# Strategic Momentum for Most Investors

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## Abstract

Using U.S. stock market data, we show that, by strategically exploiting the Almost Stochastic Dominance rules, the momentum effect can be capitalized upon to derive momentum returns. Compared to the classic momentum strategies, our strategy can generate better risk-adjusted performance and the returns are less volatile and less negatively skewed. The abnormal returns are statistically and economically significant with respect to alternative multi-factor models. Above all, the practical applicability of the strategy is ensured by resolving the computational burden when a large span of stocks is considered in practice.

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# 1 Introduction

Ever since Jegadeesh and Titman (1993), the finance literature has long documented evidence of the momentum effect.[1] The momentum effect is critically dependent on past information, e.g., past cumulative returns (Jegadeesh and Titman, 1993), price information (George and Hwang, 2004), past residual returns (Blitz, Huij, and Martens, 2011). Due to the evidence that investors care not only about the mean-variance tradeoff, but also the higher moments (of cumulative returns) when allocating their assets (Samuelson, 1970; Rubinstein 1973; Kraus and Litzenberger, 1976; Scott and Horvath, 1980), the momentum literature has made adaptations on allowing for full distributional characteristics of cumulative returns to render past information.[2]

Among these papers, Clark and Kassimatis (2014) propose to rank stocks by using a well-known rule with economic foundation: stochastic dominance (SD). SD is the cornerstone of decision theory. It compares the riskiness of assets according to the whole distributions (Hadar and Russell, 1969; Rothschild and Stiglitz, 1970; Whitmore, 1970). By adopting second-degree SD and third-degree SD to select winning and losing stocks, Clark and Kassimatis (2014) show that past SD relations indeed provide exploitable information on future returns and the positive returns are robust when tested against the modern factor models.[3]

In spite of the positive findings of Clark and Kassimatis (2014), the SD rules are too restrictive in a way that, to meet all utility functions (including the pathological ones), they may fail to rank distributions when most decision makers obviously prefer one alternative to another (Leshno and Levy, 2002). For example, assume that $X$ and $Y$ are two normal random variables that represent two asset returns in the market, respectively. Assume further that the mean and standard deviation of $X$ are 3% and 2%, respectively, whereas the mean and standard deviation

[1] See for example, De Bondt and Thaler (1985, 1987), Grinblatt and Titman (1992), Jegadeesh and Titman (1993, 2001), Moskowitz and Grinblatt (1999) and Rouwenhorst (1998).

[2] The time-series insights of the literature's prior findings also indicate that skewness is an important determinant of equilibrium asset returns (see for example, Barberis and Huang, 2008; Brunnermeier, Gollier and Parker, 2007; Mitton and Vorkink, 2007; Boyer, Mitton and Vorkink, 2010).

[3] Prior studies that apply the stochastic dominance rules to construct arbitrage portfolios include Constantinides, Jackwerth and Perrakis (2009), and Constantinides, Czerwonko, Jackwerth and Perrakis (2011). Additionally, Post (2003), Kuosmanen (2004), Kopa and Post (2009), Post (2016) and Post and Kopa (2016) construct efficient portfolios based on the stochastic dominance rules. Vinod (2004) applies the stochastic dominance rule and unconventional utility theories to rank mutual funds, and Fang (2012) use stochastic dominance criteria to analyze market efficiency with various utility theories.

of $Y$ are 30% and 2.0001%. Obviously, most investors would prefer $Y$ to $X$. Nevertheless, the SD rules can only conclude that asset $X$ does not dominate asset $Y$, and vice versa.[4] Thus, using the SD rules to rank assets may fail to identify the obvious winners and/or losers for most investors.

The purpose of our paper is to construct zero cost portfolios that yield systematic abnormal returns by using another criterion which is with economic foundation and can overcome the above drawback of SD rules: *Almost Stochastic Dominance* (ASD). ASD is first proposed by Leshno and Levy (2002) and further refined by Tzeng, Huang and Shih (2013). The ASD rules seek the consensus of almost all investors—all non-pathological, economically important agents—and can thus significantly improve the SD rules' ability to rank (Leshno and Levy, 2002). Generally speaking, ASD allows for violations of the SD rules. When risky assets are compared, as long as the violation is small enough, the ASD rule can conclude the dominance relationship. In the previous example, using the ASD rules, one can conclude that $Y$ is preferred to $X$ for all non-pathological non-satiable investors.

Applying the ASD rules to capitalize on momentum involves a critical stage of sorting among assets which could give rise to a computational burden if it were to proceed with pairwise comparisons as in Clark and Kassimatis (2014). To avoid the possibility that the required computationally-intensive methodology may limit the strategy's applications in practice, we propose to rank stocks according to their ASD "violation ratios" with respect to the return on a risk-free asset—the foregone opportunity cost of an investment. For example, during our sample period, the average number of stocks is approximately 2,000 on each portfolio formation date. By ranking the stocks according to their ASD violation ratios with respect to a risk-free asset, instead of employing the pairwise comparisons, the total number of calculation can be reduced from 1,999,000 ($C_2^{2000} = \frac{2000(2000-1)}{2}$) to 2,000.

Specifically, individual stocks are ranked according to both the almost first-degree SD (AFSD) rule and the almost second-degree SD (ASSD) rule as the winner-loser selection criteria to implement the momentum strategy. For the AFSD rule, we calculate each stock's AFSD violation ratio which denotes, roughly speaking, the area violating first-degree stochastic dominance (FSD)

[4] See Section 2 for more details of the proof.

divided by the total differences between the cumulative density functions (CDFs) of the returns of the stock and a risk-free asset. This parameter is bounded between 0 and 1. If the violation ratio is 0, AFSD concludes that all non-satiable investors would prefer the evaluated stock to the risk-free asset. If the violation ratio is 1, then all non-satiable investors would prefer the risk-free asset to the evaluated stock. The AFSD rule also concludes that the smaller the violation ratio of a stock is, the more non-pathological and non-satiable investors would prefer the evaluated stock to the risk-free asset and we would conclude that the better the stock is. Thus, we could group stocks according to the violation ratios and identify winners (losers) as the stocks with the smallest (greatest) violation ratios to avoid pairwise comparisons.

For the ASSD rule, two parameters are adopted. The first one is the mean return and the second one is another violation ratio, which denotes, roughly speaking, the area violating second-degree stochastic dominance (SSD) divided by the total differences between two CDFs. According to ASSD, it is necessary for the dominant portfolio to have a greater mean. Thus, if the mean return of the evaluated stock is less than the risk-free rate, then this evaluated stock cannot be identified as a winner even if the violation ratio is small. By comparing mean returns and the new violation ratios, stocks could be efficiently labeled as winners or losers.

It is worth noting that these AFSD and ASSD violation ratios are respectively monotonic with respect to Omega (Keating and Shadwick, 2002) and the second-order Omega (Bi, Huang, Tzeng and Zhu, 2019). Omega is a well-known performance measure. Recently, Bi, Huang, Tzeng and Zhu (2019) establish higher-order Omega which include Omega as a special case. These indices evaluate the performance of a risky asset with respect to a benchmark. They show that $N$th-order Omega can be viewed as the ratio of the area satisfying the $N$th-degree SD rule to the area violating the $N$th-degree SD rule. By using the risk-free asset as the benchmark, the reciprocal of our AFSD violation ratio is equal to 1 plus Omega, and the reciprocal of our ASSD violation ratio is equal to 1 plus second-order Omega. Therefore, that investors prefer stocks with lower AFSD (ASSD) violation ratios to those with higher AFSD (ASSD) violation ratios is equivalent to investors preferring stocks with greater values of the Omega (second-order Omega) to those with smaller values.

When implementing the ASD momentum strategies empirically, we follow Jegadeesh and

Titman (1993) and Clark and Kassimatis (2014) to consider four overlapping holding periods: 3, 6, 9 and 12 months; additionally, we adopt portfolio formation with a one-month lag between the ranking and the holding periods. To ask if the (significantly positive) arbitrage returns generated by the ASD long-short portfolios can be subsumed by the common risk factors, we regress the arbitrage returns on the Fama-French (2015) five factors augmented with the momentum factor of Fama and French (2012), the liquidity risk factor of Pástor and Stambaugh (2003), and the short-term and long-term reversal risk factors (De Bondt and Thaler, 1985; Jegadeesh, 1990; Bartram and Grinblatt, 2018).

Our main findings are markedly supportive of our hypothesis. For the AFSD momentum strategies, the standard deviation, skewness and maximum drawdown of arbitrage returns are all small in absolute terms, indicating a less "volatile" return distribution—as a consequence of risk reduction—than the standard momentum strategy of Jegadeesh and Titman (1993). Additionally, when equipped with overlapping holding periods of longer duration, the AFSD momentum strategies deliver arbitrage returns that exhibit a higher average monthly return, smaller standard deviation, smaller maximum drawdown, and a better risk-adjusted performance—under all chosen measures of reward-to-risk—than the standard momentum strategy. This result indicates that the AFSD momentum strategy is capable of generating abnormal stock returns. For the ASSD momentum strategies, the results are even more pronounced. The ASSD momentum strategies outperform both the AFSD and the standard momentum strategies in terms of the average monthly returns and the risk-adjusted performance—with the resulting return distributions being slightly more volatile and exhibiting a higher maximum drawdown than the standard momentum strategy. Above all, we find that these AFSD and ASSD arbitrage returns cannot be explained by the Fama-French (2015) five factors, the momentum factor, the liquidity risk factor, or the short-term and long-term reversal.

Our paper contributes to the momentum literature by providing evidences on the relationship between ASD and the behavior of stock returns. Note that the way we adopt ASD rule exhibits the same ranking as using Omega and second-order Omega. Since Omega and second-order Omega are performance measures, our paper contributes to the literature which adopts performance measures to form momentum strategies. For example, Rachev, Jašić, Stoyanov and

Fabozzi (2007), Choi, Kim, and Mitov (2015) analyze momentum strategies based on several reward-risk stock selection criteria. Compared with these reward-risk measures, our rule has an advantage that our ranking is consistent with the preferences of most investors, while these reward-risk measures may not.

Our paper also contributes to the literature of investment decision making based on an expected utility paradigm, and in particular, those exploit the ASD rules to capitalize on several well-documented stock market anomalies. Bali, Demirtas, Levy, and Wolf (2009), for example, find that investing in stocks is an ASD dominant strategy compared with investing in bonds in the long run. Their findings support the popular practice that recommends a higher stock to bond ratio for long investment horizons. Bali, Brown, and Demirtas (2013) utilize ASD to examine the relative performance of hedge fund portfolios. They find that several types of hedge funds outperform the U.S. equity and/or bond markets based on the ASD rules. Their findings partially explain why risk-averse investors tend to invest in hedge funds. To the best of our knowledge, our study is the first in the literature to exploit the ASD ranking relations in order to generate abnormal stock returns.

The structure of this paper is as follows. Section 2 reviews the SD and ASD rules. Section 3 describes how to construct the ASD portfolios. Section 4 presents the empirical results. Section 5 concludes this paper.

## 2 Stochastic Dominance and Almost Stochastic Dominance

We briefly review the SD and ASD rules in this section. We focus on the indeterminate cases to illustrate SD's inability to rank, and we explain how the ASD rules, by allowing for violation ratios, help to resolve this issue, which is essential to the construction of our momentum strategies.

Let $F(x)$ and $G(x)$ denote two cumulative distribution functions (CDFs) of random wealth $\tilde{x}$ with support $[a, b]$. Furthermore, define

$$F^{(2)}(x) = \int_a^x F(t)dt = E_F(x - \tilde{x})^+,$$

where $E_F$ denotes the expectation operator when the underlying wealth distribution follows $F$ and $(x - \tilde{x})^+ = (x - \tilde{x}) \cdot 1(x - \tilde{x} \geq 0)$. We define $G^{(2)}(x)$ similarly. Hadar and Russell (1969) define FSD and SSD as follows:

**Definition 1** ***(FSD and SSD)***

1. *$F(x)$ first-degree stochastically dominates $G(x)$ if $F(x) \leq G(x)$ for all $x \in [a, b]$.*

2. *$F(x)$ second-degree stochastically dominates $G(x)$ if $F^{(2)}(x) \leq G^{(2)}(x)$ for all $x \in [a, b]$ and $E_F(\tilde{x}) \geq E_G(\tilde{x})$.*

Hadar and Russell (1969) have shown the following equivalence result:

**Theorem 1** ***(FSD and SSD Equivalence)***

1. *$F(x)$ first-degree stochastically dominates $G(x)$ if and only if $E_F(u) \geq E_G(u)$ for all $u$ with $u' \geq 0$.*

2. *$F(x)$ second-degree stochastically dominates $G(x)$ if and only if $E_F(u) \geq E_G(u)$ for all $u$ with $u' \geq 0$ and $u'' \leq 0$.*

Theorem 1 shows that the advantage of these criteria is that they only require partial information regarding investor preferences. However, one disadvantage of these rules is that they are difficult to satisfy in practice. We can find many cases where most decision makers have a clear preference, but FSD or SSD rules cannot rank distributions.

For example, assume that the returns of assets $X$ and $Y$ follow normal distributions. The mean and standard deviation of the return of asset $X$ are $\mu_X = 3\%$ and $\sigma_X = 2\%$, whereas those of asset $Y$ are $\mu_Y = 30\%$ and $\sigma_Y = 2.0001\%$. From Definition 1, it is not possible to have $X$ dominating $Y$ in terms of FSD or SSD due to the fact that $\mu_X < \mu_Y$. In addition, the CDF of $Y$, $F_Y$, intersects that of $X$, $F_X$, from above at $\frac{\mu_X - \mu_Y}{\sigma_Y - \sigma_X} = -270000$ (see Levy, 2009). In other words, $F_Y(x) > F_X(x)$ and $F_Y^{(2)}(x) > F_X^{(2)}(x)$ for $x \leq -270000$. Thus, $Y$ does not dominate $X$ in terms of FSD or SSD. Specifically, it can be shown that an investor with utility function

$$u(x) = \begin{cases} c + x \text{ if } x \leq -270000 \\ c - 270000 \text{ otherwise} \end{cases} \tag{1}$$

where $c$ is a constant would prefer $X$ to $Y$. Therefore, even though most decision makers would prefer $Y$ to $X$, these two assets cannot be ranked according to FSD or SSD.

