{\sigma}}{\sqrt{T}}$. Strictly speaking, the statement is only true if the standard deviation estimator $\hat{\sigma}$ is invariant to the sample size T.
[4] Leippold and Rüegg (2020) also use the efficient sorting method, but study factor timing instead of discovering equity return factors in markets with short samples.

significant when employing the efficient sorting method have average returns close to zero, and therefore are unlikely to be present in the Chinese A-share market in the first place. Second, using the covariance structure of stock returns does not significantly change average anomaly excess returns, but significantly reduces portfolio volatility, which leads to an approximate doubling of the t-statistics. This is similar to the improvements reported by Ledoit, Wolf, and Zhao (2019) on the US stock market, which confirms the large efficiency gains that can be achieved also in this out-of-sample setting. Third, the gain from efficient sorting is markedly larger than the 20% higher t-statistics obtained when performing industry-neutral sorts that exploit the higher within-sector than across-sector correlation stock returns. Finally, we demonstrate that despite the slightly higher turnover, higher number of portfolio positions, higher concentration, and lower (tail) risk, the efficient sorting portfolios have as much as 70% average correlation with conventional sorting methods, implying that both methods are still exploiting the same anomaly. All in all, our results indicate that the efficient sorting procedure leads to more powerful tests for asset pricing anomalies and is a promising tool to evaluate signals extracted from alternative datasets with a limited number of time series observations.

The remainder of this paper has the following structure. The next section contains a description of our data. In Section 2, we explain the efficient sorting methodology. Section 3 contains the comparison of the efficient sorting method compared to conventional sorting on our sample of Chinese A-shares. Finally, Section 4 concludes.

1. Data

The data is obtained from the China Stock Market and Accounting Research database. From this database, we retrieve stock price data and quarterly financial statement data for all RMB-denominated stocks listed on the Shanghai and Shenzhen stock exchanges. To match accounting data extracted from these reports with returns data, we use statement release dates. Our sample period is from January 2008 to December 2020.[5] This starting point is chosen because Qiao (2019) shows that the Split-Share Structure Reform has been completed for 80% of relevant stocks and International Financial Reporting Standards are introduced in 2008. Moreover, Hsu et al. (2018) also use this as the starting date for their subsample.

Table 1 shows characteristics of the Chinese A-share market over the period 2000 to 2020. We clearly see that the fraction of SOEs reduces steadily after the Split-Share Structure Reform in 2005, when 71.0 percent was SOEs. This has been reduced to 61.3 percent by 2008 and is 30.1 percent at the end of our sample. The fraction of tradable shares increased substantially in 2008 (from 26.9 percent to 36.4 percent), with a further huge positive shock in 2009 (from 36.4 percent to 61.3 percent) and 81.0 percent at the end of the sample period. The frequency of trading suspensions has also decreased over

[5] We use earlier data if necessary to calculate the firm characteristics. For example, since we use 36-month returns to calculate a firm’s beta, we start with returns from January 2005.

time. The biggest decline is observed in recent years after new regulation was enacted to limit trading suspensions following the 2015 stock market crash. Finally, illiquidity measures are much lower post-2008 compared to the years before.

We apply a series of filters to exclude stocks that are not investable, have unreliable data or abnormal behavior. Similar to Liu, Stambaugh, and Yuan (2019), we drop stocks that have been suspended for more than five days in the last month or more than 120 days in the past year, and stocks with a 'special treatment' or 'particular transfer' status. These stocks are subject to trading restrictions and additional controls such as a maximum daily price change of five percent. In addition, we require stocks to have return data over the past 500 trading days to estimate the covariance matrix. If a stock has a few missing observations, we impute the returns using the stock's market beta and the market return. After applying these filters, we choose the largest 1,000 firms for our investment universe. Ledoit, Wolf, and Zhao (2019) apply comparable filters on universe size and trading history.[6] Limiting the number of stocks has two important advantages. It improves the estimation of the (singular) covariance matrix with the non-linear shrinkage estimator and speeds up convergence of the optimization problem, which is non-linear in the number of stocks. From an investor's perspective, limiting the number of stocks to 1,000 is not restrictive, as the largest 1,000 firms account for 75-90 percent of the total stock market capitalization.[7] This is shown in the right panels of Table 1, which shows the effect of our data filters on the universe size and market capitalization covered. In fact, because anomalies tend to be strongest among smaller stocks, limiting our analysis to the largest stocks implies that our results would be stronger in a broader universe; see, e.g., Fama and French (2012) and Hou, Xue, Zhang (2020).

[INSERT TABLE 1 HERE]

We follow Hsu et al. (2018) in choosing 17 firm characteristics in the Chinese A-share market.[8] The anomalies span the following categories: size, value, profitability, investments, accounting

[6] Ledoit, Wolf, and Zhao (2019) consider 1,000 stocks as their largest universe size and require stocks to have a complete return history over the past 1,250 trading days. In light of the short time series and frequent trading suspensions in China, we relax the latter restriction which would be too restrictive.

[7] The MSCI China A International Index, which is commonly used as a benchmark for foreign institutional investors in Chinese A-shares consist of 517 stocks at 30 September 2020. Hence, our selection of the largest 1,000 stocks does not seem restrictive. https://www.msci.com/documents/10199/df29e199-b270-4b2f-ad8f-285ddafa53e4. Using constituents of the MSCI China A International Index, De Groot, Swinkels, and Zhou (2021) show that a strategic allocation to value and momentum factors improves the mean-variance efficient frontier for a global investor. For reference, the S&P 500 Index in the US covers 83 percent of the market capitalization of the MSCI Investable Market Index United States on 31 December 2020.

