Overlapping Factors*

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Abstract

Characteristic-based factors, such as value, momentum, and low volatility, are constructed from the same universe of stocks. Therefore, they can contain some of the same stocks. Although the degree of overlap among these factors is not excessive, I find that the overlap matters. Stocks included simultaneously in the same leg across multiple factors, so-called overlapping stocks, earn an average abnormal return of 66 basis points per month. In contrast, pure factor stocks included in a single factor earn on average, across all factors, only 5 basis points per month, despite similar industry composition, institutional ownership, and portfolio turnover. Further, the portfolio of overlapping stocks is priced in the cross-section of stock returns, while the portfolio of all pure factor stocks is not. Exposures to macroeconomic and liquidity risks cannot explain the return difference. Only in the short leg, overlapping stocks are more exposed to investor sentiment and have a higher short interest than pure factor stocks.

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1 Introduction

Despite the large number of asset pricing factors proposed in the literature, investors typically focus on a small set of well-known characteristic-based factors, such as value (e.g., Fama and French, 1992), momentum (e.g., Jegadeesh and Titman, 1993), and idiosyncratic volatility (e.g., Ang, Hodrick, Xing, and Zhang, 2006). These factors are known to have low correlations. For example, the correlation between momentum and low volatility is 0.13 and the correlation between value and momentum is even negative at -0.22 (see also Asness et al., 2013)[1]. At the same time, characteristics-based factors are all constructed from the same universe of stocks. Therefore, stocks can be selected simultaneously across multiple factor portfolios, even for seemingly unrelated characteristics.

This paper shows that the low correlation coefficients hide important overlap in performance drivers across factor-based investment strategies. Although commonly used long-short factors do not overlap excessively compared to a random-sorting benchmark, the overlap is important for investors and for asset pricing. Particularly, I find that the subset of stocks that are included simultaneously in the same leg across multiple factors, so-called overlapping stocks, drives nearly all factor performance. Overlapping factor stocks earn on average an abnormal return of 66 basis points per month. In sharp contrast, pure factor stocks that are included only in a single factor display no abnormal returns. The average abnormal return of pure factor stocks across all factors is only 5 basis points per month.

This finding is surprising given that these pure factor stocks have similar size, industry composition, and turnover to overlapping factor stocks. Importantly, overlapping stocks are not in the extreme tails of the original factor portfolios since the characteristic spreads of the overlapping stocks are not higher than those of the pure factor stocks. The overlapping stocks are not in the extreme tails of any factor portfolio since the characteristic spreads are not larger than those of the original factor portfolios. For example, the value spread, which measures the difference in the book-to-market ratio between value and growth stocks, of the total high-minus-low (HML) portfolio is 0.95, while the value spread of the overlapping HML stocks is 0.80. Pure HML stocks have a higher value spread of 1.07.

I focus on five well-known factors, starting with value (HML), momentum (MOM),

[1]Based on monthly returns between 1952:07 and 2020:12.

and idiosyncratic volatility (IVOL). These factors have been shown to robustly predict returns in the cross-section (e.g., Ang, Hodrick, Xing, and Zhang, 2006; Asness, Moskowitz, and Pedersen, 2013; Kelly, Pruitt, and Su, 2019; Ehsani and Linnainmaa, 2022) and these strategies account for a large share of factor investment products offered by the asset management industry.[2] Furthermore, these three factors are constructed based on seemingly unrelated information (book-to-market ratio for HML, past returns for MOM, and past idiosyncratic volatility for IVOL) that are identified as independent characteristics among non-micro cap stocks (Green, Hand, and Zhang, 2017). I extend my analysis by considering the profitability factor (RMW) and the investment factor (CMA), as in Fama and French (2015).

I form factor portfolios by sorting stocks into quintiles while controlling for size.[3] I then decompose each factor into overlapping stocks that are sorted *into the same leg* of multiple factors and pure factor stocks that are uniquely sorted into a single factor. I combine all overlapping stocks into a value-weighted long-short portfolio and all pure factor stocks into another value-weighted long-short portfolio. I document three main results.

First, I examine the degree of overlap between the long-short portfolios of different factors. Compared to a benchmark that is based on random sorting stocks into quintile portfolios, I do not find excessive overlap. The benchmark predicts that 10.4% stocks will be selected into the same quintile of two or three factors. This is similar to the data, where the fraction of overlap in the long leg (i.e., top quintile) is 9.9% and in the short leg (i.e., bottom quintile) it is 13.2%.

Second, I document important differences in the performance of overlapping stocks versus pure factor stocks. The portfolio that contains all overlapping stocks generates an average return of 66 basis points per month. In sharp contrast, the average monthly return of all pure factor stocks (across the three factors) is only 5 basis points. Thus, almost the entire return performance of these factors is driven by the same overlapping subset of stocks.[4] This result is robust when I use a different set of factors that includes RMW, CMA, and IVOL.

[2]Yet Lettau, Ludvigson, and Manoel (2018) show that not all value funds systematically tilt towards value stocks.

[3]All quintile portfolios contain an equal proportion of large caps, medium caps, and small caps and I always report value-weighted returns.

[4]In addition, the mean-variance spanning tests show that overlapping stocks always span the pure factor stocks, but not vice versa.

Third, I show that overlapping stocks are priced in the cross-section of stock returns, while pure factor stocks do not carry a significant price of risk. I estimate Fama-MacBeth's (1973) regressions on different cross-sections of stock returns where I include both the value-weighted long-short portfolio of all pure factor stocks and that of all overlapping stocks as two separate factors.[5] I find that the price of risk for the overlapping portfolio is highly significant and greater than one in all specifications. In contrast, the portfolio with only pure factor stocks (across all three factors) is not significantly priced when both the overlapping and the pure factor portfolios are included as factors.

These results also shed new light on the well-known negative correlation between HML and MOM (see e.g., Asness et al., 2013). I find that this negative correlation is driven by the pure factor stocks. However, the stocks that overlap in the same leg (i.e., value stocks that are also past winners and growth stocks that are also past losers) are the ones that deliver the risk premium. Pure HML stocks and pure MOM stocks are not priced in the cross-section of returns when I control for overlapping stocks.

Finally, I seek to explain the difference in performance between overlapping stocks and pure factor stocks. An advantage of my empirical approach is that I can identify exactly which stocks are in the overlapping and pure factor portfolios. Despite the vastly different performance, the overlapping and pure factor stocks are similar across many dimensions. These stocks have similar sizes (since I control for size in my portfolios), industry composition (stocks in the manufacturing industry account for the most in both portfolios), and portfolio turnover (the average turnover rate is 26% for the pure factor portfolio and 39% for the overlapping portfolio).

I then explore several potential risk-based explanations, by comparing the exposures of overlapping and pure factor stocks with respect to various measures of consumption risk, a recession indicator, liquidity risk measures, the term spread, and the default premium. Overall, I find no important differences.

Next, I move on to mispricing-based explanations. My results suggest that they play a more significant role in overlapping stocks than for pure factor stocks when focusing on the short leg. Specifically, the short leg of the overlapping portfolio loads more negatively on investor sentiment as in Baker and Wurgler (2007) than the short leg of the pure

[5]I combine 25 size×value, 25 size×momentum, 25 size×volatility as the test portfolios. In a robustness test, I also use different test portfolios such as a combination of 25 size×net share issues and 25 size×accruals portfolios.

factor portfolio. Also, the short interest is higher for overlapping stocks than for pure factor stocks after the 2000s, which implies higher anomaly returns to the short leg of the overlapping portfolios. At the same time, I find that institutional ownership is similar for overlapping stocks and pure factor stocks. Importantly, the return difference between overlapping and pure factor stocks is not only due to the short legs but in part due to differences in the long legs of these portfolios as well.