To overcome the above drawback of the SD rules, Leshno and Levy (2002) and Tzeng, Huang and Shih (2013) propose new decision criteria for "almost stochastic dominance", which are defined as follows.[5]

**Definition 2** ***(AFSD and ASSD)***

1. ***(Leshno and Levy, 2002)*** *$F(x)$ $\varepsilon_1$-almost first-degree stochastically dominates $G(x)$ if*

$$\int_{F>G} [F(x) - G(x)]dx \leq \varepsilon_1 \int_a^b |F(x) - G(x)|\, dx. \tag{2}$$

2. ***(Tzeng, Huang and Shih, 2013)*** *$F(x)$ $\varepsilon_2$ -almost second-degree stochastically dominates $G(x)$ if $E_F(x) \geq E_G(x)$ and*

$$\int_{F^{(2)}>G^{(2)}} [F^{(2)}(x) - G^{(2)}(x)]dx \leq \varepsilon_2 \int_a^b \left| F^{(2)}(x) - G^{(2)}(x) \right| dx. \tag{3}$$

Definition 2 shows that AFSD and ASSD allow some violations of FSD and SSD, respectively. Leshno and Levy (2002) and Tzeng, Huang and Shih (2013) argue that some agents, e.g., with preferences as shown in Equation (1), are considered pathological and economically unimportant. Thus, to establish a distribution ranking criterion for most agents, these pathological preferences should be excluded. Specifically, they define two sets of decision makers excluding some preferences that are considered pathological:

$$U_1(\varepsilon_1) = \left\{ u |\, u' \geq 0 \,,\ \sup\{u'\} \leq \inf\{u'\}\,(1/\varepsilon_1 - 1) \right\}$$

and

$$U_2(\varepsilon_2) = \left\{ u |\, u' \geq 0 \,,\, u'' \leq 0 \,,\ \sup\{-u''\} \leq \inf\{-u''\}\,(1/\varepsilon_2 - 1) \right\},$$

[5] The theoretical explorations of Denuit, Huang and Tzeng (2014) and Tsetlin, Winkler, Huang and Tzeng (2015) extend univariate ASD rules to bivariate cases and establish a general definition of ASSD.

where the preference parameters $\varepsilon_i \in (0, 0.5)$, $i = 1, 2$. The smaller (closer to zero) $\varepsilon_1$ and $\varepsilon_2$ are, the larger the set of $U_1(\varepsilon_1)$ and $U_2(\varepsilon_2)$. In addition, if $\varepsilon_1$ approaches zero, then the condition $\sup\{u'\} \leq \inf\{u'\}(1/\varepsilon_1 - 1)$ always holds and $U_1(\varepsilon_1)$ contains all agents with $u' \geq 0$. If $\varepsilon_1$ approaches 0.5, then the condition $\sup\{u'\} \leq \inf\{u'\}(1/\varepsilon_1 - 1)$ requires that $\sup\{u'\} = \inf\{u'\}$. In this case, $U_1(\varepsilon_1)$ only contains risk-neutral investors ($u'' = 0$). On the other hand, if $\varepsilon_2$ approaches 0, then the condition $\sup\{-u''\} \leq \inf\{-u''\}(1/\varepsilon_2 - 1)$ always holds and $U_2(\varepsilon_2)$ contains all agents with $u' \geq 0$ and $u'' \leq 0$. If $\varepsilon_2$ approaches 0.5, then the condition $\sup\{-u''\} \leq \inf\{-u''\}(1/\varepsilon_2 - 1)$ requires that $\sup\{-u''\} = \inf\{-u''\}$. Therefore, in this case, $U_2(\varepsilon_2)$ only contains quartic utility functions. In other words, the sets $U_1(\varepsilon_1)$ and $U_2(\varepsilon_2)$ include more agents as $\varepsilon_1$ and $\varepsilon_2$ decrease, respectively.

Therefore, Leshno and Levy (2002) and Tzeng, Huang and Shih (2013) show the following equivalence results:

**Theorem 2** ***(AFSD and ASSD Equivalence)***

1. ***(Leshno and Levy, 2002)*** *$F(x)$ $\varepsilon_1$-almost first-degree stochastically dominates $G(x)$ if and only if $E_F(u) \geq E_G(u)$ for all $u \in U_1(\varepsilon_1)$.*

2. ***(Tzeng, Huang and Shih, 2013)*** *$F(x)$ $\varepsilon_2$-almost second-degree stochastically dominates $G(x)$ if and only if $E_F(u) \geq E_G(u)$ for all $u \in U_2(\varepsilon_2)$.*

# 3 AFSD and ASSD Momentum Strategies

Following the standard procedure in the literature (e.g., Jegadeesh and Titman, 1993), the empirical analysis is conducted in two stages. In the first stage, we use the historical data in the ranking period to construct the ASD arbitrage portfolios. In the second stage, we test whether the portfolios could generate abnormal returns in the holding period. In the following section, we first introduce how to form the ASD arbitrage portfolios.

### 3.1 AFSD Momentum Strategies

An AFSD momentum strategy is a strategy that constructs arbitrage (long-short) portfolios by buying AFSD dominated stocks (winners) and selling AFSD dominated stocks (losers). To classify the winner-/loser-status of each asset, this paper proposes two layers of the ASD violation ratios (the AFSD violation ratio and the ASSD violation ratio) with respect to a given return threshold that is chosen to be the return on a risk-free asset.

Let $\tilde{r}_i \in [\underline{r}, \bar{r}]$ denote the net return of risky asset $i$. Assume that $\tilde{r}_i$ follows a CDF $F_i(r)$. Let $r_f$ denote the risk-free rate of return and $K(r)$ satisfy

$$K(r) = \begin{cases} 0 & \text{if } r \leq r_f \\ 1 & \text{otherwise.} \end{cases}$$

We define the AFSD violation ratio between $F_i(r)$ and $K(r)$ as:

$$\theta_1^i = \frac{\int_{F_i \geq K} [F_i(r) - K(r)]dr}{\int_{\underline{r}}^{\bar{r}} |F_i(r) - K(r)| \, dr}. \tag{4}$$

where $\theta_1^i \in [0, 1]$. Figure 1 illustrate $F_i(r)$ and $K(r)$. In this case, $\theta_1^i$ equals A/(A+B).

<Figure 1 about here >

The asset ranking relations determined by the AFSD violation ratios, $\theta_1^i$, can be characterized as follows. By Theorem 2, when $\theta_1^i \leq 1/2$, then for any $1/2 \geq \varepsilon_1 \geq \theta_1^i$, all agents in $U_1(\varepsilon_1)$ will prefer $F_i(r)$ to $K(r)$. On the other hand, when $\theta_1^i \geq 1/2$, then for any $1/2 \geq \varepsilon_1 \geq 1 - \theta_1^i$, all agents in $U_1(\varepsilon_1)$ will prefer $K(r)$ to $F_i(r)$. In other words, if $\theta_1^i$ is closer to zero, more agents will prefer risky asset $i$ to the risk-free asset and if $\theta_1^i$ is closer to 1, more agents will instead prefer the risk-free asset to asset $i$. That is, according to the AFSD criterion proposed by Leshno and Levy (2002), the smaller that the AFSD violation ratio of an asset is, the larger will be the set of non-satiable investors with a "reasonable" preference that will prefer this asset to the risk-free return. Based on this, we consider this asset to be a better asset or a winner for the AFSD strategy.

To be specific, for asset $k$ and asset $j$, let $\theta_1^k$ and $\theta_1^j$ be their corresponding violation ratios with respect to the risk-free return. If $\theta_1^k \leq \theta_1^j \leq 1/2$, following the previous discussion, this means that more agents will prefer asset $k$ to the risk-free asset than those who prefer asset $j$ to the risk-free asset. Thus, we could conclude that asset $k$ is better than asset $j$. Similar reasoning applies to cases where $1/2 \leq \theta_1^k \leq \theta_1^j$ and $\theta_1^k \leq 1/2 \leq \theta_1^j$. Therefore, any two assets can be ranked by their violation ratios $\theta_1^i$s, i.e., a complete ranking is made feasible by using the violation ratios $\theta_1^i$s.

Interesting risk insights become apparent when an analogy is drawn between the AFSD violation ratios (with respect to the return on a risk-free asset) and the Sharpe Omega performance measure (Kazemi, Schneeweis, and Gupta, 2004), $\Omega_S$. This analogy is made feasible by setting $L = r_f$ as in

$$\Omega_S^i = \Omega^i - 1 = \frac{E(\tilde{r}_i - L)}{E(L - \tilde{r}_i)^+}.$$

where $\Omega^i = \frac{E(\tilde{r}_i - L)^+}{E(L - \tilde{r}_i)^+}$, is the Omega function defined by Keating and Shadwick (2002) that is associated with an asset $i$. Graphically, we can see from Figure 1 that $\Omega^i = B/A$. In Appendix A, we show that, under the case where $E(\tilde{r}_i) \geq r_f$, the interchangeability between $\theta_1^i$ and $\Omega_S^i$ satisfies the following condition:

$$\Omega_S^i = \frac{1}{\theta_1^i} - 2.$$

That is, the ordinality of the ranking relations determined by $\theta_1^i$ is preserved, in reverse order, by the Sharpe Omega, $\Omega_S^i$. Bi, Huang, Tzeng, and Zhu (2019) establish higher-order Omega as new performance measures. The decision-theoretic foundation for the index is based on ASD.

The Sharpe Omega, in this case, is the ratio of the expected gain (excess return) in the evaluated asset to the expected loss reflected by a put option written on the evaluated asset with the risk-free asset return chosen as the strike price. Therefore, that investors prefer stocks with lower AFSD violation ratios to those with higher AFSD violation ratios is equivalent to investors preferring stocks with greater values of the Sharpe Omega to those with smaller values.

To form the AFSD arbitrage portfolios, we first sort all stocks into decile portfolios in descending order according to their corresponding $\theta_1^i$s at each portfolio formation date. The top/bottom decile portfolio comprises stocks that are winners/losers with relatively low/high violation ratios—and hence higher/lower AFSD rankings. The high minus low, long-short arbitrage portfolios are then constructed by buying equally weighted stocks in the top-most AFSD decile and selling those in the bottom lowest AFSD decile. These arbitrage portfolios are hereafter labeled as the "AFSD 10–1 portfolios". More details will be given in the next section.

### 3.2 ASSD Momentum Strategies

Similarly, for the ASSD rule, we first define the ASSD violation ratio between risky asset $i$ and the risk-free rate as:

$$\theta_2^i = \frac{\int_{F_i^{(2)} > K^{(2)}} [F_i^{(2)}(r) - K^{(2)}(r)] dr}{\int_{\underline{r}}^{\bar{r}} \left| F_i^{(2)}(r) - K^{(2)}(r) \right| dr}, \tag{5}$$

where

$$K^{(2)}(x) = \begin{cases} 0 & \text{if } x \leq r_f, \\ x - r_f & \text{otherwise.} \end{cases}$$

Figure 2 illustrates $F_i^{(2)}(r)$ and $K^{(2)}(x)$. In this case, $\theta_2^i$ equals C/(C+D).[6] By construction, $\theta_2^i \in [0, 1]$. Theorem 2 demonstrates that if $E(\tilde{r}_i) \geq r_f$ and $\theta_2^i \leq 1/2$, then for any $1/2 \geq \varepsilon_2 \geq \theta_2^i$, all agents in $U_2(\varepsilon_2)$ will prefer risky asset $i$ to the risk-free asset. If $E(\tilde{r}_i) \leq r_f$ and $\theta_2^i \geq 1/2$, then for any $1/2 \geq \varepsilon_2 \geq 1 - \theta_2^i$, all agents in $U_2(\varepsilon_2)$ will prefer the risk-free asset to risky asset $i$. Therefore, the $\theta_2^i$ can help to form the long-short portfolios.

<Figure 2 about here >

Note that under the assumption that $E(\tilde{r}_i) \geq r_f$, $F_i(r)$ intersects $K(r)$ at most once, so that $F_i^{(2)}(x)$ also intersects $K^{(2)}(x)$ at most once. If there is an intersection, then $F_i^{(2)}(x)$ intersects

[6] Note that in Bi, Huang, Tzeng, and Zhu (2019), 2nd-order Omega is equal to D/C.

$K^{(2)}(x)$ from above. Denote the intersection point as $r_i^*$. It is obvious that $r_i^* > r_f$ and $r_i^*$ satisfies

$$F_i^{(2)}(r_i^*) = (r_i^* - r_f). \tag{6}$$

In this case, Appendix B shows that

$$\frac{1}{\theta_2^i} - 2 = \frac{(\bar{r} - r_f)^2 - E(\bar{r} - \tilde{r}_i)^2}{E\left[(r_i^* - \tilde{r}_i)^+\right]^2 - \left[(r_i^* - r_f)^+\right]^2}. \tag{7}$$

In other words, keeping other things constant, a decrease in $E(\bar{r} - \tilde{r}_i)^2$ or $E\left[(r_i^* - \tilde{r}_i)^+\right]^2$ results in a better ranking of the stock according to $\theta_2^i$.[7]

Based on the definition of ASSD in Definition 2, to rank stocks according to ASSD, we need to consider both the violation ratios $\theta_2^i$ and the difference in the means. Therefore, we only consider/rank those stocks where they either (a) ASSD dominate the risk-free rate such that the corresponding violation ratios are less than 1/2 and the means of the asset returns are higher than the risk-free rate, or (b) are ASSD dominated by the risk-free rate such that the corresponding violation ratios are more than 1/2 and the means of the asset returns are smaller than the risk-free rate.

To construct our ASSD momentum strategies, we sort those stocks (in either (a) or (b)) into decile portfolios in descending order according to their corresponding $\theta_2^i$s at each portfolio formation date, such that the top/bottom decile portfolio would comprise stocks that are winners/losers with relatively low/high violation ratios—and hence higher/lower ASSD rankings. The ASSD 10–1 portfolios are then constructed similar to the AFSD ones.

[7] While ranking stocks according to $\theta_1^i$ is related to the ranking according to the Sharpe Omega, the ranking according to $\theta_2^i$ is different from that based on Kappa, which is proposed by Kaplan and Knowles (2004). By using the risk-free rate as the reference return, Kappa could be written as

$$K_F^2(L) = \frac{E(\tilde{r}_i - r_f)}{\left\{E\left[(r_f - \tilde{r}_i)^+\right]^2\right\}^{\frac{1}{2}}}.$$

# 4 Empirical Results

## 4.1 Implementation of AFSD and ASSD momentum strategies

Using historical stock prices and 1-month T-bill returns obtained from the Center for Research in Security Prices (CRSP), we first calculate the AFSD and ASSD violation ratios for all stocks at the beginning of each month during the period 1962-2015.[8] To construct the AFSD 10–1 arbitrage portfolios, all stocks are sorted into decile portfolios in descending order of the AFSD violation ratios, and we then buy equally weighted stocks in the top-most decile (stocks with the lowest violation ratios) and sell those in the bottom-most decile (stocks with the highest violation ratios).