[8] This is a standard set of firm characteristics. More refined anomaly definitions have been investigated in the Chinese stock market more recently, such as residual momentum (Lin 2019), value adjusted for intangibles (Ho

conservatism, risk, and past returns. Corresponding anomaly definitions are described in Appendix A. In addition to their full sample, which starts in 1995, Hsu et al. (2018) also investigate a shorter sample period starting in 2008, motivated by the structural market changes that we described before. However, there is a cost of limiting the sample period: "*Over the shorter 2008–2016 sample, it is clear that the statistical significance of most results is substantially diminished.*" Although we add four years of data compared to their sample, it remains short. Therefore, we apply efficient sorting to boost statistical power and establish the existence of anomalies over a more representative period.

2. Methodology

We construct long-short anomaly portfolios using three portfolio construction methods: (1) equal-weighting, (2) industry-neutral weighting, and (3) efficient sorting. For the equally weighted portfolios, we follow the standard approach in the literature. At each month-end, we sort stocks into 10 decile portfolios based on the corresponding accounting or stock characteristic. We then calculate the return of these top and bottom portfolios for the next month, where each stock is equally weighted. We take a long position in the top decile and a short position in the bottom decile, such that the difference in returns is the anomaly return for that month.

Stocks within industries tend to have a higher correlation than stocks across industries. Using industry-neutral sorts is a straightforward method to account for correlations and reduce the risk of factors. For some factors, premiums might also be stronger within industries than across industries; see Doeswijk and Van Vliet (2011) or Vyas and Van Baren (2021). To form industry-neutral portfolios, we sort on a firm characteristic within each industry, and then form equally weighted portfolios with the same number of stocks of each industry in a decile portfolio

Following Ledoit, Wolf, and Zhao (2019), efficient sorting solves the following constrained minimum variance problem:

$$\min_{w} w^{'}\Sigma w$$

$$\text{s.t.} \quad m_t^{'} w = m_t^{'} w_t^{EW}$$

$$\sum_{w_i<0} |w_i| = \sum_{w_i>0} |w_i| = 1,$$

where w is a vector of portfolio weights, Σ is the variance-covariance matrix of daily stock returns, m_t is a vector of stock characteristics, and w_t^{EW} is the vector of portfolio weights from the equally weighted decile portfolio. Efficient sorting minimizes the variance of a fully invested long minus a fully invested short portfolio, under the restrictions that the average portfolio characteristic should be

and An 2020), gambling characteristics (Zhu, Zhang, and Yang 2021), and ownership structure (Sun 2022). We restrict our analysis to the standard set of anomalies.

the same as the equally weighted portfolio and that the gross (net) exposure of the portfolio is 200% (0%).[9] Assuming that factor exposures proxy for expected returns, constraining efficient sorting portfolios to have equal exposure to the characteristic as the conventional portfolio results in equal ex-ante expected returns. Because we minimize the variance, efficient sorting results in higher Sharpe ratios and t-statistics. Instead of only holding positions in the top and bottom deciles, efficient sorting portfolios can buy and sell positions in the intermediate deciles if the diversification benefits outweigh the lower characteristic store. For example, if a stock is replaced by two other stocks, it needs to be one with higher and one with lower factor characteristics, and diversification benefits should reduce the risk of the long-short portfolio. Note that efficient sorting is a variant of mean-variance optimization where the first moment of returns is modeled using factor exposures.

A disadvantage compared to the conventional sorting approach is that we have to estimate the covariance matrix Σ. Our choice is the optimal non-linear shrinkage estimator by Ledoit and Wolf (2020). This estimator combines the speed of linear shrinkage estimators (e.g., Ledoit and Wolf 2004b) and the accuracy of non-linear estimators (e.g., Ledoit and Wolf 2012). This differs from Ledoit, Wolf, and Zhao (2019) who use the dynamic DCC-NL estimator by Engle, Ledoit, and Wolf (2019). Since DCC-NL also models the time-varying nature of the covariance matrix, it may lead to even greater power boosts. However, DCC-NL is significantly more computationally expensive and, as noted by Ledoit, Wolf, and Zhao (2019), the static estimator is expected to perform similarly to the DCC-NL estimator at a monthly rebalancing frequency.

Since solvers are sensitive to the scaling of the inputs and outliers, we calculate the characteristic scores m_t using robust measures. Following Ledoit, Wolf, and Zhao (2019), we calculate z-scores by subtracting the trimmed mean and scaling the characteristics by their mean absolute deviations. To avoid optimizing on extreme observations, the z-scores are then winsorized at -5 and +5. In contrast to trimming, winsorizing caps extreme values and does not discard observations.

3. Comparing efficient and conventional sorting methods

Table 2 reports average long-short portfolio returns, portfolio volatility, and t-statistics for the equally weighted, industry-neutral, and efficient sorting portfolios for 17 firm characteristics in the China A-share market over the period January 2008 to December 2020.[10] Over the period 2008 to 2016, Hsu et al. (2018) find only two of the 17 firm characteristics to be statistically significant: size and reversal.

[9] This quadratic optimization problem, as specified in Ledoit, Wolf, and Zhao (2019), is not convex due to a constraint imposed on the gross exposure of the portfolio, i.e., $\sum_{w_i<0}|w_i| = \sum_{w_i>0}|w_i| = 1$. To solve this problem, we approximate this constraint by replacing the equality constraint by an upper bound and use a standard reformulation to remove the absolute value. This convex relaxation nearly always results in the desired solution. In the handful of cases where the constraint does not hold exactly, we re-scale the weights to be fully invested.