I perform several robustness tests. First, I consider an alternative set of factors that includes CMA, RMW, and IVOL. My methodology and results are robust to this alternative set of factors as the overlapping stocks again strongly outperform pure factor stocks. Second, my findings are robust across different subsample periods. Even though traditional factors have low performance in the period 2001-2020, I still observe the strong outperformance of the overlapping portfolio compared to the pure factor portfolio in this subsample period. Third, my findings are robust to sorting stocks into characteristic quintiles using NYSE breakpoints instead of assigning an equal number of stocks to each quintile. Further, my results are robust when portfolios are rebalanced every quarter. Given lower trading costs with quarterly rebalancing, this robustness test suggests that focusing on overlapping stocks is a feasible strategy for investors.

My findings have important implications for asset managers investing in smart-beta or factor-based products. Many institutional investors such as pension funds allocate a substantial share of capital to these strategies (e.g., Canada Pension Plan Investment Board, Norwegian Sovereign Wealth Fund). My results suggest that rather than removing overlap between factors or hiring separate managers for each factor product, investors should focus more on this overlap, as these stocks are the ones driving factor returns. My results also highlight the importance of academic research to provide a unified explanatory framework for cross-sectional anomalies rather than focusing on explaining each factor separately.

Related literature. During the past decades, the asset pricing literature has uncovered hundreds of factors linked to the cross-section of stock returns. Many factors are based on firm characteristics (e.g. among many others, Fama and French, 1992, 1993, 1996; Cochrane, 2011; Nagel, 2013). Analyzing this factor zoo, Harvey, Liu, and Zhu (2016) report that many do not survive a multiple testing framework. McLean and Pontiff (2016) show that many factor premiums decline after publications of the factors, while Hou, Xue, and Zhang (2020) find that their economic significance is often weaker than originally reported. These findings suggest that many seemingly distinct factors could simply reflect the same information set (Jensen, Kelly, and Pedersen, 2023; Feng, Giglio, and Xiu, 2020). This is in line with my result that the portfolio and asset pricing performance of five well-known factors are driven by exactly those stocks that appear simultaneously in multiple factors. Although I only study five well-known factors, it is straightforward to extend this method to more factors.

Many papers have tried to summarize the information or extract the commonality of factors. Stambaugh and Yuan (2017) form two mispricing factors by averaging stock rankings of anomalies that exhibit high correlations. In other words, the paper combines signals from similar factors. By contrast, I combine signals from seemingly unrelated factors, so there is no high correlation among the factors and no similar construction of the chosen factors. Chen and Velikov (2023) study the expected returns of the average anomaly. When averaging across signals, a weaker signal for one factor could be offset against strong signals for other factors. Instead, my paper focuses only on stocks with strong signals and I compare stocks with a single signal versus multiple signals.

Bryzgalova, Huang, and Julliard (2023) apply a Bayesian approach to extract the common information among factors. In my paper, I show that it is not just a common driver but actually the same subset of stocks included in different factors driving factor premia. Bessembinder (2018) finds that the long-term market returns are driven by a small subset of stocks. Consistently, I find that returns on five well-known factors are also driven by a subset of stocks, namely those that appear simultaneously in multiple factors.

Another strand of literature looks at the interaction effect between factors. Ehsani and Linnainmaa (2022) find that factors displaying momentum themselves help explain the performance of multiple factors. I also find that momentum stocks are present in the set of overlapping stocks. However, the outperformance of this set of overlapping stocks is not just due to factor rotation, since the set includes those stocks that appear in momentum and other factors at the same time. Green, Hand, and Zhang (2017) find many independent characteristics among non-micro cap stocks, which include namely book-to-market, return volatility, and momentum. My results show that factor performance of the corresponding characteristic sorted portfolios relies heavily on stocks that score high (or low) on a multiple of these characteristics.

Stambaugh, Yu, and Yuan (2015) find that, among overpriced stocks (stocks in the short leg), the IVOL characteristic is negatively related to the abnormal return. My results are consistent as I find that, in the short leg, higher IVOL implies more overlapping stocks, and then more negative returns. Asness, Moskowitz, and Pedersen (2013) finds the negative correlation between value and momentum. Ali, Hwang, and Trombley (2003) finds that the book-to-market ratio is greater for stocks with higher IVOL. Zhang (2006) reports that momentum is concentrated among stocks with high IVOL. In my paper, I find all these relationships hold in the total factor portfolios and the portfolios containing pure factor stocks but not in the portfolios containing overlapping stocks. Yet, only the portfolios of overlapping stocks earn abnormal returns and are significantly priced in the cross-section.

Müller and Schmickler (2021) consider a large set of anomalies and find evidence for many anomaly interactions. Here, I start from a portfolio perspective and focus on a smaller set of factors that are frequently implemented in practice. I compare different multi-factor strategies and decompose the factor portfolios into pure factor stocks and overlapping factor stocks. Favilukis and Zhang (2019) find that, by sorting portfolios conditionally, momentum is high among stocks in the short leg of many anomalies, including growth, high IVOL, low operating profitability, and high investment. My methodology is different in the way that I sort my portfolios independently on each characteristic. Since my paper focuses on overlap, my method is transparent in what is in the overlap.

Recently, studies in Machine Learning have developed frameworks that incorporate information from these interaction effects (see, for example, Moritz and Zimmermann, 2016; Bryzgalova, Pelger, and Zhu, 2019; Chen and Velikov, 2023; Freyberger, Neuhierl, and Weber, 2020; Kozak, Nagel, and Santosh, 2020; Avramov, Cheng, Metzker, and Voigt, 2023). In my paper, my portfolio strategy is transparent and aligns closely with the conventional approach to factor construction. Furthermore, my method enables the precise identification of stocks that overlap in factor portfolios, allowing for a detailed examination of their characteristics.

The rest of the paper is organized as follows. Section 2 describes the data and methodology. Section 3 analyzes the performance and asset pricing tests of overlapping stocks and pure factor stocks. Section 4 discusses potential explanations for the difference in performance. Section 5 presents several practical implications and robustness checks.

Section 6 concludes.

2 Data and methodology

2.1 Data

I compute the monthly firm characteristics for HML, MOM, and IVOL factors from July 1952 to December 2020. My main data source is the CRSP/Compustat U.S. stock universe. I filter all common stocks (with share code 10 or 11) traded on NYSE, AMEX, or Nasdaq (with exchange codes 1, 2, or 3).