For the ASSD 10–1 portfolios, we first eliminate the stocks whose ASSD violation ratios are less than 1/2 and average daily returns during the ranking period are smaller than the average daily risk-free rate, and eliminate the stocks whose ASSD violation ratios are more than 1/2 and average daily returns during the ranking period are larger than the average daily risk-free rate. The remaining stocks are sorted into decile portfolios in descending order of the ASSD violation ratios. The ASSD 10–1 portfolios are then constructed by buying all stocks in the top-most decile and selling those in the bottom-most decile. To alleviate the impacts of extreme price movements on the AFSD and ASSD long-short portfolio returns, which are mostly found to be associated with low-priced stocks, we follow Jegadeesh and Titman (2001) to exclude stocks with quoted prices below \$5 at the beginning of each holding period.

We follow Jegadeesh and Titman (1993) and Clark and Kassimatis (2014) to consider monthly overlapping holding periods in the construction of momentum strategies. At the beginning of each month $t$, an AFSD (ASSD) momentum strategy with an overlapping holding period $K$ and a ranking period $J$ consists of $K$ 10–1 AFSD (ASSD) portfolios. For the $K$-th 10–1 AFSD (ASSD) portfolio, all stocks are sorted in month $t-K+1$ based on the violation ratios calculated over the past $J$ months prior to month $t-K+1$. For example, a strategy using an overlapping holding period of three months and a ranking period of six months would comprise three 10–1 AFSD (ASSD) portfolios: the portfolio constructed in month $t-2$ based

[8] For the calculation of the actual violation ratios, please refer to Appendix C.

on the violation ratios computed over the past six months prior to month $t-2$; the portfolio constructed in month $t-1$ based on the violation ratios over the past six months prior to month $t-1$; and the portfolio constructed in month $t$ based on the violations over the past six months prior to month $t$. The overlapping holding period $K$ equals 3, 6, 9, or 12 and the ranking period $J$ equals 3, 6, 9, 12 or 7-12, where 7-12 indicates that the violation ratio of each stock is calculated over the period between the past seventh month and twelfth month. Note that when $K$ equals 1, the strategy then comprises only one 10–1 AFSD (ASSD) portfolio, which is constructed based on the violation ratios over the past $J$ months prior to the current month, i.e., it degenerates to a non-overlapping strategy. Moreover, following standard practices in prior studies, we use a one-month lag between the ranking and holding periods in the hope of alleviating the impacts of short-term return reversals (e.g., Novy-Marx, 2012; Clark and Kassimatis, 2014; Asness, Moskowitz and Pedersen, 2013; Daniel and Moskowitz, 2016; Jacobs, Regele and Weber, 2016).

### 4.2 Summary statistics of decile portfolios

Table 1 reports summary statistics for the decile portfolios formed on the AFSD and ASSD violation ratios over a 12-month ranking period. The summary statistics of the momentum decile portfolios are also reported for comparison purposes. The momentum decile portfolios are constructed by sorting all stocks in ascending order in relation to their past return performances over a 12-month ranking period. The average return of each decile portfolio is calculated as the equally-weighted average of the stocks' returns.[9] For each decile portfolio, we report the average daily returns, the standard deviations of daily returns, the skewness of daily returns, the average monthly returns of the subsequent 1 and 2 months following portfolio formation, and the average number of stocks included in the portfolio.

<Table 1 about here >

[9] When applying the ASSD rules, we find that in some months, the number of stocks dominated by the risk-free assets is large. These stocks cannot be further divided into decile portfolios since the ASSD violation ratios for them are all equal to 1. In this situation, we identify relative losers by sorting these stocks based on their average daily returns over the ranking period.

What is more interesting is that the average daily decile-portfolio returns increase with decreasing AFSD and ASSD violation ratios. From Table 1, the average daily decile-portfolio returns increase from $-0.1375\%$ in the lowest AFSD decile to $0.3347\%$ in the highest decile while they increase from $-0.2052\%$ to $0.4081\%$ across the ASSD deciles. This finding is consistent with the prediction in the previous section: an asset with a higher average return will result in a lower violation ratio and will have a greater chance of being classified as a winner.

Although the average daily returns of the decile portfolios formed on past returns bear a similar pattern to that formed on the AFSD and ASSD violation ratios, their distributional characteristics are nevertheless different. Specifically, while the average daily returns generated by the winners of past returns are higher than those generated by the winners of AFSD, these daily returns in fact have higher standard deviations and lower skewness. On the other hand, the average daily returns for the winners of ASSD are higher than those for the winners of past returns. In addition, the differences in skewness between the winners and the losers of AFSD and ASSD are larger than those of past returns. For example, the difference in skewness between the winner and the loser under AFSD is 1.1997 $(1.0631 + 0.1366)$, whilst it is 1.0069 $(0.9905 + 0.0164)$ under past returns.

Furthermore, the average monthly decile-portfolio returns of the subsequent 1- and 2-month post portfolio formation also exhibit similar patterns regardless of the choice of ranking criteria. The persistent pattern by which the average monthly returns increase with the AFSD and ASSD violation ratios in descending order indicates that the winners of AFSD and ASSD are likely to continue winning, and that a momentum strategy that exploits the distributional rankings of AFSD and ASSD in the selection of its winners and losers is capable of generating significantly positive profits.

## 4.3 Characteristics of the AFSD and ASSD arbitrage returns

Table 2 presents the average monthly returns of the AFSD and ASSD 10–1 portfolios in the subsequent 1 to 13 months preceding the portfolio formation date. Several interesting insights can be drawn from the results regarding the term structure of momentum-return predictability. First, average monthly returns of the AFSD and ASSD 10–1 portfolios, while increasing in the first and second months following portfolio formation, generally decrease in subsequent months. The results document a short-term return reversal that is in line with the findings of Jegadeesh (1990), Jegadeesh and Titman (1995), Lehmann (1990), Jegadeesh and Titman (1993) and Novy-Marx (2012). In particular, Jegadeesh (1990) and Jegadeesh and Titman (1993) show that there is a reversal in returns from the prior month (the “one-month reversal effect”), and that the prior twelve month returns exhibit significant positive influences on the current month returns.

<Table 2 about here >

Second, the results of Table 2 show an “echo” in momentum returns as documented by Novy-Marx (2012). The echo in momentum returns refers to the empirical regularity that long-short portfolios formed on recent past returns (the previous five months) predict lower average future returns than long-short portfolios formed on intermediate-horizon past returns (the previous seven to twelve months). In Table 2, the average monthly returns labeled “7-12 ranking period” denote the AFSD and ASSD 10–1 portfolio returns based on a seven- to twelve-month ranking period. We find that the subsequent 1-month average returns based on a 7-12 ranking period are significantly larger than those based on other ranking periods.

Third, relative to Jegadeesh and Titman (1993)’s finding that long-short portfolios tend to generate negative returns 12 months after portfolio formation, Table 2 tells a similar story with the exception of the 10-1 portfolios based on a 7-12 ranking period: the 10-1 portfolios returns based on a 7-12 ranking period seem to decrease over time and vanish in 6 months after portfolio formation. Overall, Table 2 shows that the AFSD and ASSD 10-1 portfolios are capable of generating significant profits and the term structure of their average monthly returns ex-post portfolio formation exhibits similar characteristics to those of the standard momentum strategies which construct long-short portfolios solely based on past return performances.

Table 3 presents the average monthly returns of the AFSD momentum strategies with different overlapping holding periods. Panel A of Table 3 shows the series of overlapping portfolios formed immediately after the ranking period, while Panel B of Table 3 reports the results when we include a one-month lag between the ranking period and the holding period. In Panel A, the average monthly returns increase initially and then decrease as the length of the overlapping holding period increases, except for the 12- and 7- to 12-month ranking periods. This result, consistent with the finding of Jegadeesh and Titman (1993), confirms the presence of reversal in short-term returns. With the inclusion of a one-month lag between the ranking period and the holding period, performance improves particularly for those portfolios with a 3-month overlapping period; in addition, their average monthly returns monotonically decrease with the length of holding period.

<Table 3 about here >

The best performing strategy in Panel A is attributed to its usage of a 9-month ranking period and a 6-month holding period. The average monthly return of the best performing strategy is 1.0601% and is significantly different from zero. On the other hand, when including a one-month lag between the ranking period and holding period, the best strategy therein generates an average monthly return of 1.2380% when based on a 9-month ranking period and a 3-month holding period. Overall, Table 3 shows that the average monthly returns of the AFSD strategies with overlapping holding periods are in general positive and significant, except for strategies using a 7-12 ranking period.

Table 4 reports average monthly returns of the ASSD momentum strategies with different overlapping holding periods. The average monthly returns decrease with the length of the holding period except for the 3-month ranking period when portfolios are immediately formed after the ranking period. In Panel A, the best strategy emerges with a positive and significant return of 1.5141% when based on a 9-month ranking period and a 3-month holding period. In Panel B, the best performing strategy is the one with a 9-month ranking period and a 3-month holding period, which gives rise to an average monthly return of 1.5882%. Finally, the ASSD momentum strategies generate profits that are larger in magnitude relative to the AFSD strategies. Overall, momentum profits as a result of exploiting information from the ex-post AFSD and ASSD ranking relations are found to be significant and positive.

<Table 4 about here >

## 4.4 How profitable are the AFSD and ASSD momentum strategies?

We ask how profitable the AFSD and ASSD momentum strategies are compared to standard momentum strategies that are based on historical return performances. To facilitate direct comparisons, Table 5 presents the results of the arbitrage returns following the standard momentum strategy of Jegadeesh and Titman (1993). Panel A of Table 5 shows that, without time lags between the ranking and the holding periods, the best standard momentum strategy based on a 9-month ranking period and 3-month holding period generates an average monthly return of 1.2773%, whereas Jegadeesh and Titman (1993) report an average monthly return of 1.3100% using a 12-month ranking period and a 3-month holding period. With the inclusion of a one-month lag between the ranking and the holding periods, the largest economic gain generated by following the standard momentum strategy is 1.3530%, based on a 9-month ranking period and a 3-month holding period.

<Table 5 about here >

The results of Table 5 indicate that the arbitrage returns generated by the AFSD momentum strategies are significant and positive, but moderate relative to the standard momentum strategy. This result points to the traditional reward-to-risk mechanism reinterpreted by the Sharpe Omega as gain-to-loss expectations cushioned by a return threshold—the risk-free return. In addition, the result suggests that this reinterpretation of reward-to-risk, when exploited by a long (low performance) minus short (high performance) arbitrage portfolio, gives rise to arbitrage returns that are moderate relative to the standard momentum strategy and a resulting return distribution that is less "volatile"—a point that we further clarify with the results of Table 6 in the following.

Table 6 compares the risk-adjusted performance of the AFSD and ASSD momentum strategies with the standard momentum strategy.[10] The table presents the standard deviation, the skewness, and the maximum drawdown of the monthly returns, together with the following measures of risk-adjusted performance: the Sharpe ratio, Omega, Sortino ratio, upside potential

[10] Although we illustrate our findings based on a 12-month ranking period, the results remain qualitatively the same under ranking periods of different time lengths.

ratio (UPR), Calmar ratio, Sterling ratio, excess return on value at risk (ERVaR), conditional Sharpe ratio (CSR), non-parametric estimation of the economic performance measure (EPM), the EPM when returns are assumed to be normally-distributed (EPM_Normal), and the EPM when returns are assumed to be NIG-distributed (EPM_NIG).[11]

For the AFSD momentum strategies, the standard deviation, the skewness, and the maximum drawdown of monthly returns are all small in absolute terms, resulting in arbitrage returns that are less "volatile" relative to the standard momentum strategy. In addition, the AFSD momentum strategies, relative to the standard momentum strategy, are capable of delivering better risk-adjusted performance under all chosen measures of reward-to-risk. For overlapping holding periods of longer duration, in particular, the AFSD arbitrage returns exhibit higher risk-adjusted performance, smaller maximum drawdowns, higher average monthly returns, and smaller standard deviations relative to the standard momentum strategy.

<Table 6 about here >

Furthermore, Table 6 shows that the ASSD strategies are capable of delivering the highest average monthly returns. Although the return distributions are slightly more volatile, and have a higher maximum drawdown relative to the standard momentum strategy for overlapping holding periods of longer duration, the ASSD strategies generate the best risk-adjusted performance, suggesting that the selection rules of ASSD make portfolio choices under a better risk-return trade-off which succeeds in generating higher average monthly returns: higher risk is matched by higher excess returns.

[11] The Sharpe ratio is calculated as the average monthly returns divided by the standard deviation of the monthly returns. The Omega and Sortino ratios are risk-adjusted performance measures that are based on the lower partial moments of returns, and they consider risk as negative deviations of the portfolio's returns in relation to a minimal acceptable return. The Omega ratio uses lower partial moments of order one, which defines an expected shortfall. The Sortino ratio uses lower partial moments of order two, which defines a semi-variance—as the denominators of the average monthly returns. The UPR is calculated as higher partial moments of order one divided by lower partial moments of order two. The Calmar and Sterling ratios are drawdown-based measures that divide the average monthly returns by the maximum drawdown or an average above the five largest drawdowns, respectively. The ERVaR measures risk by standard value at risk, and the CSR measures risk by conditional value at risk. For the details of the calculations, we refer readers to Eling and Schuhmacher (2007). For measures that are based on partial moments, readers can refer to the works of Keating and Shadwick (2002) and Sortino, van der Meer and Plantinga (1999); for the Calmar and Sterling ratios, also see Young (1991) and Kestner (1996); and for measures that are based on value-at-risk, see Dowd (2000) and Agarwal and Naik (2004). Finally, for the closed-form expression of EPM when returns are assumed to be normally-distributed and NIG-distributed, please see Aumann and Serrano (2008), Foster and Hart (2009) and Homm and Pigorsch (2012a and 2012b). The details for the non-parametric estimation of EPM can be found in Homm and Pigorsch (2012b).