[10] The reported results are similar to those of Jansen, Swinkels, and Zhou (2021) over the period 2007 to 2019 for the China A-share market, where they do not restrict their sample to the largest 1,000 as we do here.

For our sample running through 2020, size is no longer statistically significant (t-stat 1.19), but reversal remains significant (t-stat 3.36). In addition, we find that gross and operating profitability are significant (t-stats 2.96 and 2.83, respectively).

[INSERT TABLE 2 HERE]

The middle panel shows industry-neutral portfolio sorts, which reduce risk by reducing the industry tilts of the portfolios.[11] The median volatility is reduced from 5.78% to 4.70%, a reduction of 19%. The biggest boost is observed for the low-volatility category, where Volatility and Idiosyncratic Volatility experience large reductions in volatility and become statistically significant. The median t-statistic increases by 20%, increasing the number of significant anomalies to five.

Efficient sorting provides a stronger power boost. The right panel illustrates that median portfolio volatility more than halves from 5.78% to 2.84% per month. For each of the 17 firm characteristics, portfolio volatility decreases between 29% to 54%. By construction, the portfolios resulting from the conventional and efficient sorting procedures have the same average firm characteristics. Accordingly, median expected returns across the 17 characteristics are similar for the conventional and efficient sorting methods with 0.37% and 0.36% per month, respectively. The average returns are also of similar magnitude with 0.45% and 0.57%, respectively.[12] This shows that the design of this part of the efficient sorting procedure works, as it is not systematically improving average returns. This suggests that portfolio firm characteristics are indeed a reasonable proxy for portfolio returns, as shown by Blitz and Vidojevic (2019).

Similar average returns and lower volatilities lead to higher Sharpe ratios, and consequently to higher t-statistics. This makes it easier to statistically reject the null hypothesis for portfolio returns that are substantial from an economic perspective. Indeed, for efficient sorting we find 9 out of 17 portfolios have statistically significant excess returns, compared to only 3 with conventional sorting. The anomalies that are not statistically significant when employing the efficient sorting method have average returns close to zero, and therefore are unlikely to be present in the A-share market. Conversely, anomaly returns with sizeable economic magnitudes are also statistically significant after applying the efficient sorting procedure, as t-statistics almost double.

[11] For specific anomalies, other methods have been suggested to decrease unrewarded risks. For example, Blitz, Huij, and Martens (2011) show that when factor risks are eliminated from momentum strategies, the volatility of the momentum factor roughly halves. Lin (2019) finds similar results for the China A-share market.

[12] Two of the low-risk characteristics have notably higher average returns for the efficient sorting procedure. This may be because in addition to including a low-volatility sorting characteristic, efficient sorting also exploits low correlation.

To test whether the differences between the three portfolio construction methods are statistically significant, we perform a Wilcoxon paired signed rank test on the means, standard deviations, and t-statistics. With a p-value of 0.01, we reject the null hypothesis that the median t-values of the equally weighted portfolios (1.04) and efficient sorting (2.00) are equal. The p-values from the mean and volatility confirm that this is indeed driven by the reduction in volatility, as the null hypothesis of different median returns cannot be rejected (p-value 0.31). We arrive at the same conclusion when comparing with the middle column, where the efficient sorting t-values are significantly larger than those from the industry-neutral portfolios. This confirms the added value of efficient sorting for researchers confronted with data sets with limited history.

[INSERT FIGURE 1 HERE]

Figure 1 summarizes the main message of Table 1 graphically. For each of the seven groups of firm characteristics, we show the average t-statistics from conventional sorting, industry-neutral sorting, and efficient sorting procedures. All group average t-values are highest for the efficient sorting procedure, except for ‘Accounting conservatism’. For this group and the ‘Investments’ group, previous studies in the China-A market over longer sample periods have also found these anomalies not to yield significant premiums, see e.g., Hsu et al. (2018) and Jansen, Swinkels, and Zhou (2021). For the other groups, improvements are substantial.

[INSERT TABLE 3 HERE]

Table 3 contains CAPM alphas of the long-short portfolios. Results on excess returns or alphas are quantitatively similar, with average t-statistics increasing from 1.19 to 1.92 for the alphas. Interestingly, low-volatility portfolios constructed using efficient sorting have a less negative market exposure. This combined with the fact that efficient sorting not only incorporates volatilities but also correlations helps to explain why average returns for the low-volatility anomalies increase with efficient sorting. Table B1 in Appendix B reports alphas relative to the Liu, Stambaugh, and Yuan (2019) three-factor model, which supplements the CAPM with a size factor and a value factor based on EP. Correcting for size and value renders the size and value anomalies insignificant for all portfolio construction methods. However, efficient sorting still delivers a considerable power boost by increasing average t-statistics from 0.04 to 1.12.

[INSERT TABLE 4 HERE]

One drawback of efficient sorting is that this relies on optimization, which results in lower tractability compared to conventional portfolio sorts. To better understand the differences between equal-weighting and efficient sorting, Table 4 reports a number of portfolio characteristics for both portfolio construction methods. Efficient sorting results in 20% higher turnover, increasing average turnover from 52% to 61%. Turnover increases most for the low-risk anomalies, which also experienced the largest power boosts, while turnover decreases less for quicker signals such as momentum and short-term reversal. The moderate increase in turnover implies that not only gross Sharpe ratios double but also net Sharpe ratios are expected to increase by a similar margin.