HML is formed on the book-to-market ratio. I follow closely the standard method described in Kenneth R. French's data library[6]. MOM is formed on prior 12-to-2 returns. I follow Jegadeesh (1990) and Jegadeesh and Titman (1993) by using monthly returns from the past months $t-2$ to $t-12$, skipping the most recent month to avoid market microstructure issues. IVOL is formed on residual volatility, which is the standard deviation of residuals in the Fama-French three-factor model as in Ang, Hodrick, Xing, and Zhang (2006).

$$R_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i.$$

For each stock, I regress the excess returns on the Fama-French three factors using a window of 60 days (minimum of 20 days). I then compute the residual volatility by the standard deviation of all residuals in each month for a given stock.[7]

I choose the HML, MOM, and IVOL factors for the main analysis since these factors robustly predict cross-sectional returns and have received the most attention from prior academic research. Asness, Moskowitz, and Pedersen (2013) find evidence for value and momentum return premiums across markets and asset classes. Ang, Hodrick, Xing, and Zhang (2006) find that the returns on stocks with high idiosyncratic volatility cannot be

[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[7] I use a window of 60 days (minimum of 20 days) instead of 20 days (minimum of 15 days) as in Ang, Hodrick, Xing, and Zhang (2006). 60 days give more observations for each rolling regression, which can yield more reliable estimates. In comparison with the paper, I find a similar pattern that the short portfolio, containing stocks with highest idiosyncratic volatilities, yields the lowest expected return. The difference in average returns between the long and the short portfolios is 0.25% per month. Ang et al. report 1.06% per month (Table VI, Panel B), which is based on a shorter sample period (1963-2000) and a shorter window for rolling regressions (20 days).

explained by the size, value, and momentum factors. Kelly, Pruitt, and Su (2019) find that value, momentum, and idiosyncratic volatility are three among ten firm characteristics that necessarily explain the variation in stock returns[8]. Besides, these three factors seem to be unrelated in terms of the type of information used to extract a signal for expected returns. HML is purely based on accounting data. MOM relies on past performance. Whereas, IVOL is formed on residual volatility of the asset pricing model.

For robustness checks, I replicate the CMA and RMW factors. CMA is formed on the change in total assets from the fiscal year ending in $t-2$ to the fiscal year ending in $t-1$, divided by the total assets in $t-1$. RMW is formed on operating profitability. In each June, operating profitability is the annual revenue less cost of goods sold, interest expense and selling general, and administrative expenses, divided by the book equity in the previous fiscal year.

In my analysis, I either include HML or I include CMA and RMW in the set of factors. Fama and French (2015) find that HML is redundant when adding CMA and RMW, and they are based on related information. The construction of HML requires book equity which in turns requires total assets. CMA and RMW also require the book equity and total assets, resulting in a higher correlation between these factors and a potentially larger degree of overlap. Table A1 shows that none of the five characteristic values is on average highly correlated with each other. The correlation between momentum and low volatility is 0.13 and the correlation between value and momentum is negative at -0.22. The return correlations show that CMA is highly correlated with HML (0.65 on average); however, I do not include these two factors in the same set. My conclusions are highly robust to alternative choices of factors.

2.2 Factor decomposition methodology

I decompose the universe of stocks into overlapping stocks and pure factor stocks. I also decompose each factor into so-called pure factor stocks and so-called overlapping stocks that also appear in the same (long or short) leg of other factors. This section discusses my empirical approach.

First, I construct each factor portfolio based on the characteristic ranking of stocks

[8]Kelly, Pruitt, and Su (2019) investigate 36 firm characteristics and find ten of them remain statistically significant at 1%.

while controlling for size. Specifically, in each month, I first sort stocks into the 30^{th} and 70^{th} percentile of market cap, using NYSE breakpoints. Then, within each size tercile, I rank stocks by the characteristic value and split them *equally* into quintiles. Thus, each characteristic quintile portfolio contains the same amount of stocks. Portfolios are value-weighted and rebalanced every month.

This deviation is a mild difference from the traditional approach by Fama and French, where stocks are sorted into characteristic quintiles by using NYSE breakpoints. Here, I make sorting univariately distributed so that I can derive the benchmark. Since the number of stocks is the same in every quintile, the probability that a stock appears in any portfolio is simply 1/5. With this probability, I can calculate the benchmark fraction that each factor overlaps with each other. Yet my robust results show that the conclusions remain the same when I sort all characteristics by using NYSE breakpoints.

For another technical convenience, I do not sort stocks from the lowest to the highest characteristic values, but from the least attractive to the most attractive manners of characteristic. In other words, for every factor, Quintile 5 or the top quintile denotes the long portfolio, while Quintile 1 or the bottom quintile denotes the short portfolio. Henceforth, I reverse the sort from high to low values for idiosyncratic volatility and investment. The final data set is the characteristic scores from one to five for each stock in each month.[9]

I define each time that a stock appears in a top or bottom characteristic quintile as the stock receiving a signal for its positive or negative return. I do not count stocks in the intermediate quintiles (Quintiles 2, 3, and 4) as stocks receiving a signal, so in my methodology, I only consider strong signals.[10] To measure the fraction of overlap, for each stock in each month, I count how many signals the stock receives for a given top or bottom quintile. I denote frequency k in Quintile j as the number of times that a stock has score j, for $j \in \{1, 5\}$, among all factors in the strategy. Thus, k ranges from 0 to S signals, where S denotes the number of factors such as $S = 3$ in the strategy that invests in HML, MOM, and IVOL. I identify the number of signals by three cases. Namely in Quintile j, a stock can receive

i. no signal ($k = 0$): The stock exhibits no signal when it does not appear in Quintile

[9]The correlation between my returns and French's data is above 97% for all factors.

[10]Stambaugh and Yuan (2017) study average signals from the percentile ranks of 11 anomalies. Here, I only count strong signals that are from the top 20% and the bottom 20% of the characteristic rankings.

j of any characteristic. The stock is not sorted into the quintile of my interest so I do not investigate this case.

ii. a single signal ($k = 1$): The stock exhibits a single signal when it appears in Quintile j of only one factor but not in this quintile of any other factors. This stock is defined as a pure factor stock. For example, if a stock scores 3 for momentum and volatility but 5 for value, then this stock only exhibits a positive signal for high expected returns for value. Thus, this stock receives a pure value signal.

iii. multiple signals ($k \geq 2$): The stock exhibits multiple signals when it appears in Quintile j of at least two factors. In other words, at least two factors contain the same stock in the same leg. This stock is defined as an overlapping stock. In an extreme case, if a stock scores 5 in all three factors, then it exhibits multiple signals for high expected returns for all three factors.

   Note that I only consider signals *in the same leg* of multiple factors as multiple signals. Although a stock sorted in the top quintile of one factor can also be in the bottom quintile of another factor, these two signals cancel out in my equal-weighted multi-factor strategy, so I do not consider this stock as an overlapping stock.

Signals in the extreme quintiles indicate the decision to go long, if stocks appear in the top portfolio, or to go short if stocks appear in the bottom portfolio. With this measure, I can decompose our universe of stocks into stocks receiving a single signal (so-called pure factor stocks) and stocks receiving multiple signals (so-called overlapping stocks). The overlapping portfolio contains overlapping stocks that overlap between factors: HML & MOM, HML & IVOL, MOM & IVOL, or HML & MOM & IVOL, illustrated as the shaded regions in Figure 1. The pure factor portfolio contains pure factor stocks across the three factors, so this portfolio contains all pure HML, pure MOM and pure IVOL stocks.

[Figure 1 about here.]

This measure also allows me to decompose each factor into the pure factor portfolio that contains stocks receiving only a signal for that factor and the overlapping portfolio that contains stocks receiving the same signal for that factor and some other factors. For example, in the long leg of HML, the pure HML portfolio contains pure value stocks, while the overlapping HML portfolio contains value & winner, value & low-vol, and value & winner & low-vol stocks.

2.3 Analysis of degree of overlap

Since all long-short factors are constructed from the same universe of stocks, by chance there can be overlap. In this section, I compare the degree of overlap based on a random-sorting benchmark to the actual degree of overlap I observe in the data.