Finally, it is well-documented that the positive returns of standard momentum strategies are punctuated with infrequent crashes (Grundy and Martin, 2001; Cooper, Gutierrez, and Hameed, 2004; Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). Daniel and Moskowitz (2016) highlight two momentum crashes: June 1932 to December 1939, and March 2009 to March 2013, which represent the two largest sustained drawdown periods for the momentum strategy. Figure 3 compares the dollar value of $1 investment on AFSD, ASSD, and standard momentum strategies, respectively, starting from January 2008 to the end of our sample period. For simplicity, we only report the results with a 12-month ranking period, and with a 9-month or 12-month holding period. The figure shows that all strategies experience large losses after March 2009. The largest loss occurs in April 2009, where the percentage losses are -20.18%, -28.28%, and -32.99% for the AFSD, ASSD, and standard momentum strategies with a 12-month ranking and a 12-month holding period, respectively. After February 2010, the dollar value of $1 investment starts to recover for all momentum strategies, however, the AFSD and ASSD momentum strategies recover faster than the standard momentum strategies. The result suggests that the AFSD and ASSD momentum strategies suffer smaller losses during the period of momentum crash and regain the dollar investment faster compared with the standard momentum strategies. Such advantage is even more pronounced when we use a 12-month ranking and a 1-, 3-, or 6-month holding period.

<Figure 3 about here >

## 4.5 Can common risk factors explain the ASD arbitrage returns?

Next, we ask if the positively significant arbitrage returns generated by the AFSD and ASSD 10–1 portfolios can be subsumed by risk factors typical of the cross-sectional stock returns. To answer that, we regress the arbitrage returns on a nine-factor model that includes the following risk factors: the Fama-French (2015) five factors; the momentum factor, which is defined as in Fama and French (2012);[12] Pástor and Stambaugh's (2003) liquidity risk factor;[13] and the short-term and long-term reversal factors. Formally, we implement the following regressions:

$$\begin{aligned} r_{AFSD,t} &= \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t \\ &\quad + \beta_6 MOM_t + \beta_7 LIQ_t + \beta_8 ST\_Rev_t + \beta_9 LT\_Rev_t + e_t \end{aligned} \tag{8}$$

and

$$\begin{aligned} r_{ASSD,t} &= \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t \\ &\quad + \beta_6 MOM_t + \beta_7 LIQ_t + \beta_8 ST\_Rev_t + \beta_9 LT\_Rev_t + e_t \end{aligned} \tag{9}$$

where $MKT$, $SMB$, $HML$, $RMW$,and $CMA$ are Fama and French's (2015) five factors, with $MKT$ denoting the excess return on a broad market index, $SMB$ and $HML$ referring to the portfolio returns generated by "small minus big" market capitalizations and "high minus low" book-to-market ratios, $RMW$ to the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and $CMA$ to the difference between the returns on diversified portfolios of the stocks of low and high investment firms; $MOM$ denotes the momentum risk factor; $LIQ$ refers to the liquidity risk factor of Pástor and Stambaugh (2003); and $ST\_Rev$ and $LT\_Rev$ refer to the short-term reversal and long-term reversal factors, respectively.[14] $r_{AFSD,t}$ ($r_{ASSD,t}$) denotes the monthly returns generated by the 10-1 portfolios formed on AFSD (ASSD) using different ranking periods, and with or without monthly overlapping

[12] Fama and French use six value-weighted portfolios formed on the basis of size and past performance over the ranking period from the twelfth month to the second month prior to portfolio formation. The momentum factor is the average return on the two high prior return portfolios (small size high and big size high) minus that on the two low prior return portfolios (small size low and big size low). For details on constructing the risk factor, please refer to French's web site at Dartmouth, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

[13] We use the time-series of the traded liquidity risk factor of Pástor and Stambaugh (2003) as a proxy for the market liquidity risk. The factor is derived from dividing stocks into ten groups based on the stocks' sensitivity to a non-traded liquidity innovation factor. The non-traded liquidity measure is the equally weighted average of the liquidity measures of individual stocks on the NYSE and AMEX. For more details, please refer to Pástor and Stambaugh (2003).

[14] The historical data of Fama and French's (2015) five factors, $MOM$, $ST\_Rev$ and $LT\_Rev$ can be downloaded from the following website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The inclusion of $ST\_Rev$ and $LT\_Rev$ in the French data library is consistent with the research of Bartram and Grinblatt (2017). Furthermore, the results remain unchanged for Tables 7, 8 and 9 when we regress the monthly returns of the 10-1 portfolios formed on AFSD and ASSD on Fama and French's (1993) three factors with momentum and liquidity factors, or on Fama and French's (2015) five factors with momentum and liquidity factors.

holding periods. The historical monthly returns of all risk factors are obtained from CRSP.

Table 7 presents the abnormal returns—the intercepts (alphas) of our linear regressions—for the AFSD long-short portfolios, with or without monthly overlapping holding periods. Panel A reports the regression results for the portfolios formed without including a one-month lag between the ranking period and the holding period. Most of the intercepts are positive and significant at the 1% level, suggesting that the AFSD strategies are indeed capable of generating abnormal returns. The smallest and insignificant return generated by the strategy with a ranking period of 3 months and a holding period of exactly 1 month (without monthly overlapping) indicates, again, the presence of a short-term return reversal. Without monthly-overlapping periods, most strategies without a one-month lag, except for the one based on a 7-12 ranking period, generate smaller abnormal returns than those with a one-month lag. This result suggests that, for the portfolios formed without a one-month lag and without monthly overlapping periods, a short-term return reversal could severely impede the profitability of the AFSD strategies.

<Table 7 about here >

Panel B of Table 7 shows that almost all strategies generate abnormal returns regardless of the lengths of the holding periods and when we include a one-month lag between the ranking period and the holding period. All strategies generate abnormal returns that are significant at the 1% level. Consistent with the findings of Novy-Marx (2012), Table 7 also documents winning strategies that are based on past performances of the intermediate horizon rather than the recent past. The best performing abnormal returns are generated by the strategy that uses a 7-12 ranking period without monthly overlapping holding periods. Second to that is a profitable strategy that is based on a 9-month ranking period and a 3-month holding period. Overall, Table 7 shows that the abnormal returns generated by the AFSD strategies cannot be fully explained by Fama and French's (2015) five factors augmented by the momentum factor of Fama and French (2012), the liquidity risk factor of Pástor and Stambaugh (2003), and the short-term reversal and long-term reversal risk factors.

Table 8 presents the abnormal returns to the ASSD strategies. The implications therein are similar to those given in Table 7. In most cases, these abnormal returns cannot be explained by standard risk factors. In addition, we find that the ASSD strategies are, in general, more profitable than the AFSD strategies.

<Table 8 about here >

Tables 9 and 10 report the factor loadings for the regression of the 10-1 monthly portfolio returns on the nine risk factors. We illustrate our findings using arbitrage returns of the portfolios formed with matching ranking and holding periods. The factor loadings of market returns are negative and significant, which is consistent with the findings of Novy-Marx (2012) and Clark and Kassimatis (2014) who suggest that the premia of the momentum and ASD portfolios are countercyclical. Tables 9 and 10 also find positive and significant factor loadings on the momentum risk factor, indicating that the ASD and momentum portfolios exhibit commonalities. However, the intercepts are positive and significant, indicating that the AFSD and ASSD portfolios are capable of generating abnormal returns even when the momentum risk factor is accounted for.[15] The results show that the Fama-French five factors augmented with the momentum factor, the liquidity factor, and the short-term and long-term reversal factors cannot explain the variations in the AFSD and ASSD premia.

<Table 9 about here >

<Table 10 about here >

In addition, we would like to test if the abnormal return on the AFSD is greater than that on the 10-1 portfolio formed on past returns. To test this, we regress the differences between the returns on the AFSD and the 10-1 portfolio formed on past returns on the nine risk factors and test if the intercept is significantly greater than zero. We test the same null hypothesis for the ASSD and the 10-1 portfolio formed on past returns. We find that the returns of the ASSD 10-1 portfolio minus the returns of the corresponding (with the same ranking period and holding period) momentum portfolio are all significant at the 1% level, indicating that portfolios

[15] The momentum risk factor in Table 9 is available on French's web site at Dartmouth. Alternatively, we construct the monthly returns of standard momentum strategies as in Table 5 and find that the intercepts are still significant when we replace French's momentum factor with the constructed momentum factor.

formed on the ASSD ranking perform better than those formed on past returns. For the returns of the AFSD 10-1 portfolio minus the returns of the corresponding momentum portfolio, the results are weaker than for the ASSD portfolio. However, still more than half of the intercepts are significantly different from zero.

Lastly, we also calculate the overlapping ratios when forming AFSD, ASSD and momentum decile portfolios in each period. Each ratio is defined as the number of the stocks in the same decile before and after the holding period, divided by the number of stocks in that decile before the holding period. If the overlapping ratio is small, then the trading frequency and trading cost would be high, which also indicates that the rankings are less stable across the formation dates. We find that there is little difference in the overlapping ratios of the 10 and 1 decile portfolios, regardless of whether the portfolios are formed on the AFSD or ASSD rankings, or the ranking based on the past returns.

## 5 Conclusion

In this paper, we show that the ASD momentum strategies (AFSD and ASSD) are capable of generating abnormal returns. For the AFSD momentum strategies, the standard deviation, the skewness, and the maximum drawdown of the resulting monthly returns are all small in absolute terms, resulting in arbitrage return distributions that are less "volatile" relative to the standard momentum strategy of Jegadeesh and Titman (1993). In addition, the AFSD and the ASSD momentum strategies are capable of delivering better risk-adjusted performance (under all pre-chosen performance measures) relative to the standard momentum strategy. For overlapping holding periods of longer duration, the AFSD arbitrage returns exhibit higher risk-adjusted performance, smaller maximum drawdowns, higher average monthly returns, and smaller standard deviations relative to the standard momentum strategy. These abnormal returns cannot be fully explained by Fama and French's (2015) five-factor model augmented by the momentum factor, the liquidity risk factor, and the short-term reversal and long-term reversal factors.

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## Appendix A The Relationship between the AFSD Violation Ratio and Sharpe Omega

Under the assumption that $E(r_i) \geq r_f$, $F_i(r)$ intersects $K(r)$ at most once from above at $r_f$. Thus, Equation (4) can be written as

$$\theta_1^i = \frac{\int_{\underline{r}}^{r_f} [F_i(r) - K(r)]\, dr}{\int_{\underline{r}}^{r_f} [F_i(r) - K(r)]\, dr - \int_{r_f}^{\bar{r}} [F_i(r) - K(r)]\, dr}. \tag{A.1}$$

Rearranging the above equation yields

$$\frac{1}{\theta_1^i} - 2 = \frac{\int_{\underline{r}}^{\bar{r}} [K(r) - F_i(r)]\, dr}{\int_{\underline{r}}^{r_f} [F_i(r) - K(r)]\, dr}. \tag{A.2}$$

By integration by parts, we have

$$\begin{aligned} \int_{\underline{r}}^{\bar{r}} [K(r) - F_i(r)]\, dr &= \int_{\underline{r}}^{\bar{r}} r\, [dF_i(r) - dK(r)] \\ &= E(\tilde{r}_i - r_f), \end{aligned}$$

and

$$\begin{aligned} \int_{\underline{r}}^{r_f} [F_i(r) - K(r)]\, dr &= r_f F_i(r_f) - r_f - \int_{\underline{r}}^{r_f} r\, [dF_i(r) - dK(r)] \\ &= r_f F_i(r_f) - \int_{\underline{r}}^{r_f} r dF_i(r) \\ &= \int_{\underline{r}}^{r_f} (r_f - r)\, dF_i(r) \\ &= E(r_f - \tilde{r}_i)^+. \end{aligned}$$

Thus, we have

$$\frac{1}{\theta_1^i} - 2 = \frac{E(\tilde{r}_i - r_f)}{E(r_f - \tilde{r}_i)^+}. \tag{A.3}$$

In other words, ranking risky assets according to $\theta_1^i$ is the same as ranking them according to $\frac{E(\tilde{r}_i - r_f)}{E(r_f - \tilde{r}_i)^+}$ but in reverse order.

## Appendix B The ASSD Violation Ratio

Under the assumption that $E(r_i) \geq r_f$, $F_i^{(2)}(r)$ intersects $K^{(2)}(r)$ at most once from above at $r_i^*$, where

$$F_i^{(2)}(r_i^*) = r_i^* - r_f.$$

Rewriting Equation (5) yields

$$\theta_2^i = \frac{\int_{\underline{r}}^{r_i^*} \left[ F_i^{(2)}(r) - K^{(2)}(r) \right] dr}{\int_{\underline{r}}^{r_i^*} \left[ F_i^{(2)}(r) - K^{(2)}(r) \right] dr - \int_{r_i^*}^{\bar{r}} \left[ F_i^{(2)}(r) - K^{(2)}(r) \right] dr}. \tag{A.4}$$

Rewriting the above equation yields

$$\frac{1}{\theta_2^i} - 2 = \frac{\int_{\underline{r}}^{\bar{r}} \left[ K^{(2)}(r) - F_i^{(2)}(r) \right] dr}{\int_{\underline{r}}^{r_i^*} \left[ F_i^{(2)}(r) - K^{(2)}(r) \right] dr}. \tag{A.5}$$

Note that given $r_0 \in [\underline{r}, \bar{r}]$, by integration by parts, we have

$$\begin{aligned} \int_{\underline{r}}^{r_0} F_i^{(2)}(r) dr &= \frac{1}{2} \int_{\underline{r}}^{r_0} (r_0 - r) dF_i^{(2)}(r) \\ &= \frac{1}{2} E \left[ (r_0 - \tilde{r}_i)^+ \right]^2. \end{aligned}$$

Thus, Equation (A.5) can be rewritten as

$$\frac{1}{\theta_2^i} - 2 = \frac{(\bar{r} - r_f)^2 - E(\bar{r} - \tilde{r}_i)^2}{E\left[(r_i^* - \tilde{r}_i)^+\right]^2 - \left[(r_i^* - r_f)^+\right]^2}. \tag{A.6}$$

In other words, ranking assets according to $\theta_2^i$ is the same as defining them in a reverse ranking according to

$$\frac{(\bar{r} - r_f)^2 - E(\bar{r} - \tilde{r}_i)^2}{E\left[(r_i^* - \tilde{r}_i)^+\right]^2 - \left[(r_i^* - r_f)^+\right]^2}.$$