While conventional portfolio sorts only hold positions in the top and bottom quantiles, efficient sorting may also buy positions in intermediate portfolios to reduce risk. The median number of positions increases from 196 (i.e., roughly 100 in the long leg and 100 in the short leg) to 232. Positions increase most for investment and accounting conservatism anomalies, which have neither economically nor statistically significant premiums. For the low-risk anomalies, the number of holdings decreases or remains equal. Figure 2 visualizes the distribution of portfolio turnover and number of holdings. We display turnover and holdings at each month for each anomaly, resulting in a distribution of 156 months times 17 characteristics observations. The right figure shows that there is considerable variability in the number of portfolio holdings for efficient sorting, as indicated by the wider bands around the median. This higher variability in holdings contributes to the higher portfolio turnover. Value and reversal anomalies have the highest fluctuations in the number of stocks over time.

[INSERT FIGURE 2 HERE]

In addition to the number of positions, we examine the concentration of portfolio holdings by calculating the effective number of positions. This is calculated as the reciprocal of the Herfindahl-Hirschman index. As shown in Table 4, for equally weighted portfolios the effective and actual number of positions are equal. Efficient sorting results in more concentrated portfolios with the median effective number of names decreasing by 40%. Once again, we observe the biggest change for the low-risk anomalies. While portfolios constructed using investment and accounting conservatism anomalies experienced a substantial increase in positions compared to equal-weighting, the effective positions are nearly equal. This suggests that efficient sorting concentrates positions in a small number of diversified names with high factor exposure. This is supplemented by a large number of very small holdings to adhere to the portfolio constraints.

More concentrated portfolios might expose investors to more idiosyncratic risk. However, efficient sorting portfolios do not only have lower volatility, but also lower tail risk compared to equal-weighting. The 10% lowest returns are nearly 50% lower on average and improve for each of the 17 anomalies. Finally, the return correlation between the two types of portfolios is 70%. This demonstrates that despite the slightly higher turnover, higher number of portfolio positions, higher concentration, and lower (tail) risk, efficient sorting portfolios are comparable to conventional sorting methods and represent a more powerful test for asset pricing anomalies.

4. Conclusions

The efficient sorting procedure is a useful tool for extracting information from datasets with limited history, such as the post-reform China A-share market. Whereas a conventional sorting procedure finds enough statistical evidence for only three firm characteristics, the efficient sorting procedure increases this to nine. We find evidence for significant size, value, low-risk, and returns-based anomalies in the A-share market in the post-reform period. This confirms that efficient sorting grants researchers increased power to detect anomalies present in short time series. In the age of big data, efficient sorting may also serve as a powerful test to evaluate the significance of signals extracted from alternative datasets with a short data history such as consumer transaction data, sustainability, or social media sentiment data.

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Figure 1: t-statistics for conventional and efficient sorting

Average t-statistics for seven anomaly groups. t-statistics correspond to long-short portfolio returns for three different portfolio construction techniques. 'Equally weighted' uses equal-weighting of the top and bottom portfolios. 'Industry-neutral' uses equal-weighting within each industry. 'Efficient sorting' uses the efficient sorting method by Ledoit, Wolf, and Zhao (2019). t-statistics are calculated using Newey and West (1987) standard errors with four lags. The sample period is from January 2008 to December 2020.

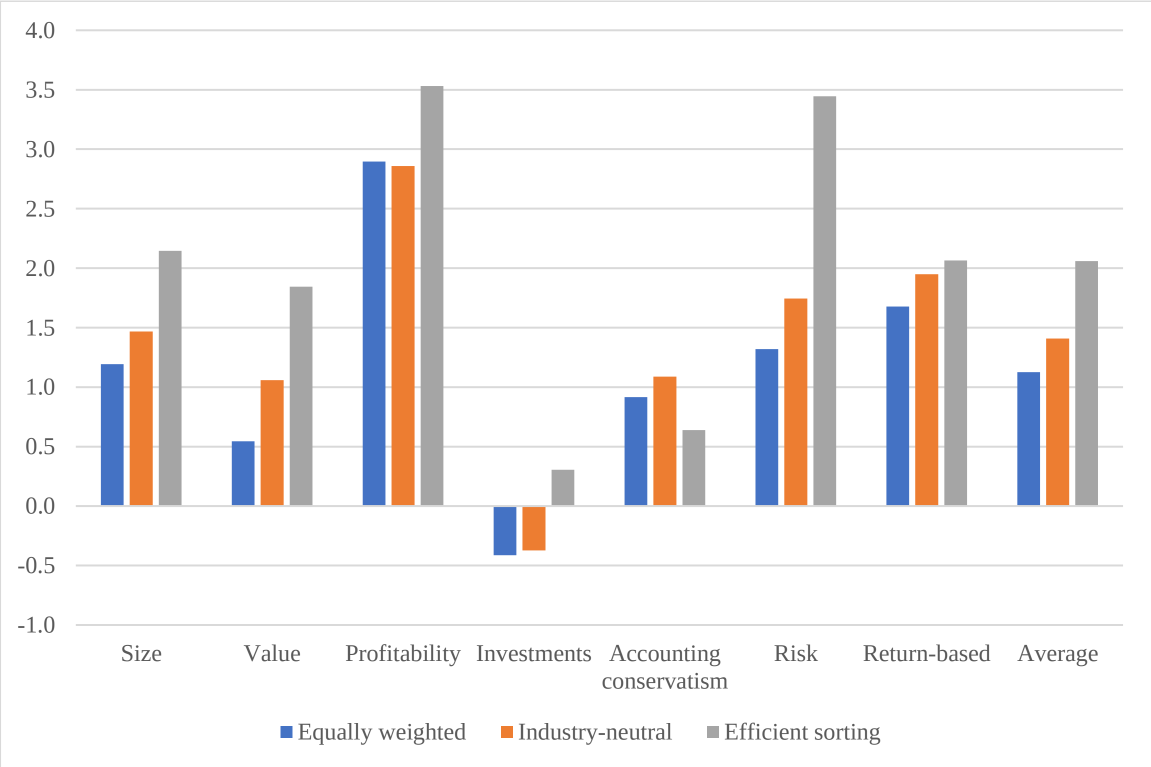

Figure 2: Turnover and number of portfolio holdings

Left: median, interquartile range, minimum, and maximum of one-sided monthly turnover. Turnover is calculated at each month for each firm characteristic. Right: the average number of stocks per anomaly portfolio. The statistics are reported for equally weighted, industry-neutral, and efficient sorting portfolios. The sample period is January 2008 to December 2020 and 17 firm characteristics are used.