I derive a benchmark fraction of overlap assuming all signals follow a uniform distribution. When initially sorting on size, the probability that a stock appears in the i^{th} size percentile equals

$$\Pr(size = i) = \frac{1}{m}, \quad i = 1, \dots, m.$$

Then within each size percentile, the probability that a stock has a characteristic score j equals

$$\Pr(char = j | size = i) = \frac{1}{5}, \quad i = 1, \dots, m; j \in \{1, 5\}.$$

The unconditional probability is hence given by

$$\begin{aligned} p := \Pr(char = j) &= \sum_{i=1}^{m} \Pr(char = j | size = i) \Pr(size = i) \\ &= m \times \frac{1}{5} \times \frac{1}{m} = \frac{1}{5}. \end{aligned}$$

This likelihood represents the probability that a stock exhibits a signal to a given quintile portfolio. By independent sorting, the size controls do not affect the signal likelihood p. Let $f_S(k)$ be the fraction of signal k in an S-factor strategy. Then k follows the Binomial(S, p) distribution and $f_S(k)$ is the probability that takes the form

$$\begin{aligned} f_S(k) &= \binom{S}{k} p^k (1-p)^{S-k} \\ &= \binom{S}{k} \left(\frac{1}{5}\right)^k \left(\frac{4}{5}\right)^{S-k}, \quad k = 0, \dots, S. \end{aligned}$$

Under this notation, the fraction of a single signal is then $f_S(1)$, and the fraction of multiple signals is given by $\sum_{k=2}^{S} f_S(k)$, the total probability that the stock has from two to S signals in the given factor portfolio.

[Table 1 about here.]

Table 1 reports the average fractions of signals in our universe of stocks, in each factor portfolio, with the corresponding benchmark fractions. Figure 1 also visualizes in the Venn diagram these factions in our universe of stocks, in comparison to the benchmark. I find that on average the fraction of overlapping stocks and the fraction of pure factor stocks in all portfolios are almost the same as the benchmark. The difference is economically small, approximately by a few percent per month.

For example, while the random-sorting benchmark predicts that the fraction of overlapping stocks is 10.4%, I find that my data contains on average 9.9% stocks with multiple signals in the long leg and 13.2% stocks with multiple signals in the short leg (Panel A). Within the HML portfolio, the long leg contains 62.8% pure value stocks and 37.2% overlapping value stocks, while the short leg contains 57.9% pure growth stocks and 42.1% overlapping growth stocks (Panel B). The benchmark predicts that each leg contains 64% pure value stocks and 36% overlapping value stocks, so the difference in each leg is relatively small. Hence, in the data, there is no excessive overlap in either our universe of stocks or in each individual factor portfolios. This natural overlap occurs because, given the same universe of stocks, I choose the top 20% and the bottom 20% of stocks in each characteristic. In overall, I find that there is overlap between factors but the degree of overlap is not excessive relative to the random-sorting benchmark. Yet it is surprising when I show that these overlapping stocks nearly drive all the factor performance.

3 Performance and asset pricing test

3.1 Portfolio performance

In this section, I study the performance of each decomposed portfolio to examine whether the overlap between factors matters and which subset of stocks drives the performance of the multi-factor strategy. I start with a multi-factor strategy that equally invests 1/3 in HML, 1/3 in MOM and 1/3 in IVOL. I then disentangle stocks that appear in the same leg of two or more factors at the same time (overlapping stocks) and stocks that appear in only one factor (pure factor stocks).

[Table 2 about here.]

Table 2 reports the summary statistics of each portfolio in comparison to the market and the equal-weighted multi-factor portfolio. Market is the value-weighted average of all stocks in the sample, giving an excess return of approximately 65.1 basis points per month. The multi-factor portfolio, which contains both the pure factor and overlapping stocks, is the average of all three factor returns, so the mean return of this portfolio is between the long-short overlapping and the long-short pure factor portfolios ($5.0 < 28.7 < 65.6$ basis points).

I observe the outperformance of overlapping stocks in several aspects. First, only the long-short overlapping portfolio performs closely to the market ($65.6 \approx 65.1$ basis points). This implies that a subset of stocks overlapped in multiple factor portfolios can generate the same average return as the market portfolio which invests in the entire universe of stocks. The long-short pure factor portfolio, by contrast, generates almost no average return compared to the market (5.0 basis points).

Second, the long-short overlapping portfolio yields a higher expected return so it also results in higher volatility, specifically 4.71% per month. However, this portfolio yields a higher Sharpe ratio than the equal-weighted multi-factor portfolio and the long-short pure-factor portfolio ($0.14\% > 0.11\% > 0.04\%$). Third, the long-short overlapping portfolio yields the largest and most significant CAPM alpha ($1.0 > 0.46 > 0.10$). Especially in the short leg, only overlapping stocks deliver a negative alpha of -0.60. It implies that only stocks overlapped in the short leg of multiple factors can deliver shorting benefits.

Overall, the average returns on pure factor stocks are very close to zero (even though I combine pure factor stocks of three different factors). In contrast, overlapping stocks appear to drive the entire average return across seemingly unrelated factor strategies.

[Figure 2 about here.]

Figure 2 visualizes the performance of each portfolio by plotting the cumulative excess returns. The figure supports the previous finding and suggests including especially overlapping stocks in the short leg. I observe that only the overlapping short portfolio underperforms the market cumulatively. It is important that not only the short leg but also the long leg of the overlapping portfolio outperforms the market over time. The combination of the long and short legs of overlapping stocks accumulates the most returns, as the gap between these two portfolios is the widest. Moreover, this gap increases over time.

Next, I decompose each factor portfolio to study the characteristics of the stocks that drive each factor return. I classified stocks in each factor portfolio by two types: (1) those appearing in this factor only (pure factor stocks with a single signal to this factor), and (2) those appearing in this factor and other factors (overlapping stocks with the same signal to multiple factors). The first subset of stocks forms a pure factor portfolio and the second subset forms an overlapping portfolio.

[Table 3 about here.]

Table 3 reports the average returns and characteristics of each decomposed factor portfolio. In all factors, I find that the overlapping portfolios drive almost the entire performance of the factors. The long-short overlapping portfolios generate higher average returns than the total factor portfolios ($49.8 > 10.1$ basis points in HML, $89.1 > 59.6$ basis points in MOM, and $58.5 > 16.5$ basis points in IVOL). In contrast, the return of the pure factor portfolio falls below that of the total factor. The average long-short returns for the pure MOM portfolio is 43.9 basis points, while the returns are even negative for the pure HML portfolio (-11.8 basis points) and for the pure IVOL portfolio (-10.4 basis points).

Interestingly, I find that the value premium is driven by those value stocks that are also past winners (positive momentum) and those growth stocks that are also past losers (negative momentum). The return outperformance of HML & MOM stocks over the pure HML stocks comes from both legs ($1.26\% > 0.98\%$ in the long leg and $0.63\% < 1.10\%$ in the short leg). The difference makes the long-short return of the HML & MOM portfolio on average higher than that of the pure HML portfolio.

This result might at first seem to contradict Asness, Moskowitz, and Pedersen (2013)'s finding that HML and MOM are negatively correlated. I observe the same in that the total HML portfolio has a negative prior return of -3.03% per month. The pure HML portfolio has a large negative prior return, but the HML & MOM portfolio has a large positive prior return. Therefore, the negative correlation between HML and MOM seems to come from the negative comovement between pure HML and pure MOM stocks. I find that the correlation between the pure HML portfolio returns and the pure MOM portfolio returns is indeed negative (-0.54, not shown in the table).