## Appendix C Actual Violation Ratio

To calculate the violation ratio of each stock with respect to the risk-free asset, we first follow Babbel and Herce (2007) and Clark and Kassimatis (2014) to obtain the vertical distance between two empirical CDFs. Let $F_i$ be the empirical CDF of the $i$-th risky asset $X$, and $K$ be the empirical CDF of the risk-free asset $Y$ (we use daily quotes of the one-month T-Bill rate as a proxy of the returns to the risk-free asset). Define $I_1^i$ as representing the vertical distance $G(r) - F_i(r)$ for different values of $r$, where $r$ denotes the realized returns. The vertical distances $I_1^i$ are evaluated at each point of the joint unique realized return values. That is:

$$I_1^i(r) = F_i(r_t) - K(r_t), \quad r_t \leq r < r_{t+1} \quad t = 1, ..., m$$

where $m$ denotes the number of the joint unique realized returns of $X$ and $Y$, and $r_1, ..., r_m$ are the joint unique realized returns sorted in ascending order. The actual violation ratio $\theta_1^i$ in Equation 4 can thus be approximated by:

$$\theta_1^i = \frac{\int_{F_i \geq K} [F_i(r) - K(r)] dr}{\int_{\underline{r}}^{\bar{r}} |F(r) - K(r)| \, dr} = \frac{\sum\limits_{\forall t \ s.t. \ I_1^i(r_t) > 0} I_1^i(r_t)(r_{t+1} - r_t)}{\sum\limits_{\forall t} \left| I_1^i(r_t)(r_{t+1} - r_t) \right|} \tag{A.7}$$

For the actual violation ratios under the ASSD criterion, we first compute the integral of difference in the CDFs. Define $I_2^i$ as:

$$I_2^i(r) = I_2^i(r_{t-1}) + I_1^i(r_{t-1})(r - r_{t-1}), \quad r_t \leq r < r_{t+1} \quad t = 2, ..., m$$

with $I_2^i(r_1) = 0$. The actual violation ratio in Equation 5 can be approximated by:

$$
\begin{aligned}
\theta_2^i &= \frac{\int_{F_i^{(2)} > K^{(2)}} [F_i^{(2)}(r) - K^{(2)}(r)] dr}{\int_{\underline{r}}^{\bar{r}} \left| F_i^{(2)}(r) - K^{(2)}(r) \right| dr} \\
&= \frac{\sum\limits_{\forall t \ s.t. \ I_2^i(r_t) > 0} \frac{1}{2} I_2^i(r_t) \{ r_t - s_t 1(I_2^i(r_{t-1}) < 0) - r_t 1(I_2^i(r_{t-1}) > 0) \}}{\sum\limits_{\forall t} \left| \frac{1}{2} I_2^i(r_t) \{ r_t - s_t 1(I_2^i(r_t) I_2^i(r_{t-1}) < 0) - r_t 1(I_2^i(r_t) I_2^i(r_{t-1}) > 0) \} \right|}
\end{aligned} \tag{A.8}
$$

where $1(E)$ denotes the indicator function of the event $E$. Note that when $I_2^i(r_t)$ and $I_2^i(r_{t-1})$ have different signs, the integral of two CDFs has an intersection between $r_t$ and $r_{t-1}$. The return value of the intersection can be obtained as $s_t = \frac{((r_{t-1} F_i^{(2)}(r_t) - r_t F_i^{(2)}(r_{t-1})) - (r_{t-1} K^{(2)}(r_t) - r_t K^{(2)}(r_{t-1})))}{((F_i^{(2)}(r_t) - F_i^{(2)}(r_{t-1})) - (K^{(2)}(r_t) - K^{(2)}(r_{t-1})))}$, where the empirical functions of $F_i^{(2)}$ and $K^{(2)}$ are defined as $F_i^{(2)}(r) = F_i^{(2)}(r_{t-1}) + F_i(r_{t-1})(r - r_{t-1})$ and $K^{(2)}(r) = K^{(2)}(r_{t-1}) + K(r_{t-1})(r - r_{t-1})$, respectively.

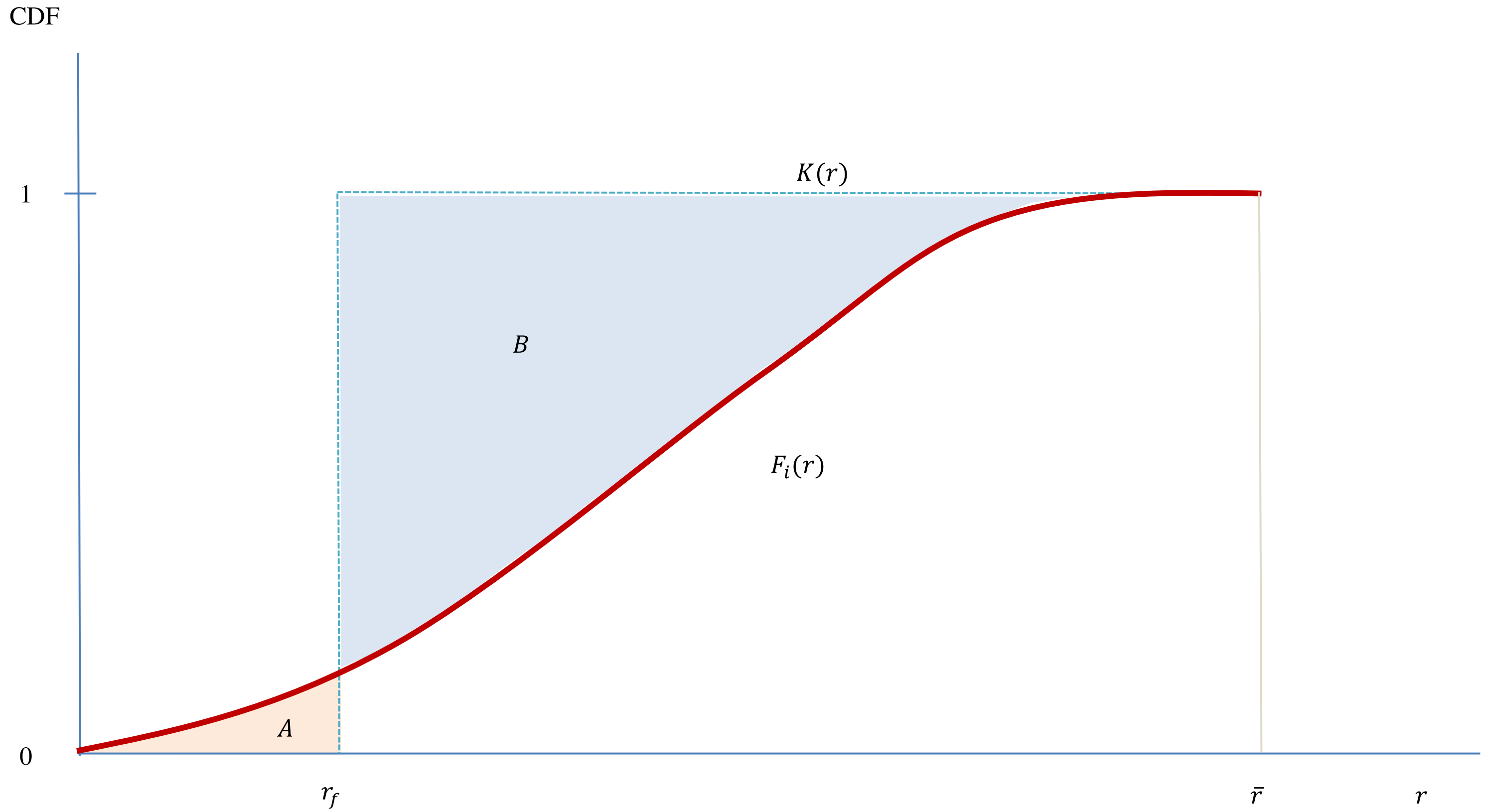


Figure 1. $F_i(r)$ and $K(r)$

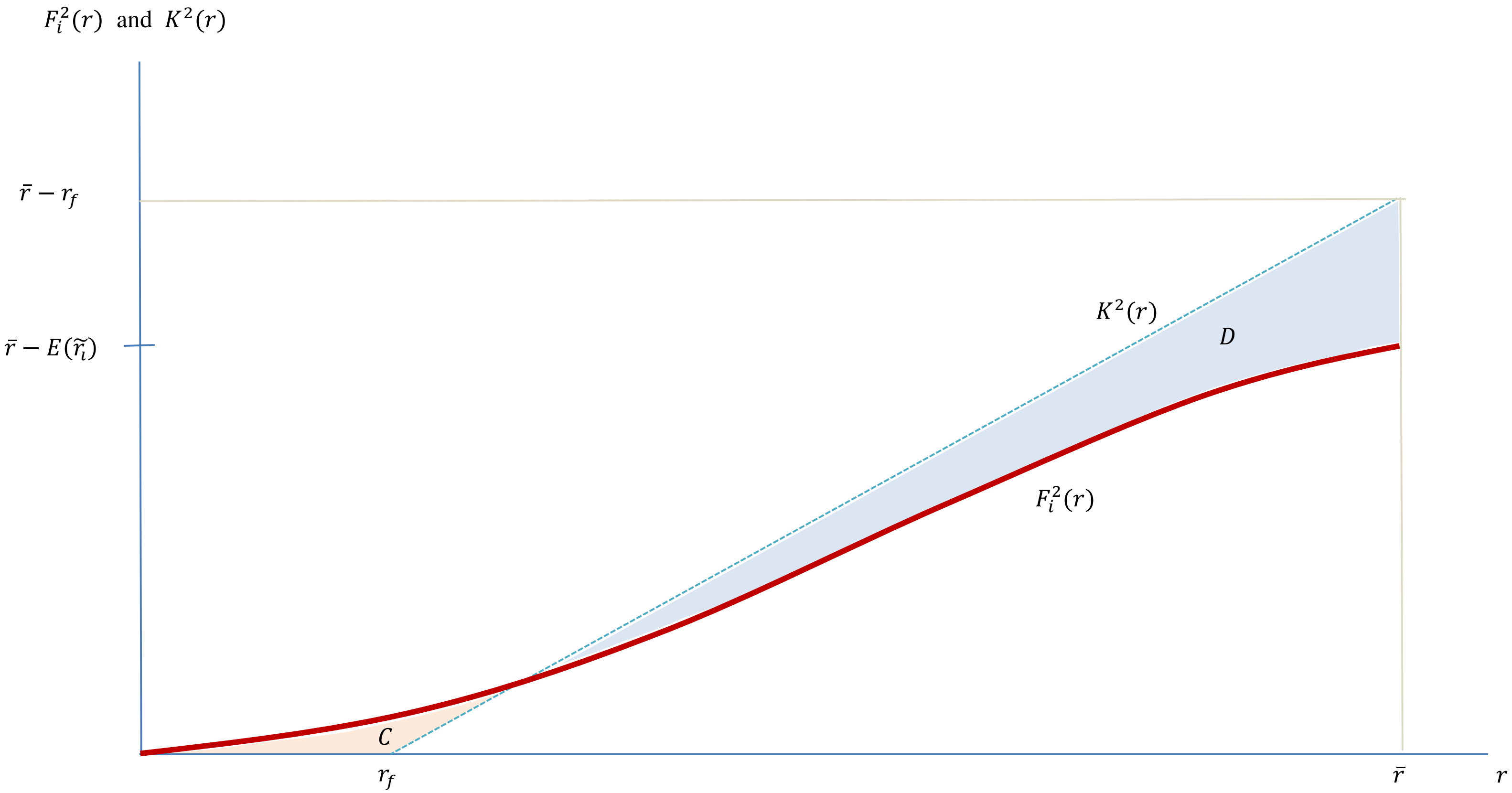


Figure 2. $F_i^2(r)$ and $K(r)$

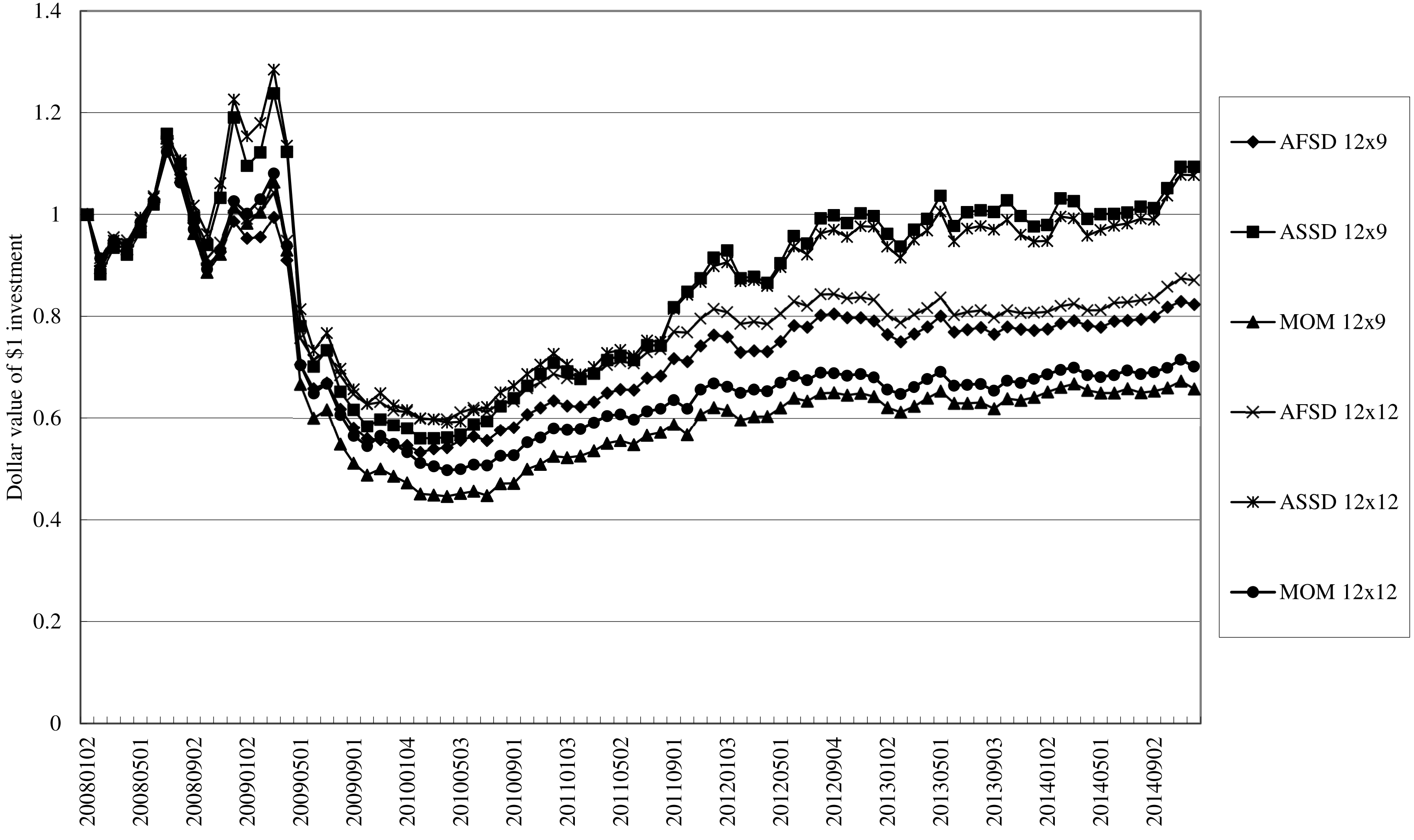


Figure 3. Dollar value of $1 investment on AFSD, ASSD and standard momentum strategies during 2008-2014.