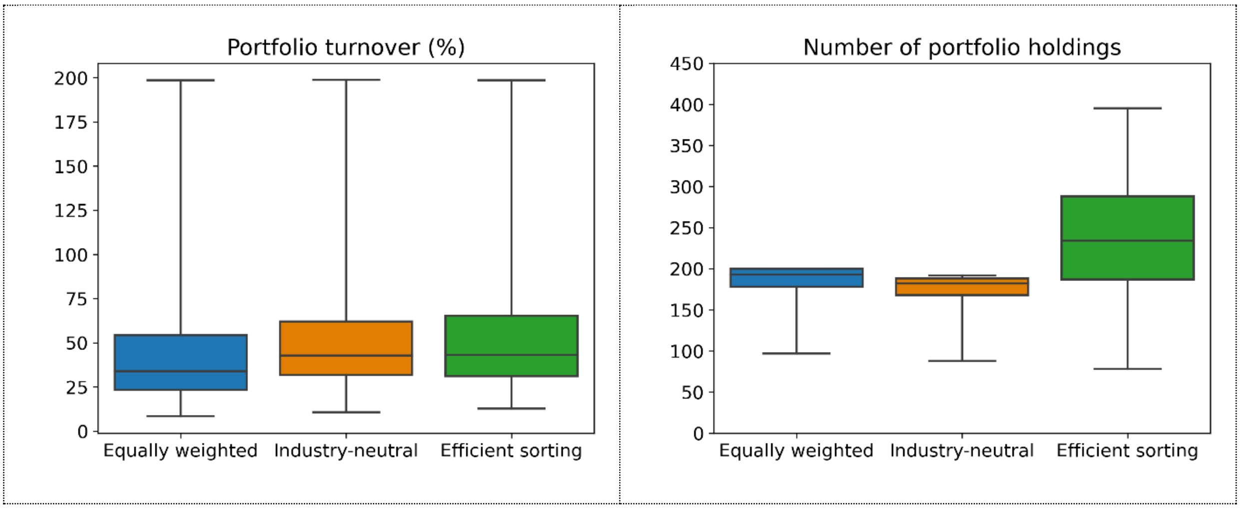

Table 1: Summary statistics for Chinese A-shares from 2000 to 2020

The left panel reports the number of listed firms (Firms), free-float market capitalization of all A-shares (Mcap), the number of state-owned enterprises as a percentage of total listed firms (SOE), the percentage of tradable shares (Tradable), the percentage of stocks suspended for at least one day in the past year (Susp), and the median Amihud (2002) illiquidity of stocks (Illiq). The middle panel shows the number of stocks and the percentage of total free-float market capitalization after imposing sample. The right panel further limits the universe to the largest 1,000 stocks by market capitalization and requires stocks to have return data for at least 500 days. Market capitalization is in USD billions. All statistics are year-end statistics.

	All A-shares						Sample filters		Largest 1000 stocks	
Year	**Firms**	**Mcap**	**SOE**	**Tradable**	**Susp**	**Illiq**	**Firms**	**% of mcap**	**Firms**	**% of mcap**
2000	971	177	73.1	32.5	84.8	1.16	631	78.1	507	64.8
2001	1044	152	73.6	31.2	90.3	3.74	732	82.7	573	68.2
2002	1104	135	74.7	31.5	92.8	4.03	775	84.5	677	74.2
2003	1138	142	74.4	29.5	93.8	2.79	810	87.3	747	79.2
2004	1220	128	73.6	30.1	91.3	5.64	880	90.4	806	83.5
2005	1091	107	71.0	31.3	98.4	3.19	728	83.5	669	80.1
2006	1173	285	69.3	26.3	94.7	0.87	799	86.8	789	86.3
2007	1273	1135	64.9	26.9	89.7	0.40	866	87.5	797	78.2
2008	1410	620	61.3	36.4	94.3	0.93	996	93.2	875	75.8
2009	1486	2101	58.5	61.3	93.3	0.29	1006	94.1	942	91.6
2010	1823	2794	50.0	72.4	80.5	0.34	1213	93.9	1000	90.2
2011	2097	2500	44.3	76.3	86.0	1.11	1442	95.5	1000	89.6
2012	2323	2796	41.6	78.6	91.2	0.66	1598	95.6	1000	89.0
2013	2305	3165	42.0	83.4	40.2	0.43	1622	94.0	1000	85.7
2014	2303	4915	41.0	84.8	49.9	0.23	1498	91.5	1000	85.5
2015	2496	5937	37.9	78.3	69.0	0.11	1639	88.2	1000	77.7
2016	2774	5330	35.2	77.5	46.0	0.16	1770	87.9	1000	75.3
2017	3186	6521	31.6	79.1	31.3	0.32	2040	92.7	1000	81.2
2018	3469	5059	31.0	81.0	25.5	0.47	2368	94.3	1000	81.5
2019	3609	6839	30.7	81.3	8.9	0.23	2449	95.2	1000	81.2
2020	3873	9727	30.1	81.0	7.5	0.26	2605	95.5	1000	81.5