However, what drives the performance of multiple factors are overlapping stocks. If I look at the decomposition of the overlapping HML portfolio, the HML & MOM portfolio not only generates a high average return but also yields the highest past performance. The high average prior returns indicate that the past performance of the HML portfolio is driven by MOM when HML stocks are also sorted into the MOM portfolio. I find that only uniquely sorted stocks in either HML or MOM make these two factors negatively correlated, but they contribute almost no returns to the factors, especially to HML. Hedging HML stocks against MOM stocks implies removing any overlapping stocks that are both these two factors, which weigh for 15.2% in the HML portfolio and 14.8% in the MOM portfolio, that drive the factor premiums.

I find no peculiar characteristics in the overlapping portfolios. Since I control for size, the long leg and short leg in each factor have approximately the same log-market cap. Importantly, the value spread (i.e., the average book-to-market ratio of value stocks minus that of the growth stocks) is smaller for the overlapping HML portfolio (0.80) than for the total HML portfolio (0.95) and than for the pure HML stocks (1.068). In all other overlapping portfolios, the characteristic spreads are roughly the same as in the total factor portfolio, so stocks in the overlapping portfolios do not appear in the extreme tails of the factors.

[Figure 3 about here.]

I also check the portfolio turnover and find that the turnover rate of the overlapping portfolio is reasonable. Figure 3 plots the proportion of stocks in a portfolio this month staying in the same portfolio in the following month. In most months, the proportion of stocks staying in the same portfolio is high and stable at an average of 61.5%. Thus, the average turnover rate in the overlapping portfolio is about 38.5% per month. The average turnover rate is 26% for the pure factor portfolio. This result implies that for practitioners, the strategy that invests in overlapping stocks is feasible. Also, it infers a stability link for future research to study the portfolio turnover of the subset of stocks driving the factor performance[11].

[11] The turnover rate is possibly lower if portfolios are rebalanced quarterly. In my robustness check for quarterly rebalancing, I still find abnormal returns in the overlapping stocks. Therefore, focusing on the overlapping stocks would be a feasible strategy for investors.

In the MOM factor, the long-short portfolio of HML & MOM stocks also yields a higher average return and a higher past performance than that of pure momentum stocks. The outperformance of the overlapping MOM portfolio over the pure MOM portfolio seems to come from the short leg, with an average return of 0.48% per month. However, the prior return gap in the overlapping MOM portfolio is not considerably different from that in the pure MOM or the whole MOM portfolio. I find similar conclusions for the IVOL factor. The average return of the MOM & IVOL portfolio is higher than that of other decomposed portfolios. The outperformance of the overlapping IVOL and the MOM & IVOL portfolio comes from both legs. Indeed, MOM stocks seem to drive other factor performance, which is in line with the finding of Ehsani and Linnainmaa (2022). However, I find that what drives multiple factor performance is not just factor rotation, but it is a subset of stocks appearing in multiple factors at the same moment in time.

[Figure 4 about here.]

Figure 4 plots the cumulative returns of the decomposed overlapping portfolios in each factor. I observe that all portfolios containing overlapping stocks perform as least as well as the total factor portfolio, in all panels. In contrast, the pure HML, pure MOM, and pure IVOL portfolios underperform the total factor portfolios cumulatively over time.

3.2 Cross-sectional asset pricing tests

The previous section shows the difference in portfolio performance when I compare pure factor stocks to overlapping stocks. This section analyzes the asset pricing implications. I run the Fama and MacBeth (1973) regressions for different cross-sections of stock returns.

The test portfolios combine 25 portfolios formed on size and value, 25 portfolios formed on size and momentum, and 25 portfolios formed on size and idiosyncratic volatility. Alternatively, I also test on a combination of 25 portfolios formed on size and net stock issues and 25 portfolios formed on size and accruals. In each specification, I include the MKT factor, SMB factor, the three original factors (HML, MOM and IVOL), the long-short overlapping portfolio as a factor, and the long-short pure factor portfolio as a factor. Note that the pure factor portfolio contains pure factor stocks across all three factors. In the first stage, I run a time-series regression for each test portfolio i, yielding estimates for the factor loadings β_i for each factor portfolio f_t

$$R_{i,t} = \alpha_i + \beta_i f_t + \varepsilon_{i,t}, \quad i = 1, ..., N.$$

In the second stage, I run a cross-sectional regression of estimated factor loadings $\hat{\beta}_i$ for each month t

$$R_{i,t} = \lambda_0 + \lambda_t \hat{\beta}_i + \epsilon_{i,t}, \quad t = 1, ..., T.$$

The risk premium for each factor portfolio λ is the time average of the estimated $\hat{\lambda}_t$. Table 4 reports the time-series mean and t-statistic of the cross-sectional regression coefficients.

[Table 4 about here.]

I find strong evidence that a value-weighted long-short portfolio with all overlapping stocks is priced in the cross-section of stock returns. When the test portfolios include size with value, momentum, and volatility (in Panel A), the estimated price of risk of this overlapping portfolio is significant and positive at 1.23, with a t-value of 9.15 (Column 3). This is much larger and more significant than each factor risk premium when I include all three total factors in the model. The price of risk estimate of the pure factor portfolio is significant and positive (Column 4), but the unpriced risk λ_0 is also significantly different from zero. Note that the pure factor portfolio is exposed to all three factors as it contains all pure HML, all pure MOM, and all pure IVOL stocks. When I include both the overlapping portfolio and the pure factor portfolio as two separate factors in the model (Column 5), only the overlapping portfolio remains significantly priced.

Indeed, the overlapping portfolio is priced in almost all cross-sections of stock returns. When I use the test portfolios sorted on completely different characteristics such as net share issues and accruals (Panel B), the total IVOL factor is no longer significantly priced. However, the estimated price of risk of the overlapping portfolio is still greater than one and highly significant. I find the same evidence that the overlapping stocks are priced in every scenario but the pure factor stocks are not priced when the model includes both returns of the overlapping and the pure factor portfolios as separate factors. Also, when I only include the overlapping portfolio, the intercept becomes insignificant, while it is significant and positive when I only include the pure factor portfolio.

Finally, I study the asset pricing implications of the overlapping stocks contained in each factor separately. I run the Fama-Macbeth cross-sectional regressions of returns of 25 portfolios formed on size and the characteristic of each individual factor, the overlapping and pure factor portfolios. Table 5 reports the estimated risk premiums for value (Panel A), momentum (Panel B), and volatility (Panel C).

[Table 5 about here.]

I find that overlapping stocks are also priced in the cross-section of each characteristic test portfolio. The lambda estimate of the overlapping portfolio is more than one and highly significant whenever I add the returns of this portfolio to the model (Columns 3 and 5 in all panels). Whereas, the lambda estimate of pure factor stocks loses its significance and even flips the sign when I add the betas with respect to both portfolios to the model (from Column 4 to Column 5 in all panels). When decomposing each factor into the portfolio that contains overlapping stocks and the one that contains pure factor stocks, I draw the same conclusions. In all panels, the OLS adjusted R-squared shows that the goodness of fit of the model increases by a bit when I add the overlapping portfolio to the FF2 model. Although λ_0 is not close to zero in all regressions, they are all insignificant when the model includes the overlapping portfolios.

In brief, these findings imply that factor performance is driven by the performance of a subset of stocks that makes factor portfolios overlap. The overlapping stocks are priced in almost all cross sections. In contrast, when I add a combination of all pure factor stocks of the three factors, the pure factor stocks are not significantly priced.