Table 1. Summary statistics of decile portfolios formed on AFSD, ASSD and momentum ranking (ranking period: 12 months)

This table reports the average daily returns, the standard deviations, and the skewness of decile portfolios formed on the AFSD, ASSD and momentum ranking during the ranking period, respectively. At the beginning of each month, the decile portfolios are constructed by sorting all stocks in descending order according to the AFSD violation ratio, in descending order according to the ASSD violation ratio, and in ascending order according to the prior realized returns during the ranking period, respectively. The AFSD and the ASSD violation ratios are obtained by comparing the return distribution of each stock with the risk-free asset. The average daily returns are calculated as the equally-weighted averages of the ranking-period daily returns on each stock in the decile portfolio. We also report the average violation ratios and the average monthly returns of each decile portfolio over the first and the second month after portfolio formation. The average daily returns and the standard deviations are expressed as percentages.

| AFSD decile portfolio | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Ranking-period daily return | -0.1375 | -0.0502 | -0.0058 | 0.0293 | 0.0605 | 0.0916 | 0.1250 | 0.1631 | 0.2163 | 0.3347 |
| Std. dev. of ranking-period return | 2.5756 | 2.5452 | 2.5261 | 2.5045 | 2.4997 | 2.4991 | 2.5221 | 2.5348 | 2.5989 | 2.7514 |
| Skewness of ranking-period return | -0.1366 | 0.1298 | 0.2326 | 0.2990 | 0.3565 | 0.4091 | 0.4743 | 0.5471 | 0.6715 | 1.0631 |
| Kurtosis of ranking-period return | 9.1183 | 7.5922 | 7.2463 | 7.1275 | 7.0711 | 7.1447 | 7.3643 | 7.6830 | 8.3826 | 11.7294 |
| Average violation ratio | 0.5451 | 0.5194 | 0.5067 | 0.4967 | 0.4876 | 0.4786 | 0.4691 | 0.4584 | 0.4444 | 0.4126 |
| Average return of the first month | 1.0122 | 1.0013 | 1.0184 | 1.0612 | 1.1008 | 1.2543 | 1.3121 | 1.3836 | 1.5856 | 1.8462 |
| Average return of the second month | 0.6502 | 0.9142 | 0.9934 | 1.0722 | 1.1786 | 1.2997 | 1.3929 | 1.4208 | 1.5709 | 1.7848 |
| Average number of stocks | 200.08 | 199.94 | 200.09 | 199.95 | 200.26 | 199.76 | 200.06 | 199.97 | 200.05 | 199.97 |
| ASSD decile portfolio | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Ranking-period daily return | -0.2052 | -0.1010 | -0.0554 | -0.0205 | 0.0149 | 0.0565 | 0.1012 | 0.1650 | 0.2502 | 0.4081 |
| Std. dev. of ranking-period return | 3.2412 | 2.7766 | 2.5867 | 2.4727 | 2.4051 | 2.3750 | 2.3934 | 2.4658 | 2.6709 | 3.0942 |
| Skewness of ranking-period return | -0.2058 | 0.0093 | 0.1084 | 0.1828 | 0.2536 | 0.3623 | 0.4826 | 0.7068 | 1.0551 | 2.5390 |
| Kurtosis of ranking-period return | 10.0507 | 8.5175 | 7.9657 | 7.6903 | 7.5743 | 7.5941 | 7.9262 | 8.9695 | 11.1526 | 26.1904 |
| Average violation ratio | 0.9985 | 0.9846 | 0.9688 | 0.9512 | 0.9225 | 0.8706 | 0.8064 | 0.7010 | 0.5669 | 0.2978 |
| Average return of the first month | 0.6553 | 0.9082 | 0.9864 | 0.9513 | 1.1268 | 0.9998 | 1.1220 | 1.3186 | 1.7691 | 1.9410 |
| Average return of the second month | 0.2526 | 0.6656 | 0.8686 | 0.9596 | 1.0243 | 0.9496 | 1.2206 | 1.2342 | 1.6783 | 1.8045 |
| Average number of stocks | 89.56 | 88.51 | 87.65 | 87.81 | 86.32 | 84.17 | 83.14 | 79.04 | 76.17 | 62.91 |
| Momentum decile portfolio | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Ranking-period daily return | -0.1431 | -0.0456 | -0.0040 | 0.0270 | 0.0550 | 0.0828 | 0.1139 | 0.1532 | 0.2122 | 0.3758 |
| Std. dev. of ranking-period daily return | 3.2686 | 2.6499 | 2.4037 | 2.2723 | 2.2093 | 2.1980 | 2.2457 | 2.3759 | 2.6258 | 3.3084 |
| Skewness of ranking-period return | -0.0164 | 0.1692 | 0.2396 | 0.2873 | 0.3437 | 0.4011 | 0.4705 | 0.5674 | 0.7073 | 0.9905 |
| Kurtosis of ranking-period return | 9.5748 | 7.8610 | 7.3515 | 7.1284 | 7.0500 | 7.1530 | 7.4641 | 7.8980 | 8.6501 | 10.3281 |
| Average return of the first month | 0.7051 | 0.9860 | 1.0854 | 1.1502 | 1.1664 | 1.2453 | 1.3260 | 1.4443 | 1.5696 | 1.8971 |
| Average return of the second month | 0.4614 | 0.9391 | 1.0888 | 1.1261 | 1.2395 | 1.2820 | 1.3538 | 1.4207 | 1.5905 | 1.7760 |
| Average number of stocks | 200.08 | 199.94 | 200.09 | 199.95 | 200.26 | 199.76 | 200.06 | 199.97 | 200.05 | 199.97 |

Table 2. Average monthly returns of AFSD and ASSD 10-1 portfolios after portfolio formation

This table reports the average monthly returns and the *t*-statistics of the 10-1 portfolios formed on the AFSD and ASSD ranking with different ranking periods. At the beginning date of each month during the sample period, all stocks are sorted in descending order according to the AFSD (ASSD) violation ratios derived from comparing the return distribution of each stock with the risk-free asset using the AFSD (ASSD) rule. In Panel A, the 10-1 portfolios are constructed by buying all stocks in the highest AFSD decile (with the lowest violation ratio) and selling all stocks in the lowest AFSD decile (with the highest violation ratio). The ASSD 10-1 portfolios in Panel B are constructed similarly to those in Panel A except that the decile portfolios are formed on the ASSD ranking. The ranking periods include 3, 6, 9 and 12 months. The ranking period of "7-12" is also included and refers to the portfolio returns when the ranking period is from the twelfth to the seventh month prior to portfolio formation (Novy-Marx, 2012). The table reports the summary statistics for each month after the portfolio formation. The average monthly returns are expressed as percentages and the *t*-statistics are reported in parentheses.

Panel A. 10-1 portfolio formed on AFSD ranking

| Ranking period | Months after portfolio formation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| 3 | -0.1647 | 0.8384 | 0.8333 | 0.8162 | 0.7667 | 0.8024 | 0.7087 | 0.6599 | 0.6715 | 0.7452 | 0.5256 | 0.1578 | -0.1918 |
| | (-0.8144) | (4.8211) | (5.0227) | (5.0548) | (4.8887) | (5.3417) | (4.8919) | (4.5404) | (4.6941) | (5.3541) | (3.9209) | (1.1885) | (-1.3515) |
| 6 | 0.4055 | 1.0612 | 1.1688 | 1.1181 | 1.0183 | 1.0094 | 1.0021 | 0.8036 | 0.5893 | 0.3435 | 0.1986 | -0.0297 | -0.2014 |
| | (1.8682) | (5.3115) | (6.3115) | (6.2714) | (5.7603) | (5.9891) | (6.3433) | (5.0963) | (3.7353) | (2.1584) | (1.2460) | (-0.1936) | (-1.3713) |
| 9 | 0.6829 | 1.1811 | 1.2950 | 1.2667 | 1.0204 | 0.8886 | 0.6754 | 0.5411 | 0.4194 | 0.2654 | 0.1684 | -0.0664 | -0.2215 |
| | (3.0047) | (5.5740) | (6.3777) | (6.7471) | (5.5389) | (4.9708) | (3.8146) | (3.1726) | (2.4725) | (1.6380) | (1.0630) | (-0.4334) | (-1.4467) |
| 12 | 0.8341 | 1.1346 | 1.1049 | 0.9156 | 0.7766 | 0.6722 | 0.5621 | 0.4230 | 0.3337 | 0.1794 | 0.1157 | -0.0116 | -0.0639 |
| | (3.6361) | (5.3244) | (5.3562) | (4.5815) | (4.0492) | (3.5706) | (3.1622) | (2.5016) | (1.9723) | (1.0853) | (0.7092) | (-0.0736) | (-0.4036) |
| 7-12 | 1.1678 | 0.9257 | 0.7066 | 0.4403 | 0.2525 | 0.0090 | -0.2423 | -0.2305 | -0.2239 | -0.1029 | -0.1385 | -0.0207 | 0.1431 |
| | (7.2600) | (5.9723) | (4.4941) | (2.7572) | (1.6104) | (0.0588) | (-1.6545) | (-1.6325) | (-1.6272) | (-0.7808) | (-1.0664) | (-0.1664) | (1.1393) |

Panel B. 10-1 portfolio formed on ASSD ranking

| Ranking period | Months after portfolio formation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| 3 | 0.4397 | 1.3862 | 1.1424 | 1.0937 | 0.9874 | 1.0613 | 0.8451 | 0.7712 | 0.7557 | 0.9313 | 0.7429 | 0.1911 | -0.2109 |
| | (1.6625) | (5.8421) | (5.0792) | (4.8950) | (4.4435) | (5.0145) | (4.0813) | (3.8270) | (3.9525) | (5.1895) | (4.4565) | (1.0415) | (-1.0769) |
| 6 | 0.9224 | 1.6130 | 1.4560 | 1.4793 | 1.1828 | 1.1741 | 1.0198 | 0.8695 | 0.6066 | 0.4216 | 0.2368 | -0.1048 | -0.1994 |
| | (3.2862) | (6.4012) | (5.8887) | (6.0579) | (4.8741) | (5.0218) | (4.7714) | (4.1961) | (2.8232) | (1.9671) | (1.1491) | (-0.5042) | (-0.9425) |
| 9 | 1.2638 | 1.6306 | 1.6353 | 1.5356 | 1.0663 | 0.8075 | 0.7746 | 0.6664 | 0.4090 | 0.2929 | 0.2877 | -0.1696 | -0.2636 |
| | (4.4245) | (6.1065) | (6.2608) | (6.2884) | (4.3442) | (3.2588) | (3.3514) | (2.8530) | (1.7369) | (1.2937) | (1.2837) | (-0.7801) | (-1.1586) |
| 12 | 1.2857 | 1.5519 | 1.3242 | 1.0804 | 0.9578 | 0.8285 | 0.6267 | 0.3611 | 0.3643 | 0.1627 | 0.1807 | -0.0771 | 0.0228 |
| | (4.4067) | (5.6303) | (4.8836) | (4.0515) | (3.6966) | (3.0702) | (2.4971) | (1.4599) | (1.4473) | (0.7012) | (0.7725) | (-0.3486) | (0.1022) |
| 7-12 | 1.3755 | 1.0413 | 0.7498 | 0.7294 | 0.3444 | 0.0264 | -0.2114 | -0.1677 | -0.2063 | -0.2439 | -0.0848 | 0.0454 | 0.1386 |
| | (6.6009) | (5.3653) | (3.6246) | (3.1097) | (1.8132) | (0.1371) | (-1.0632) | (-0.9076) | (-1.1450) | (-1.2629) | (-0.4949) | (0.2547) | (0.8407) |

Table 3. Average monthly returns of AFSD strategies with overlapping holding period

This table reports the average monthly returns and the *t*-statistics of the AFSD strategies with different ranking periods. The monthly return is calculated as the average returns across the 10-1 portfolio formed on the beginning date of month *t* to the portfolio formed in month *t-K*, where *K* equals 3, 6, 9 and 12 for the portfolios with an overlapping holding period of 3, 6, 9 and 12 months, respectively. The 10-1 portfolio in month *t* is constructed by sorting all stocks in descending order according to their AFSD violation ratios, and then buying all stocks in the top decile and selling those in the bottom decile. The ranking period includes 3, 6, 9 and 12 months. The ranking period of "7-12" is also included and refers to the portfolio returns when the ranking period is the twelfth to the seventh month prior to portfolio formation (Novy-Marx, 2012). Panel A reports the results of the overlapping portfolios when the portfolios are formed immediately after the ranking period and Panel B reports those of the overlapping portfolios formed after we skip one month between the portfolio formation month and the ranking period. The average monthly returns are expressed as percentages and the *t*-statistics are reported in parentheses.