Table 2: Conventional and efficient sorting returns

Average long-short returns ('Mean'), standard deviation ('Std') and t-statistics ('t-stat') for three different portfolio construction techniques. The left part 'Equally weighted' uses equal-weighting of the top and bottom portfolios. The middle part, 'Industry-neutral' uses equal-weighting within each industry. The right part, 'Efficient sorting', uses the efficient sorting method by Ledoit, Wolf, and Zhao (2019). t-statistics are calculated using Newey and West (1987) standard errors with four lags. Returns that are significant at the 5% level are in bold. The bottom three rows contain the average and median of each column, and the p-value of a Wilcoxon paired signed rank test that compares the column with that of the efficient sorting procedure. The sample period is from January 2008 to December 2020.

	Equally weighted			**Industry-neutral**			**Efficient sorting**		
	Mean	*Std*	*t-stat*	*Mean*	*Std*	*t-stat*	*Mean*	*Std*	*t-stat*
Size	0.57	6.26	1.19	0.60	5.11	1.47	**0.74**	3.99	2.15
Book-to-Price	0.21	7.26	0.38	0.42	5.61	0.92	**0.83**	3.55	2.58
Earnings-to-Price	0.63	6.28	1.44	0.65	4.70	1.89	**0.60**	3.22	2.36
Sales-to-Price	0.11	5.93	0.24	0.20	5.25	0.49	0.27	2.70	1.23
Dividend-to-Price	0.04	5.78	0.11	0.30	4.11	0.95	0.25	2.65	1.20
Gross Profitability	**1.11**	4.71	2.96	**0.92**	4.23	2.64	**1.10**	2.84	4.60
Operating Profitability	**0.69**	3.12	2.83	**0.73**	3.21	3.08	**0.36**	1.84	2.46
Asset growth	-0.17	2.85	-0.77	-0.19	2.57	-0.97	0.09	1.57	0.73
Book value growth	-0.01	2.61	-0.05	0.03	2.20	0.23	-0.01	1.42	-0.12
Total Accrual	0.20	2.62	1.04	0.25	2.47	1.41	0.01	1.61	0.07
Net Operating Assets	0.19	2.84	0.79	0.17	2.85	0.77	0.20	1.98	1.20
Volatility	0.74	7.13	1.53	**0.82**	5.89	2.15	**1.49**	5.04	4.10
Beta	0.43	6.28	1.04	0.29	5.36	0.82	0.28	4.00	0.99
Idiosyncratic Volatility	0.66	6.92	1.39	**0.87**	5.50	2.27	**1.56**	4.21	5.24
Momentum	0.37	5.84	0.76	0.14	4.89	0.35	0.04	3.72	0.11
Reversal	**1.52**	5.68	3.36	**1.71**	4.71	4.27	**1.41**	3.79	4.09
Long-term Reversal	0.33	5.04	0.91	0.39	4.01	1.23	**0.45**	2.59	2.00
Average	0.45	5.13	1.13	0.49	4.27	1.41	0.57	2.98	2.06
Median	0.37	5.78	1.04	0.39	4.70	1.23	0.36	2.84	2.00
Wilcoxon rank test (p-value)	0.31	0.00	0.01	0.41	0.00	0.03	-	-	-

Table 3: Conventional and efficient sorting alphas

Average long-short alphas relative to the CAPM ('Alpha'), Market beta (Mkt), and t-statistics ('t-stat') for three different portfolio construction techniques. The left part 'Equally weighted' uses equal-weighting of the top and bottom portfolios. The middle part, 'Industry-neutral' uses equal-weighting within each industry. The right part, 'Efficient sorting', uses the efficient sorting method by Ledoit, Wolf, and Zhao (2019). t-statistics are calculated using Newey and West (1987) standard errors with four lags. Coefficients that are significant at the 5% level are in bold. The sample period is from January 2008 to December 2020.

	Equally weighted				**Industry-neutral**				**Efficient sorting**			
	Alpha	*t-stat*	*Mkt*	*t-stat*	*Alpha*	*t-stat*	*Mkt*	*t-stat*	*Alpha*	*t-stat*	*Mkt*	*t-stat*
Size	0.54	1.15	0.11	1.11	0.56	1.40	0.15	2.15	**0.73**	2.18	0.09	1.89
Book-to-Price	0.21	0.38	-0.02	-0.18	0.40	0.89	0.06	0.81	**0.83**	2.63	0.03	0.48
Earnings-to-Price	**1.06**	2.70	-0.10	-1.23	**0.68**	2.00	-0.12	-1.69	**0.58**	2.57	**0.21**	4.90
Sales-to-Price	0.37	0.91	-0.07	-0.92	0.20	0.49	0.00	-0.02	0.29	1.28	-0.02	-0.44
Dividend-to-Price	0.65	1.19	-0.11	-1.18	0.33	1.05	-0.09	-1.45	0.12	0.76	0.08	1.85
Gross Profitability	**0.95**	2.96	**-0.23**	-5.70	**0.81**	2.87	**-0.24**	-5.82	**0.54**	3.10	**-0.13**	-5.35
Operating Profitability	**0.04**	0.19	**-0.04**	-1.23	**0.31**	1.46	**-0.11**	-3.01	0.06	0.48	0.02	0.96
Asset growth	-0.12	-0.53	-0.03	-1.11	-0.18	-0.93	-0.04	-1.37	0.07	0.56	-0.02	-1.07
Book value growth	0.07	0.43	-0.05	-1.89	0.04	0.27	-0.02	-0.91	0.06	1.05	-0.01	-1.10
Total Accrual	-0.07	-0.37	**-0.07**	-2.31	0.27	1.57	**-0.07**	-2.08	0.04	0.24	**-0.05**	-2.74
Net Operating Assets	0.26	1.08	-0.07	-1.78	0.19	0.86	**-0.07**	-2.27	0.16	0.99	0.01	0.28
Volatility	**0.87**	1.94	**-0.44**	-5.35	**0.94**	2.74	**-0.41**	-6.34	**1.58**	4.20	**-0.26**	-4.42
Beta	0.54	1.44	**-0.42**	-4.52	0.41	1.33	**-0.40**	-5.51	0.34	1.33	**-0.21**	-3.62
Idiosyncratic Volatility	**0.71**	1.73	**-0.28**	-3.93	**0.95**	2.57	**-0.26**	-3.69	**1.56**	5.34	**-0.22**	-4.64
Momentum	0.39	0.82	-0.09	-1.20	0.17	0.42	-0.09	-1.21	0.03	0.10	-0.04	-0.88
Reversal	**1.51**	3.31	0.05	0.58	**1.69**	4.18	0.08	1.16	**1.42**	3.89	0.10	1.82
Long-term Reversal	0.34	0.95	-0.04	-0.69	0.39	1.24	0.01	0.29	**0.44**	1.96	0.00	0.13
Average	0.49	1.19	-0.11	-1.86	0.48	1.44	-0.09	-1.82	0.52	1.92	-0.03	-0.70