Next, I study the diversification benefits of each portfolio. I test whether the overlapping portfolio adds to the mean-variance efficiency of the pure factor portfolio, and vice versa. I regress the returns of the test assets on the market, size factors, and the returns of the benchmark assets. If the test assets exactly price the benchmark assets, then the intercept alphas should equal zero. This is known as the Jensen measure. Under the null hypothesis, the benchmark assets span the test assets. If the Jensen measure is significantly different from zero, then adding the test assets to the benchmark improves the mean-variance efficiency. Table 6 reports the results of spanning tests.

[Table 6 about here.]

In panel A, the overlapping portfolios are the test assets while the counter-part pure factor portfolios are the benchmark assets. In the total factor strategy and in each factor portfolio, adding the pure factor portfolio leads to smaller alphas but all coefficients are still large and significantly positive, in comparison to when including only the market and the size factor. Therefore, the overlapping portfolio is not spanned by the pure factor portfolio.

In panel B, I run the same analysis but the overlapping portfolios are the benchmark assets while the counter-part pure factor portfolios are the test assets. Except for HML, all alphas in the regressions on the market and size factors are significantly positive. The smaller magnitude in comparison to the alphas in Panel A is consistent with my first result that the overlapping portfolios yield a higher Sharpe ratio than the pure factor portfolio, given relatively the same volatility. Furthermore, when adding the overlapping portfolio returns, the estimates for alphas become smaller and some even flip their signs (in the overlapping portfolio and the overlapping IVOL portfolio). I confirm that the overlapping portfolio spans the pure factor portfolios. However, the pure factor portfolios are not always spanned by overlapping portfolios. Overlapping stocks with multiple signals to their expected returns can improve the efficient frontier.

4 Potential explanations

In this final section, I seek to explain the difference in performance between overlapping stocks and pure factor stocks. This analysis is my work in progress. An advantage of my empirical approach is that I can identify exactly which stocks are in the overlapping and pure factor portfolios. Despite the vastly different performance, the overlapping and pure factor stocks are similar across many dimensions. These stocks have similar size (since I control for it in my portfolios), industry composition[12], and portfolio turnover. Importantly, overlapping stocks are not in the extreme tails of the original factor portfolios since the characteristic spreads of the overlapping stocks are not higher than those of the pure factor stocks. I look at several risk exposures that are either risk-based or mispricing.

[12]Stocks in the manufacturing industry account for the most in both overlapping and pure factor portfolios.

4.1 Risk-based explanations

A natural explanation for the performance difference is consumption growth risk since it is an appropriate measure of systematic risk in the Consumption-based CAPM (e.g., Breeden, 1979; Mankiw and Shapiro, 1986).

I regress the excess returns on each leg of the overlapping and pure factor portfolios on the real consumption growth rate, per capita, CG_t. In each month, real consumption per capita is the total real consumption of nondurable goods and services, divided by the total population. All data to construct this measure are obtained from the Bureau of Economic Analysis. In the regressions, I also control for other macroeconomic variables including a recession indicator from NBER $I_{recession,t}$, term spread $TERM_t$ measured by 10Y government bond minus 3M Treasury Bills, and default premium DEF_t measured by BAA minus AAA rated corporate bonds.

$$R_t = a + bCG_t + cI_{recession,t} + dTERM_t + eDEF_t + \epsilon_t.$$

Panel B of Table 7 reports the estimates. I observe that, in the long leg, the overlapping portfolio has a significantly positive exposure to the real consumption growth per capita. A percent increase in the real consumption growth rate is associated with an average of 46.4 basis points increase in returns of overlapping stocks. Whereas, the pure factor portfolio has a lower exposure (14.7 basis points), and this coefficient is not significant. In other positions and other variables, I do not find evidence to explain the difference in performance of these two portfolios. Although significant, the recession indicator loads similarly on both overlapping and pure factor portfolios, which is reasonable because recessions affect the market as a whole so it affects both overlapping and pure factor stocks.

I find that the real consumption growth risk can explain some of the abnormal returns of overlapping stocks in the long leg. However, when I estimate the same exposure to different measures such as Parker and Julliard (2005)'s ultimate consumption risk, consumption growth rate on durable goods, Kroencke (2017)'s unfiltered NIPA consumption on quarterly rebalanced portfolios, I find no such significant result (see Table A3). Hence, consumption risk is not yet sufficient to explain the outperformance on a quarterly basis.

[Table 7 about here.]

Besides, Panel B of Table 7 reports the estimates for risk exposure to several liquidity measures such as Stambaugh, Yu, and Yuan (2012)'s liquidity factor, the implied market volatility, and the funding liquidity measured by the TED spread. Generally, in the long legs, I observe that only consumption growth and market liquidity are significant. However, these variables affect the overlapping and the pure factor portfolios in a similar fashion, since the coefficients are similar in the sign and magnitude. When consumption grows and the market liquidity rises, stocks in the long leg of both the overlapping and pure factor portfolios receive higher positive returns.

4.2 Mispricing explanations

Next, I examine several mispricing-based explanations by looking at investor sentiment, short interest, and institutional ownership.

4.2.1 Investor sentiment

Investor sentiment seems to be a natural candidate to explain the short leg of overlapping stocks since intuitively investors are more sensitive to growth, past-loser, and high-volatility stocks. It is because these stocks might be more difficult to arbitrage and to value (Baker and Wurgler, 2007). In this analysis, I follow Stambaugh and Yuan (2017) by regressing the portfolio excess returns on the lag of investor sentiment as in Baker and Wurgler (2007)

$$R_t = a + bS_{t-1} + \epsilon_t$$

Panel C of Table 7 reports the estimates. In the short leg, I observe a strong result that investor sentiment loads significantly and more negatively on the overlapping portfolios: -62.4 basis points for the long-short returns of overlapping portfolios. Whereas, the investor sentiment does not load significantly on the pure factor portfolio. Consequently, the exposure of investor sentiment on overlapping stocks is five times that on pure factor stocks (50.77 basis points in the overlapping portfolio versus 10.3 basis points in the pure factor portfolio). My result is consistent with the result of Stambaugh, Yu, and Yuan (2012): High investor sentiment period follows by lower returns on the short leg. When investor sentiment is higher, stocks are more overpriced, so more overlap in the short leg.

4.2.2 Short interest

I look at the short leg of the portfolios to find whether the amount of short selling can explain the difference. I do so by constructing short interest at the portfolio level. Figure 5 plots the value-weighted average short interest in the short leg of the overlapping and the pure factor portfolios over time. Figure A2 reports equal-weighted values.

[Figure 5 about here.]

In all panels, I find that short interest is higher in the overlapping portfolios than in the pure factor portfolios. Especially in the last decade, the gap has become widen. This result implies that investor increases shorting selling in stocks that are overlapped in multiple factors. All these results somewhat explain the outperformance of overlapping stocks. Yet the outperformance of overlapping stocks comes from both legs.

4.2.3 Institutional ownership

Finally, I look into who owns overlapping stocks and pure factor stocks. I compute the institution ownership (IO) ratio, which is the total institutional ownership divided by adjusted total shares outstanding, using data from the SEC 13F. Figure 6 plots the value-weighted IO ratios for the long leg of the overlapping portfolio and the pure factor portfolio. Table A3 reports equal-weighted IO ratios.

[Figure 6 about here.]