| Ranking period | Panel A. Portfolios formed immediately after ranking period | | | | Panel B. Portfolios formed after skipping one month | | | |
|---|---|---|---|---|---|---|---|---|
| | Months of overlapping holding period (*K*) | | | | Months of overlapping holding period (*K*) | | | |
| | 3 | 6 | 9 | 12 | 3 | 6 | 9 | 12 |
| 3 | 0.5024 | 0.6569 | 0.6611 | 0.6132 | 0.8269 | 0.7972 | 0.7573 | 0.6071 |
| | (3.0144) | (4.6609) | (5.2834) | (5.5863) | (5.3809) | (6.0331) | (6.4870) | (5.7929) |
| 6 | 0.8803 | 0.9678 | 0.9113 | 0.7270 | 1.1083 | 1.0622 | 0.8992 | 0.6700 |
| | (4.5483) | (5.6001) | (5.9206) | (5.1657) | (6.1394) | (6.5070) | (6.1239) | (4.9361) |
| 9 | 1.0561 | 1.0601 | 0.8887 | 0.6915 | 1.2380 | 1.0533 | 0.8366 | 0.6084 |
| | (5.0613) | (5.6612) | (5.1475) | (4.3498) | (6.3264) | (5.8685) | (5.0299) | (3.9459) |
| 12 | 1.0242 | 0.9045 | 0.7424 | 0.5715 | 1.0373 | 0.8542 | 0.6636 | 0.4892 |
| | (4.8254) | (4.6049) | (4.0907) | (3.3821) | (5.1263) | (4.5268) | (3.7866) | (2.9840) |
| 7-12 | 0.9308 | 0.5797 | 0.3011 | 0.1907 | 0.6796 | 0.3416 | 0.1548 | 0.0994 |
| | (6.1810) | (4.1054) | (2.3215) | (1.6125) | (4.5358) | (2.4442) | (1.2202) | (0.8592) |

Table 4. Average monthly returns of ASSD strategies with overlapping holding period

This table reports the average monthly returns and the *t*-statistics of the ASSD strategies with different ranking periods. The monthly return is calculated as the average returns across the 10-1 portfolio formed on the beginning date of month *t* to the portfolio formed in month *t-K*, where *K* equals 3, 6, 9 and 12 for the portfolios with an overlapping holding period of 3, 6, 9 and 12 months, respectively. The 10-1 portfolio in month *t* is constructed by sorting all stocks in descending order according to their AFSD violation ratios, and then buying all stocks in the top decile and selling those in the bottom decile. The ranking period includes 3, 6, 9 and 12 months. The ranking period of "7-12" is also included and refers to the portfolio returns when the ranking period is the twelfth to the seventh month prior to portfolio formation (Novy-Marx, 2012). Panel A reports the results of the overlapping portfolios when the portfolios are formed immediately after the ranking period and Panel B reports those of the overlapping portfolios formed after we skip one month between the portfolio formation month and the ranking period. The average monthly returns are expressed as percentages and the *t*-statistics are reported in parentheses.

| Ranking period | Panel A. Portfolios formed immediately after ranking period | | | | Panel B. Portfolios formed after skipping one month | | | |
|---|---|---|---|---|---|---|---|---|
| | Months of overlapping holding period (*K*) | | | | Months of overlapping holding period (*K*) | | | |
| | 3 | 6 | 9 | 12 | 3 | 6 | 9 | 12 |
| 3 | 0.9866 | 1.0215 | 0.9410 | 0.8569 | 1.2041 | 1.0840 | 0.9917 | 0.7990 |
| | (4.4748) | (5.2418) | (5.3189) | (5.4989) | (5.8166) | (5.7893) | (5.9699) | (5.3008) |
| 6 | 1.3303 | 1.3067 | 1.1463 | 0.9049 | 1.5100 | 1.3174 | 1.0877 | 0.8055 |
| | (5.3489) | (5.7057) | (5.6035) | (4.7869) | (6.3764) | (6.0607) | (5.5393) | (4.3650) |
| 9 | 1.5141 | 1.3230 | 1.0867 | 0.8408 | 1.5882 | 1.2351 | 0.9726 | 0.7059 |
| | (5.8119) | (5.5528) | (4.9308) | (4.0607) | (6.4331) | (5.4007) | (4.5293) | (3.4673) |
| 12 | 1.3891 | 1.1694 | 0.9173 | 0.6991 | 1.3042 | 1.0517 | 0.7856 | 0.5819 |
| | (5.1652) | (4.6833) | (3.9017) | (3.1509) | (5.0193) | (4.3198) | (3.4057) | (2.6684) |
| 7-12 | 1.0538 | 0.7060 | 0.3955 | 0.2595 | 0.8296 | 0.4410 | 0.2131 | 0.1536 |
| | (5.6098) | (4.0392) | (2.4678) | (1.7482) | (4.2977) | (2.5526) | (1.3508) | (1.0606) |

Table 5. Average monthly returns of momentum strategies with overlapping holding period

This table reports the average monthly returns and the *t*-statistics of the momentum strategies with different ranking periods. The monthly return is calculated as the average returns across the 10-1 portfolio formed on the beginning date of month *t* to the portfolio formed in month *t*-*K*, where *K* equals 3, 6, 9 and 12 for the portfolios with an overlapping holding period of 3, 6, 9 and 12 months, respectively. The momentum ranking at the beginning of month *t* is derived from sorting the prior realized returns of all stocks during different ranking periods. The ranking period includes 3, 6, 9 and 12 months. The ranking period of "7-12" is also included and refers to the portfolio returns when the ranking period is the twelfth to the seventh month prior to portfolio formation (Novy-Marx, 2012). Panel A reports the results of the overlapping portfolios when the portfolios are formed immediately after the ranking period and Panel B reports those of the overlapping portfolios formed after we skip one month between the portfolio formation month and the ranking period. The average monthly returns are expressed as percentages and the *t*-statistics are reported in parentheses.

| Ranking period | Panel A. Portfolios formed immediately after ranking period | | | | Panel B. Portfolios formed after skipping one month | | | |
|---|---|---|---|---|---|---|---|---|
| | Months of overlapping holding period (*K*) | | | | Months of overlapping holding period (*K*) | | | |
| | 3 | 6 | 9 | 12 | 3 | 6 | 9 | 12 |
| 3 | 0.6659 | 0.7671 | 0.7522 | 0.6964 | 0.8940 | 0.8667 | 0.8249 | 0.6534 |
| | (3.3671) | (4.5548) | (5.0431) | (5.4384) | (4.7557) | (5.3863) | (5.9216) | (5.2878) |
| 6 | 1.0684 | 1.1015 | 1.0203 | 0.7981 | 1.2098 | 1.1621 | 0.9607 | 0.7001 |
| | (4.5643) | (5.2461) | (5.5720) | (4.8246) | (5.4956) | (5.9212) | (5.5399) | (4.4087) |
| 9 | 1.2773 | 1.2055 | 0.9722 | 0.7337 | 1.3530 | 1.1260 | 0.8646 | 0.6068 |
| | (5.1925) | (5.5132) | (4.8598) | (4.0012) | (5.8718) | (5.4058) | (4.5049) | (3.4169) |
| 12 | 1.2210 | 1.0142 | 0.7728 | 0.5684 | 1.1350 | 0.8791 | 0.6403 | 0.4478 |
| | (4.9620) | (4.4802) | (3.7362) | (2.9605) | (4.8498) | (4.0623) | (3.2065) | (2.4043) |
| 7-12 | 0.9801 | 0.5713 | 0.2527 | 0.1216 | 0.6534 | 0.2802 | 0.0725 | 0.0149 |
| | (5.9193) | (3.7048) | (1.7952) | (0.9483) | (3.9441) | (1.8276) | (0.5254) | (0.1184) |

Table 6. Performance measures of AFSD, ASSD and momentum strategies (ranking period: 12 months)

This table compares the performance of the AFSD, ASSD and momentum strategies. We report the average monthly returns, the standard deviations, the skewness, the maximum drawdowns and the following risk-adjusted performance measures: the Sharpe ratio, Omega, Sortino ratio, upside potential ratio (UPR), Calmar ratio, Sterling ratio, excess return on value at risk (ERVaR), conditional Sharpe ratio (CSR), non-parametric estimation of the economic performance measure (EPM), the EPM when returns are assumed to be normally-distributed (EPM_Normal), and the EPM when returns are assumed to be NIG-distributed (EPM_NIG). The average monthly returns, the standard deviations and the maximum drawdowns are expressed as percentages.

| AFSD overlapping portfolio | Months of overlapping holding period (*K*) | | | |
|---|---|---|---|---|
| | 3 | 6 | 9 | 12 |
| Average monthly return | 1.0373 | 0.8542 | 0.6636 | 0.4892 |
| Std. Dev. | 4.8057 | 4.4815 | 4.1622 | 3.8931 |
| Skew | -0.0936 | -0.2498 | -0.4776 | -0.6611 |
| Kurtosis | 9.2309 | 8.2896 | 7.8957 | 7.8910 |
| Maximum drawdown | -27.1161 | -24.7805 | -22.4556 | -20.1842 |
| Sharpe ratio | 0.2159 | 0.1906 | 0.1594 | 0.1256 |
| Omega | 1.8529 | 1.7160 | 1.5764 | 1.4382 |
| Sortino ratio | 0.3417 | 0.2933 | 0.2355 | 0.1790 |
| UPR | 0.7423 | 0.7030 | 0.6440 | 0.5874 |
| Calmar ratio | 0.0383 | 0.0345 | 0.0296 | 0.0242 |
| Sterling ratio | 0.0591 | 0.0513 | 0.0403 | 0.0293 |
| ERVaR | 0.1540 | 0.1312 | 0.1084 | 0.0844 |
| CSR | 0.0967 | 0.0828 | 0.0658 | 0.0499 |
| EPM_Normal | 0.0932 | 0.0727 | 0.0508 | 0.0316 |
| EPM_NIG | 0.0806 | 0.0642 | 0.0456 | 0.0289 |
| EPM | 0.0853 | 0.0670 | 0.0470 | 0.0294 |
| ASSD overlapping portfolio | Months of overlapping holding period (*K*) | | | |
| | 3 | 6 | 9 | 12 |
| Average monthly return | 1.3042 | 1.0517 | 0.7856 | 0.5819 |
| Std. Dev. | 6.1709 | 5.7819 | 5.4782 | 5.1789 |
| Skew | -0.8233 | -0.8777 | -1.0204 | -1.1956 |
| Kurtosis | 8.4981 | 8.4774 | 8.1745 | 8.1991 |
| Maximum drawdown | -36.3868 | -33.5997 | -30.4766 | -29.4741 |
| Sharpe ratio | 0.2113 | 0.1819 | 0.1434 | 0.1124 |
| Omega | 1.8158 | 1.6696 | 1.5014 | 1.3814 |
| Sortino ratio | 0.3125 | 0.2647 | 0.2017 | 0.1532 |
| UPR | 0.6956 | 0.6599 | 0.6041 | 0.5550 |
| Calmar ratio | 0.0358 | 0.0313 | 0.0258 | 0.0197 |
| Sterling ratio | 0.0497 | 0.0404 | 0.0307 | 0.0233 |
| ERVaR | 0.1366 | 0.1177 | 0.0887 | 0.0677 |
| CSR | 0.0867 | 0.0749 | 0.0575 | 0.0431 |
| EPM_Normal | 0.0893 | 0.0662 | 0.0411 | 0.0253 |
| EPM_NIG | 0.0727 | 0.0558 | 0.0359 | 0.0226 |
| EPM | 0.0764 | 0.0578 | 0.0368 | 0.0229 |
| Momentum overlapping portfolio | Months of overlapping holding period (*K*) | | | |
| | 3 | 6 | 9 | 12 |
| Average monthly return | 1.1350 | 0.8791 | 0.6403 | 0.4478 |
| Std. Dev. | 5.5587 | 5.1392 | 4.7421 | 4.4231 |
| Skew | -0.6695 | -0.6986 | -0.8689 | -1.1514 |
| Kurtosis | 10.5846 | 9.4978 | 8.9201 | 9.6093 |
| Maximum drawdown | -37.5992 | -32.9996 | -28.2469 | -26.9019 |
| Sharpe ratio | 0.2042 | 0.1711 | 0.1350 | 0.1012 |
| Omega | 1.8031 | 1.6328 | 1.4752 | 1.3417 |
| Sortino ratio | 0.3061 | 0.2514 | 0.1915 | 0.1381 |
| UPR | 0.6872 | 0.6487 | 0.5944 | 0.5423 |
| Calmar ratio | 0.0302 | 0.0266 | 0.0227 | 0.0166 |
| Sterling ratio | 0.0500 | 0.0408 | 0.0306 | 0.0215 |
| ERVaR | 0.1405 | 0.1164 | 0.0912 | 0.0637 |
| CSR | 0.0851 | 0.0706 | 0.0536 | 0.0387 |
| EPM_Normal | 0.0834 | 0.0585 | 0.0365 | 0.0205 |
| EPM_NIG | 0.0678 | 0.0502 | 0.0324 | 0.0186 |
| EPM | 0.0711 | 0.0519 | 0.0331 | 0.0188 |

Table 7. Abnormal returns of AFSD strategies with non-overlapping and overlapping holding periods

This table reports the abnormal returns of the AFSD strategies with different ranking periods. The intercepts are obtained from regressing the monthly returns of the 10-1 overlapping portfolios formed on the AFSD ranking against the following variables: the market excess returns (*MKT*), the portfolio returns of the small market capitalization minus big (*SMB*), the high book-to-market ratio minus low portfolio returns (*HML*), the portfolio returns of the stocks with robust profitability minus those with weak profitability (*RMW*), the portfolio returns of the stocks of low investment minus those of high investment (*CMA*), the momentum risk factor (*MOM*), Pástor and Stambaugh's (2003) traded liquidity factor (*LIQ*), and the short-term reversal (*ST_Rev*) and long-term reversal factors (*LT_Rev*). The monthly returns of the 10-1 overlapping portfolios are calculated as the average returns across the 10-1 portfolio formed on the beginning date of month *t* to the portfolio formed in month *t*-*K*, where *K* equals 0, 3, 6, 9 and 12 for the portfolios with non-overlapping holding periods, and with overlapping holding periods of 3, 6, 9 and 12 months, respectively. Panel A reports the regression results of the overlapping portfolios when the portfolios are formed immediately after the ranking period and Panel B reports those of the overlapping portfolios formed after we skip one month between the portfolio formation month and the ranking period. The abnormal returns are expressed as percentages and the *t*-statistics are reported in parentheses.