Table 4: Portfolio characteristics

This table reports the portfolio characteristics for portfolios formed using equal-weighting and the efficient sorting method by Ledoit, Wolf, and Zhao (2019). 'Turn' is the average monthly single-counted portfolio turnover, 'Pos' is the average number of stocks held in the portfolio, 'Eff pos' is the average effective number of stocks held in the portfolio, and '10% worst' is the average of the 10% worst portfolio returns. 'Corr' is the correlation between equally weighted and efficient sorting portfolio returns. Effective positions are calculated as the reciprocal of the Herfindahl–Hirschman index. The sample period is from January 2008 to December 2020.

	Equally weighted				Efficient sorting				
	Turn	*Pos*	*Eff pos*	*10% worst*	*Turn*	*Pos*	*Eff pos*	*10% worst*	*Corr*
Size	66.0	196.5	196.5	-10.1	54.0	222.0	108.6	-6.4	78.7
Book-to-Price	40.3	196.4	196.4	-12.9	52.5	229.7	116.3	-4.4	78.4
Earnings-to-Price	46.1	182.4	182.4	-9.0	55.0	221.5	114.3	-4.2	52.4
Sales-to-Price	35.8	191.1	191.1	-9.9	42.4	232.3	137.0	-4.3	71.4
Dividend-to-Price	39.0	154.4	154.4	-12.9	46.7	207.0	115.0	-3.4	44.7
Gross Profitability	27.4	189.6	189.6	-7.1	37.5	241.8	124.3	-4.6	79.9
Operating Profitability	30.0	196.0	196.0	-5.1	38.1	359.0	172.3	-3.1	60.6
Asset growth	40.8	193.5	193.5	-5.8	47.7	367.0	192.7	-2.7	64.2
Book value growth	39.1	216.8	216.8	-4.3	47.0	659.8	202.4	-1.4	47.7
Total Accrual	37.2	175.1	175.1	-5.0	43.2	360.5	186.6	-2.9	76.0
Net Operating Assets	32.6	175.3	175.3	-4.9	40.0	370.6	186.4	-3.0	76.6
Volatility	42.1	196.5	196.5	-12.7	61.3	162.1	84.1	-8.2	81.6
Beta	47.5	196.5	196.5	-12.1	76.5	151.6	68.0	-6.9	72.3
Idiosyncratic Volatility	42.6	195.6	195.6	-10.0	58.2	201.0	106.0	-6.1	73.1
Momentum	80.5	196.5	196.5	-9.8	89.8	277.9	141.1	-6.3	84.0
Reversal	182.0	196.5	196.5	-8.4	182.7	329.2	166.5	-4.7	80.4
Long-term Reversal	49.8	165.9	165.9	-8.7	60.1	206.4	110.8	-4.4	59.6
Average	51.7	189.1	189.1	-8.7	60.7	282.3	137.2	-4.5	69.5
Median	40.8	195.6	195.6	-9.0	52.5	232.3	124.3	-4.4	73.1

Appendix A

Categorization of the anomalies that we examine is from Hsu et al. (2018). Below we describe in more detail how we calculate each firm characteristic.

Size

The firm's size is calculated as the natural logarithm of a firm's end-of-month total A-share market capitalization.

Value

The book-to-price ratio is calculated as the ratio of book value to market value. Book value is defined as the most recently reported common shareholder's equity (total shareholder's equity minus the book value of preferred stocks) excluding minority interests. Market value refers to a proxy of end-of-month total market capitalization; the number of shares outstanding (including B- and H-shares) times the A-share's price. Book value at the quarterly frequency is used. We exclude firms with negative book values.

The earnings-to-price ratio is calculated as the ratio of total earnings to price. Total earnings is defined as the most recently reported net profit excluding minority interest income. Price refers to a proxy of end-of-month total market capitalization; the number of shares outstanding (including B- and H-shares) times the A-share's price. Earnings at the quarterly frequency is used. We exclude firms with negative earnings.

The sales-to-price ratio is calculated as the ratio of total sales to price. Total sales is equal to the most recently reported operating revenue. Price refers to a proxy of end-of-month total market capitalization; the number of shares outstanding (including B- and H-shares) times the A-share's price. Total sales at the quarterly frequency is used.