I find that institutional ownership has increased over the years in all portfolios. Until recently, the IO ratio has hit approximately 70%. Regardless of the trend, I find no difference in the ratio that institutional investors own in overlapping versus pure factor stocks. Perhaps there are times that the IO ratio in the overlapping portfolio is slightly lower than in the pure factor portfolio. However, this might be due to limits to arbitrage. As institutional investors are less willing and able to establish the overlapping strategy, it is harder for them to trade these stocks. Therefore, it might be because investors find it more difficult to exploit these opportunities, although overlapping stocks outperform pure factor stocks in the long leg. In general, I find no difference in IO between the overlapping and the pure factor portfolios.[13]

[13] I also find similar industry composition (unreported result).

5 Practical implications and robustness checks

5.1 Alternative choice of factors

So far my multi-factor strategy focuses on HML, MOM and IVOL, controlling for size. I now show that my findings are robust when I use an alternative set of factors, consisting of investment (CMA), profitability (RMW), and IVOL. Fama and French (2015) find that the HML factor is redundant with respect to the CMA and RMW factors. I therefore remove HML and consider CMA and RMA instead. Furthermore, I leave out MOM, as the previous analysis revealed an important role of overlapping momentum stocks. Table 8 shows the same setup of results for portfolio decomposition.

[Table 8 about here.]

I find that the long-short return is the highest in the overlapping factor portfolio that contains stocks from the factor appearing in the same leg of one or two other factors. These stocks again have normal size and similar characteristic spreads to the total factor portfolio. Therefore, stocks in the overlapping factor portfolio are not small-cap stocks and they are not sorted into the extreme tails of the factors. CMA & RMW, CMA & IVOL, and RMW & IVOL stocks have similar long-short returns to each other, so there is not one category of overlapping stocks that drives the overall returns on overlapping stocks.

[Table 9 about here.]

I also run the Fama-Macbeth regressions on the returns of 75 portfolios formed by sorting stocks on size and the characteristics of these alternative factors. when including the three individual total factors, I find that only IVOL is significantly priced (the lambda of RMW is marginally significant). However, the lambda of the overlapping portfolio is again positive and highly significant. The lambda of the pure factor portfolio loses its significance when I also add the overlapping portfolio to the model. In short, my findings are robust to this alternative choice of long-short factors.

5.2 Subsample periods

With respect to the portfolio performance of the multi-factor strategy consisting of HML, MOM, and IVOL, I replicate the results by splitting my main sample period into subsample periods. Panel A of Table A4 in the Online Appendix reports the portfolio statistics for the subsample period from July 1952 to December 1980. Panel B reports the statistics for the subsample period from January 1981 to December 2000. Panel C reports the statistics for the subsample period from January 2001 to December 2020.

In all subsample periods, the long-short overlapping portfolio has a higher mean excess return and a higher Sharpe ratio than the multi-factor portfolio. Whereas, the long-short pure factor portfolio shows the opposite. Factors are known to be mostly profitable during the 1980-2000 and die out after 2000. I observe the same trends since during the 1981-2000 period: the mean excess returns in all portfolios are high and the return distributions are positively skewed in all long-short portfolios. During 2001-2010, the mean excess returns are lower, but the positive CAPM alphas still survive. Therefore, my main findings are robust to different sample periods.

5.3 Sorting on NYSE breakpoints

In my main analysis, I sort stocks proportionally into the characteristic quintiles. By doing so, stocks are univariate distributed, so I can compare the fractions of overlapping stocks and pure factor stocks in my data with the random-sorting benchmark. For robustness check, I sort stocks into the characteristic quintiles by using NYSE breakpoints as in the traditional Fama-French factor formation. Table A5 in the Online Appendix shows the average fraction of stocks in each quintile. I observe that the average fractions of overlap in this table are similar to the fractions when I sort stocks proportionally as shown in Table 1. The fraction of overlapping stocks is relatively higher in the short leg i.e. 20.4% compared to 13.2% in the main analysis. However, the performance of overlapping and pure factor portfolios is not different from the ones in my main analysis.

Table A6 in the Online Appendix reports the summary statistics of portfolios sorted using NYSE breakpoints. I observe little difference in the average returns, Sharpe ratio, and the average characteristic values in the overlapping and pure factor portfolios from when I sort stocks equally into the quintiles. Therefore, my previous conclusions regarding the performance of overlapping stocks versus pure factor stocks remain the same.

I also run the Fama-MacBeth regressions on the portfolios sorted by using NYSE breakpoints. Table A7 and Table A8 in the Online Appendix report the cross-sectional regressions. It still holds that the portfolio contains overlapping stocks that are priced in all cross sections. The estimated price of risk of this portfolio is significant and exceeds one, and the intercept of these regressions is insignificant and close to zero. In contrast, the the estimated price of risk of the pure factor portfolio when included alone has a significant and large intercept, while it is not priced when included with the overlapping portfolio. Of all, my results are robust to sorting by NYSE breakpoints.

5.4 Quarterly rebalancing

I perform another check for robustness as well as another practical implication for investors by rebalancing portfolios on a quarterly basis. For investors, quarterly rebalancing could be a more feasible strategy than monthly rebalancing in terms of lower trading costs. To construct the factor portfolios, I use the characteristic scores in the last month of the quarter. The portfolio returns are value-weighted and the portfolios are rebalanced every quarter.

Table A9 in the Online Appendix reports the portfolio statistics. All returns are expressed in percentages per quarter, so the values in this table can be divided by three if I want to compare them with the results of the monthly returns. I still observe the outperformance of the overlapping portfolio whose average long-short return is 1.39% per quarter while the pure factor portfolio only generates an average return of 0.19% per quarter. The Sharpe ratio of the overlapping portfolio is approximately triple that of the pure factor portfolio (0.35 versus 0.14). Again, the abnormal returns of the factors are driven by overlapping stocks within these factors. In comparison to investing in the multi-factor portfolio, the overlapping portfolio results in higher abnormal returns on average (1.39% $>$ 0.75% per quarter). As an implication for investors, focusing on overlapping stocks could be a feasible strategy.

Table A10 in the Online Appendix reports the Fama-Macbeth cross-sectional regressions on 75 test portfolios formed on size and value, momentum, and idiosyncratic volatility (Panel A) and 25 portfolios formed on size and net share issues and accruals (Panel B). Again, I observe that only the overlapping portfolio is significantly priced and the unpriced risk is not significant in the model that includes the returns on the overlapping portfolio and the pure factor portfolio (Column 5). The adjusted R-squared increases as I include the overlapping portfolio as a factor in the model. Hence, my results are robust to quarterly rebalancing. Although the sample size drops from 882 monthly returns to 274 quarterly returns and the trading costs are possibly lower on the quarterly rebalancing, I still find abnormal returns in the overlapping stocks.

6 Conclusion

Characteristics-based long-short factors are all constructed from the same universe of stocks. Already by chance alone, they can have some stocks in common. This paper shows that although the degree of overlap between HML, MOM, and IVOL is not excessive compared to a random-sorting benchmark, the overlap is important for investors and for asset pricing. I find strong evidence that these overlapping stocks drive the portfolio performance and the asset pricing performance of factors. This result also holds when I decompose each factor portfolio and when I consider CMA and RMW as alternative factors. Importantly, these overlapping stocks are not in the extreme tails of any factor, so I am not selecting outliers. In addition, I find that overlapping stocks are priced in all cross sections while pure factor stocks are not priced when added to the overlapping portfolio. Furthermore, including overlapping stocks improves the efficient frontier while it is not always true for pure factor stocks.