| Ranking period | Panel A. Portfolios formed immediately after ranking period | | | | | Panel B. Portfolios formed after skipping one month | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Months of overlapping holding period (*K*) | | | | | Months of overlapping holding period (*K*) | | | | |
| | Non-overlapping | 3 | 6 | 9 | 12 | Non-overlapping | 3 | 6 | 9 | 12 |
| 3 | 0.0562 | 0.4506 | 0.5543 | 0.5270 | 0.5319 | 0.6768 | 0.6342 | 0.6277 | 0.5875 | 0.5319 |
| | (0.4202) | (4.0007) | (6.5065) | (8.0245) | (9.3186) | (5.2011) | (5.8794) | (7.8783) | (9.4402) | (9.1180) |
| 6 | 0.3888 | 0.7011 | 0.7536 | 0.7361 | 0.6627 | 0.7854 | 0.8457 | 0.8111 | 0.7451 | 0.6317 |
| | (2.8828) | (5.9630) | (7.8721) | (9.3113) | (8.5000) | (6.1192) | (7.7172) | (9.0396) | (9.3154) | (7.8425) |
| 9 | 0.5518 | 0.7775 | 0.8371 | 0.7689 | 0.6703 | 0.8068 | 0.9027 | 0.8580 | 0.7552 | 0.6206 |
| | (4.4557) | (7.2837) | (8.7514) | (8.1038) | (7.1044) | (7.1482) | (8.8444) | (8.7193) | (7.6026) | (6.3685) |
| 12 | 0.6210 | 0.7933 | 0.7859 | 0.6970 | 0.6031 | 0.8505 | 0.8522 | 0.7797 | 0.6651 | 0.5648 |
| | (5.5299) | (7.4285) | (7.1761) | (6.4344) | (5.6580) | (7.6985) | (7.5785) | (6.8250) | (5.9448) | (5.1780) |
| 7-12 | 0.9251 | 0.8177 | 0.6445 | 0.4282 | 0.3159 | 0.8209 | 0.7019 | 0.4986 | 0.3239 | 0.2548 |
| | (8.2809) | (7.4986) | (5.8515) | (4.2439) | (3.5166) | (6.8845) | (5.9115) | (4.3930) | (3.2222) | (2.8465) |

Table 8. Abnormal returns of ASSD strategies with non-overlapping and overlapping holding periods

This table reports the abnormal returns of the ASSD strategies with different ranking periods. The intercepts are obtained from regressing the monthly returns of the 10-1 overlapping portfolios formed on the AFSD ranking against the following variables: the market excess returns (*MKT*), the portfolio returns of the small market capitalization minus big (*SMB*), the high book-to-market ratio minus low portfolio returns (*HML*), the portfolio returns of the stocks with robust profitability minus those with weak profitability (*RMW*), the portfolio returns of the stocks of low investment minus those of high investment (*CMA*), the momentum risk factor (*MOM*), Pástor and Stambaugh's (2003) traded liquidity factor (*LIQ*), and the short-term reversal (*ST_Rev*) and long-term reversal factors (*LT_Rev*). The monthly returns of the 10-1 overlapping portfolios are calculated as the average returns across the 10-1 portfolio formed at the beginning of month *t* to the portfolio formed in month *t-K*, where *K* equals 0, 3, 6, 9 and 12 for the portfolios with non-overlapping holding periods, with overlapping holding periods of 3, 6, 9 and 12 months, respectively. Panel A reports the regression results of the overlapping portfolios when the portfolios are formed immediately after the ranking period and Panel B reports those of the overlapping portfolios formed after we skip one month between the portfolio formation month and the ranking period. The abnormal returns are in percentages and the *t*-statistics are reported in parentheses.

| Ranking period | Panel A. Portfolios formed immediately after ranking period | | | | | Panel B. Portfolios formed after skipping one month | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Months of overlapping holding period (*K*) | | | | | Months of overlapping holding period (*K*) | | | | |
| | Non-overlapping | 3 | 6 | 9 | 12 | Non-overlapping | 3 | 6 | 9 | 12 |
| 3 | 0.5933 | 0.8254 | 0.8190 | 0.7080 | 0.7034 | 1.1155 | 0.9103 | 0.8013 | 0.7285 | 0.6558 |
| | (3.2999) | (5.5504) | (7.1437) | (7.6601) | (8.9528) | (5.9668) | (6.4615) | (7.3051) | (8.3136) | (8.2076) |
| 6 | 0.8816 | 1.1178 | 1.0758 | 0.9866 | 0.8736 | 1.3081 | 1.2212 | 1.0584 | 0.9677 | 0.8026 |
| | (4.7238) | (7.0557) | (8.1911) | (9.0177) | (8.3528) | (7.6147) | (8.2190) | (8.6286) | (8.8461) | (7.4951) |
| 9 | 1.1347 | 1.2727 | 1.1597 | 1.0371 | 0.9081 | 1.3556 | 1.3047 | 1.1045 | 0.9791 | 0.8189 |
| | (6.3920) | (8.2344) | (8.4362) | (7.8305) | (6.9682) | (7.7342) | (8.6518) | (7.9337) | (7.1214) | (6.0706) |
| 12 | 1.1319 | 1.2121 | 1.1546 | 0.9774 | 0.8379 | 1.3043 | 1.1829 | 1.0778 | 0.8995 | 0.7691 |
| | (6.3813) | (7.5082) | (7.4768) | (6.4320) | (5.6089) | (7.2491) | (7.1421) | (6.7429) | (5.7232) | (5.0032) |
| 7-12 | 1.0894 | 0.9695 | 0.8103 | 0.5662 | 0.4071 | 0.9978 | 0.9282 | 0.6544 | 0.4387 | 0.3306 |
| | (6.6327) | (6.4140) | (5.5168) | (4.2816) | (3.3610) | (5.9257) | (5.4586) | (4.4023) | (3.3219) | (2.7368) |

Table 9. Factor loadings of AFSD strategies on risk factors

This table reports the regression results from regressing the monthly returns of the 10-1 overlapping portfolios formed on the AFSD ranking against the following variables: the market excess returns (*MKT*), the portfolio returns of the small market capitalization minus big (*SMB*), the high book-to-market ratio minus low portfolio returns (*HML*), the portfolio returns of the stocks with robust profitability minus those with weak profitability (*RMW*), the portfolio returns of the stocks of low investment minus those of high investment (*CMA*), the momentum risk factor (*MOM*), Pástor and Stambaugh's (2003) traded liquidity factor (*LIQ*), and the short-term reversal (*ST_Rev*) and long-term reversal factors (*LT_Rev*). Panel A reports the regression results of the overlapping portfolios when the portfolios are formed on the AFSD ranking immediately after the ranking period, and Panel B reports those of the overlapping portfolios formed on the AFSD ranking after skipping one month. The intercepts are expressed as percentages and the *t*-statistics are reported in parentheses.

Panel A. AFSD 10-1 portfolios formed immediately after ranking period

| Ranking period ×Holding period | *Intercept* | *MKT* | *SMB* | *HML* | *RMW* | *CMA* | *MOM* | *LIQ* | *ST_Rev* | *LT_Rev* |
|---|---|---|---|---|---|---|---|---|---|---|
| 3×3 | 0.4506 | -0.0451 | -0.0015 | -0.1477 | -0.2228 | 0.1372 | 0.5419 | -0.0250 | -0.0389 | -0.3971 |
| | (4.0007) | (-1.6718) | (-0.0393) | (-2.6986) | (-4.3075) | (1.6814) | (20.8866) | (-0.8391) | (-0.7249) | (-11.2479) |
| 6×6 | 0.7536 | -0.0839 | -0.0353 | -0.1491 | -0.3064 | -0.0334 | 0.7496 | -0.0268 | -0.0268 | -0.1206 |
| | (7.8721) | (-3.6591) | (-1.0622) | (-3.2045) | (-6.9700) | (-0.4813) | (33.9893) | (-1.0584) | (-0.5880) | (-4.0184) |
| 9×9 | 0.7689 | -0.0807 | -0.1043 | -0.2312 | -0.3587 | -0.2096 | 0.7368 | -0.0181 | -0.0759 | -0.0244 |
| | (8.1038) | (-3.5512) | (-3.1655) | (-5.0155) | (-8.2332) | (-3.0490) | (33.7101) | (-0.7228) | (-1.6789) | (-0.8194) |
| 12×12 | 0.6031 | -0.0705 | -0.1329 | -0.3169 | -0.3850 | -0.2034 | 0.6126 | -0.0263 | -0.2290 | 0.0096 |
| | (5.6580) | (-2.7608) | (-3.5920) | (-6.1190) | (-7.8644) | (-2.6341) | (24.9501) | (-0.9318) | (-4.5076) | (0.2859) |

Panel B. AFSD 10-1 portfolios after skipping one month

| Ranking period ×Holding period | *Intercept* | *MKT* | *SMB* | *HML* | *RMW* | *CMA* | *MOM* | *LIQ* | *ST_Rev* | *LT_Rev* |
|---|---|---|---|---|---|---|---|---|---|---|
| 3×3 | 0.6342 | -0.0354 | 0.0136 | -0.0944 | -0.2260 | 0.0874 | 0.5833 | -0.0328 | -0.0858 | -0.1498 |
| | (5.8794) | (-1.3718) | (0.3638) | (-1.8037) | (-4.5649) | (1.1192) | (23.4801) | (-1.1507) | (-1.6704) | (-4.4351) |
| 6×6 | 0.8111 | -0.0799 | -0.0604 | -0.1388 | -0.2723 | -0.1003 | 0.7360 | -0.0200 | -0.0140 | -0.0128 |
| | (9.0396) | (-3.7187) | (-1.9411) | (-3.1868) | (-6.6142) | (-1.5432) | (35.6177) | (-0.8451) | (-0.3278) | (-0.4570) |
| 9×9 | 0.7552 | -0.0808 | -0.1277 | -0.2445 | -0.3494 | -0.2285 | 0.6767 | -0.0232 | -0.1144 | 0.0340 |
| | (7.6026) | (-3.3966) | (-3.7081) | (-5.0714) | (-7.6658) | (-3.1766) | (29.5822) | (-0.8858) | (-2.4172) | (1.0916) |
| 12×12 | 0.5648 | -0.0765 | -0.1433 | -0.3267 | -0.3685 | -0.2081 | 0.5483 | -0.0233 | -0.2736 | 0.0434 |
| | (5.1780) | (-2.9306) | (-3.7865) | (-6.1705) | (-7.3614) | (-2.6344) | (21.8278) | (-0.8078) | (-5.2665) | (1.2704) |

Table 10. Factor loadings of ASSD strategies on risk factors

This table reports the regression results from regressing the monthly returns of the 10-1 overlapping portfolios formed on the ASSD ranking against the following variables: the market excess returns (*MKT*), the portfolio returns of the small market capitalization minus big (*SMB*), the high book-to-market ratio minus low portfolio returns (*HML*), the portfolio returns of the stocks with robust profitability minus those with weak profitability (*RMW*), the portfolio returns of the stocks of low investment minus those of high investment (*CMA*), the momentum risk factor (*MOM*), Pástor and Stambaugh's (2003) traded liquidity factor (*LIQ*), and the short-term reversal (*ST_Rev*) and long-term reversal factors (*LT_Rev*). Panel A reports the regression results of the overlapping portfolios when the portfolios are formed on the ASSD ranking immediately after the ranking period, and Panel B reports those of the overlapping portfolios formed on the ASSD ranking after skipping one month. The intercepts are expressed as percentages and the *t*-statistics are reported in parentheses.

Panel A. ASSD 10-1 portfolios formed immediately after ranking period

| Ranking period ×Holding period | *Intercept* | *MKT* | *SMB* | *HML* | *RMW* | *CMA* | *MOM* | *LIQ* | *ST_Rev* | *LT_Rev* |
|---|---|---|---|---|---|---|---|---|---|---|
| 3×3 | 0.8254 | -0.2027 | -0.1583 | -0.0732 | -0.0413 | 0.3020 | 0.6570 | 0.0317 | 0.0075 | -0.4669 |
| | (5.5504) | (-5.6926) | (-3.0655) | (-1.0136) | (-0.6041) | (2.8036) | (19.1779) | (0.8064) | (0.1053) | (-10.0191) |
| 6×6 | 1.0758 | -0.3093 | -0.2697 | -0.0866 | -0.2245 | 0.1107 | 0.8866 | -0.0193 | -0.0298 | -0.1596 |
| | (8.1911) | (-9.8361) | (-5.9151) | (-1.3563) | (-3.7221) | (1.1633) | (29.3017) | (-0.5562) | (-0.4755) | (-3.8775) |
| 9×9 | 1.0371 | -0.3328 | -0.3393 | -0.2004 | -0.3015 | -0.1455 | 0.8329 | -0.0487 | -0.0215 | -0.0631 |
| | (7.8305) | (-10.4945) | (-7.3772) | (-3.1129) | (-4.9566) | (-1.5161) | (27.2990) | (-1.3909) | (-0.3410) | (-1.5198) |
| 12×12 | 0.8379 | -0.3335 | -0.3735 | -0.3280 | -0.3777 | -0.1657 | 0.7267 | -0.0645 | -0.1990 | -0.0144 |
| | (5.6089) | (-9.3238) | (-7.2008) | (-4.5182) | (-5.5062) | (-1.5314) | (21.1177) | (-1.6336) | (-2.7947) | (-0.3086) |

Panel B. ASSD 10-1 portfolios after skipping one month

| Ranking period ×Holding period | *Intercept* | *MKT* | *SMB* | *HML* | *RMW* | *CMA* | *MOM* | *LIQ* | *ST_Rev* | *LT_Rev* |
|---|---|---|---|---|---|---|---|---|---|---|
| 3×3 | 0.9103 | -0.2058 | -0.1671 | -0.0378 | -0.0852 | 0.2605 | 0.7233 | 0.0249 | -0.0740 | -0.1978 |
| | (6.4615) | (-6.1028) | (-3.4200) | (-0.5532) | (-1.3182) | (2.5535) | (22.2932) | (0.6678) | (-1.1027) | (-4.4817) |
| 6×6 | 1.0584 | -0.3078 | -0.3080 | -0.0702 | -0.2001 | 0.0173 | 0.8744 | -0.0137 | -0.0129 | -0.0437 |
| | (8.6286) | (-10.4812) | (-7.2406) | (-1.1796) | (-3.5548) | (0.1942) | (30.9547) | (-0.4232) | (-0.2212) | (-1.1374) |
| 9×9 | 0.9791 | -0.3407 | -0.3701 | -0.2070 | -0.3015 | -0.1939 | 0.7726 | -0.0575 | -0.0608 | -0.0017 |
| | (7.1214) | (-10.3518) | (-7.7618) | (-3.1012) | (-4.7796) | (-1.9476) | (24.4001) | (-1.5839) | (-0.9285) | (-0.0401) |
| 12×12 | 0.7691 | -0.3379 | -0.3857 | -0.3414 | -0.3544 | -0.1654 | 0.6595 | -0.0685 | -0.2577 | 0.0256 |
| | (5.0032) | (-9.1817) | (-7.2351) | (-4.5751) | (-5.0236) | (-1.4855) | (18.6302) | (-1.6865) | (-3.5188) | (0.5326) |