The dividend-to-price ratio is calculated as the ratio of total dividends to price. Total dividends is calculated as the total monetary value of dividends paid out to shareholder's over the previous reporting period. Price refers to a proxy of end-of-month total market capitalization; the number of shares outstanding (including B- and H-shares) times the A-share's price. We exclude firms that do not pay dividends.

Profitability

Gross profitability is calculated as the ratio of gross profit to total assets. Gross profit is defined as operating revenue minus operating costs.

Operating profit is calculated as the ratio of operating profit excluding interest expense to book value. Interest expense is excluded by subtracting total interest expense from operating profit. Book value is defined as common shareholder's equity (total shareholder's equity minus the book value of preferred stocks) excluding minority interests.

Investments

Asset growth is calculated as the year-on-year asset growth rate, i.e., the difference between total assets in the most recent year divided by total assets in the previous year.

Book value growth is calculated as the year-on-year book value growth rate, i.e., the difference between total book value in the most recent year divided by total book value in the previous year. Book value is defined as common share-holder's equity (total shareholder's equity minus the book value of preferred stocks) excluding minority interests.

Accounting conservatism

Firm-level accruals are calculated as

$$ACC = 2 \times Accrual_t / (TA_{t-1} + TA_t)$$

$$Accrual_t = (\Delta CA_t - \Delta Cash_t) - (\Delta CL_t - \Delta STD_t - \Delta TP_t) - DP_t$$

where TA_t is total assets, $Cash_t$ is the balance of cash and cash equivalents, CL_t is current liabilities, STD_t is the sum of notes payable and long-term debt due within one year, TP_t is taxes payable, DP_t is the sum of depreciation of fixed assets, oil and gas assets, and bearer biological assets, and intangible asset amortization. Δ denotes the year-on-year difference and t denotes the year.

Net operating assets is calculated as net operating assets in year t scaled by total assets in year t-1. The numerator is calculated as the difference between operating assets and operating liabilities. Operating assets is defined as total assets minus balance sheet cash, minus short-term investment. Operating liabilities represents total assets minus short-term loans, minus long-term loans, minus minority interest, minus common shareholder's equity excluding minority interest.

Risk

Volatility is calculated as the standard deviation of daily stock returns over the past 250 trading days.

Market beta is used as a proxy for systematic risk. Beta is defined as the estimated slope coefficient from a regression of daily excess stock returns over the past 250 trading days on an intercept and the daily returns from the value-weighted market portfolio. The value-weighted market portfolios is calculated using all available A-share stocks.

Idiosyncratic volatility is calculated as the standard deviation of residuals from a regression of daily excess stock returns over the past 250 trading days on an intercept and the daily returns from the value-weighted market, size, and value factor.

Returns-based

Momentum at month t is calculated as the cumulative monthly stock return over the previous twelve months excluding the most recent month.

Short-term reversal is calculated as the cumulative stock return over the past twenty trading days.

Long-term reversal is calculated as the cumulative monthly stock return over the past five years excluding the previous year, i.e., month t = 60 to month t-13.

Appendix B

Table B.1: Conventional and efficient sorting three-factor model alphas

Average long-short alphas ('Alpha') relative to the Liu, Stambaugh, and Yuan (2019) three-factor model and t-statistics ('t-stat') for three different portfolio construction techniques. The left part 'Equally weighted' uses equal-weighting of the top and bottom portfolios. The middle part, 'Industry-neutral' uses equal-weighting within each industry. The right part, 'Efficient sorting', uses the efficient sorting method by Ledoit, Wolf, and Zhao (2019). t-statistics are calculated using Newey and West (1987) standard errors with four lags. Alphas that are significant at the 5% level are in bold. The sample period is from January 2008 to December 2020.

	Equally weighted		**Industry-neutral**		**Efficient sorting**	
	Alpha	*t-stat*	*Alpha*	*t-stat*	*Alpha*	*t-stat*
Size	-0.03	-0.19	0.01	0.06	-0.02	-0.10
Book-to-Price	-0.80	-1.38	-0.32	-0.60	0.55	1.64
Earnings-to-Price	0.07	0.33	0.05	0.17	0.12	0.70
Sales-to-Price	-0.48	-1.24	-0.43	-1.06	0.06	0.28
Dividend-to-Price	-0.26	-0.52	-0.11	-0.26	-0.14	-0.68
Gross Profitability	**1.09**	2.89	**0.80**	2.66	**0.48**	2.54
Operating Profitability	0.05	0.20	0.22	1.14	0.02	0.14
Asset growth	-0.41	-1.66	-0.38	-1.63	-0.02	-0.14
Book value growth	-0.03	-0.17	0.00	0.00	0.02	0.29
Total Accrual	-0.12	-0.64	0.33	1.79	0.09	0.62
Net Operating Assets	0.11	0.47	0.11	0.58	0.18	1.01
Volatility	-0.13	-0.40	0.23	0.96	**1.04**	3.15
Beta	-0.23	-0.61	-0.14	-0.46	0.06	0.21
Idiosyncratic Volatility	0.04	0.14	0.49	1.41	**1.34**	4.76
Momentum	0.99	1.50	0.51	0.89	0.44	1.16
Reversal	**1.12**	2.74	**1.25**	3.55	**1.02**	2.72
Long-term Reversal	-0.29	-0.76	-0.11	-0.33	0.16	0.69
Average	0.04	0.04	0.15	0.52	0.32	1.12
Median	-0.03	-0.19	0.05	0.17	0.12	0.69