Despite the vast difference in performance, overlapping and pure factor stocks are surprisingly similar in many dimensions; in terms of size, sorting characteristics, turnover, industry composition, institutional ownership, and exposure to various macro-economic risks. While I have not found a single variable that can explain the return difference between the long-short portfolios, I find that in the long leg, overlapping stocks load more on ultimate consumption risk than pure factor stocks. In the short leg, overlapping stocks have higher short interest than pure factor stocks and they are more exposed to investor sentiment.

My paper provides some important implications for asset managers investing in smart-beta or factor-based products. My results suggest that rather than removing overlap between factors or hiring separate managers for each factor product, investors should focus more on these overlapping stocks as they are the dominant ones driving most of the factor returns.

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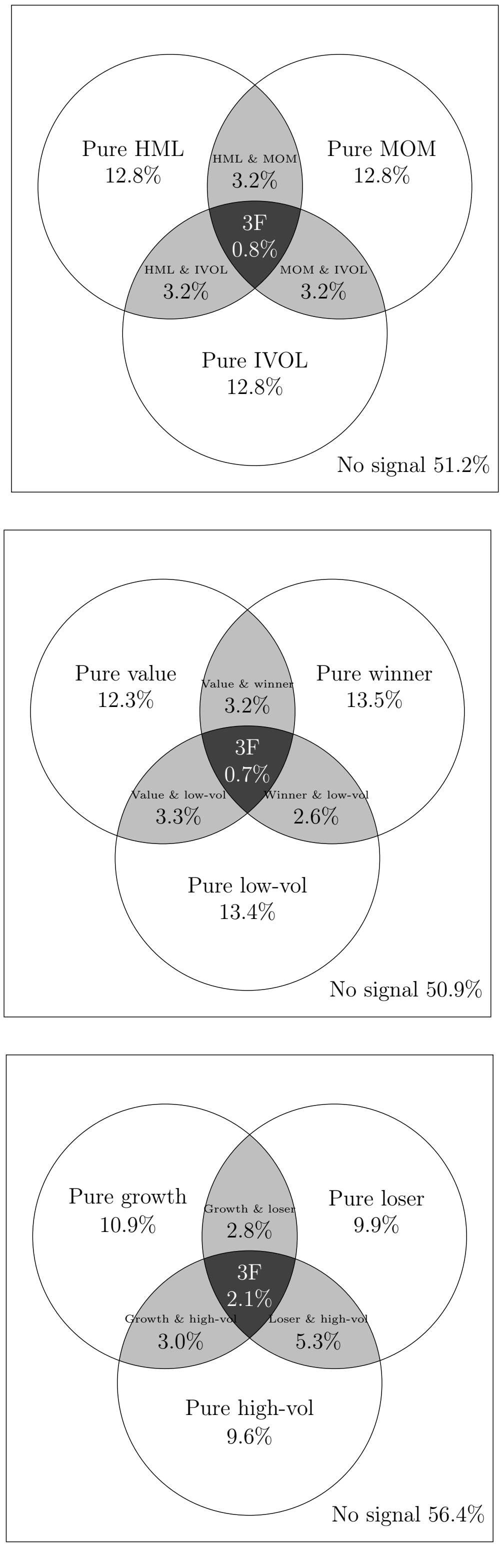
Figure 1: Fractions of overlapping stocks and pure factor stocks

Panel A: Benchmark
Overlapping 10.4%
Pure factor 38.4%

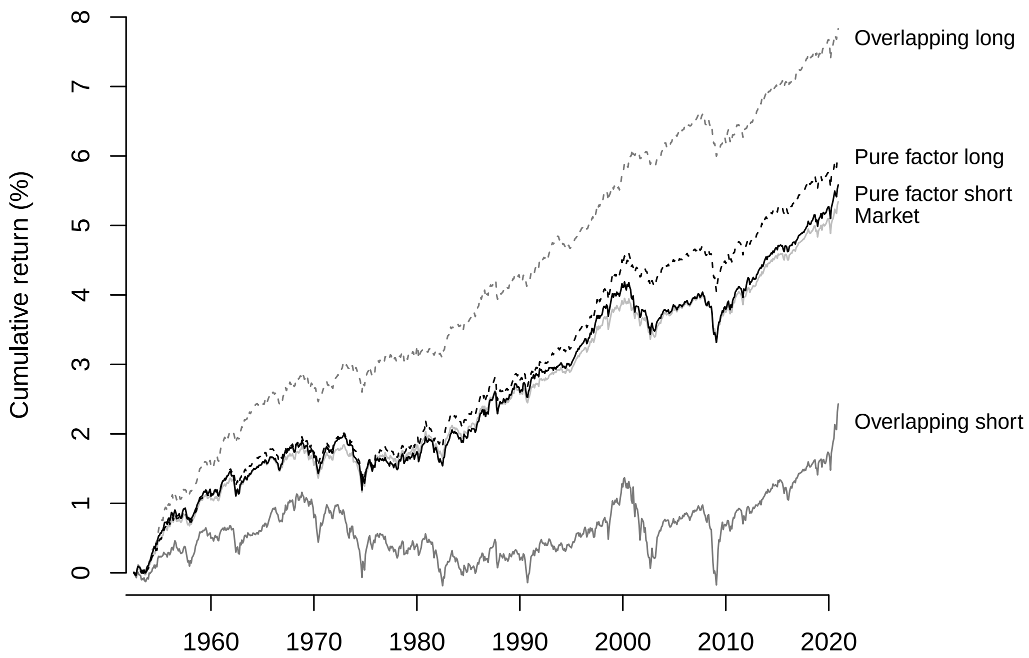
Panel B: Long leg
Overlapping 9.9%
Pure factor 39.2%

Panel C: Short leg
Overlapping 13.2%
Pure factor 30.4%



This figure presents a Venn diagram of HML, MOM, and IVOL portfolios. Within the portfolios, the shaded areas represent overlapping stocks and the non-shaded areas represent pure factor stocks. The areas outside the portfolios represent stocks that are not sorted into the portfolio of any factor. The benchmark is the same for the long leg and short leg.

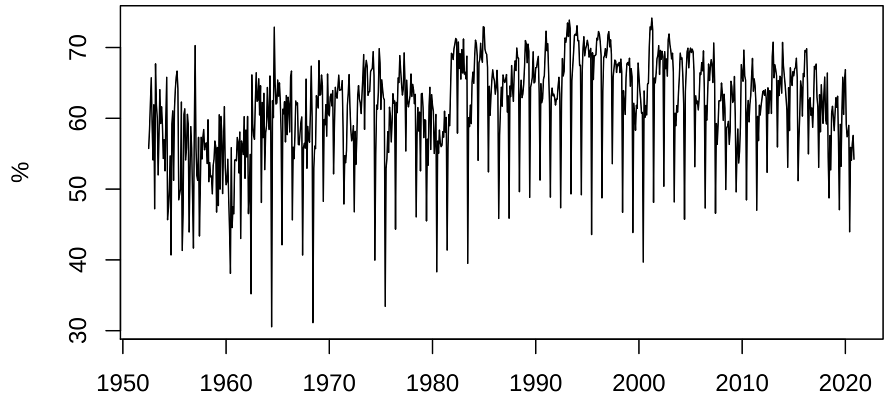
Figure 2: Cumulative returns of the overlapping and pure factor portfolios



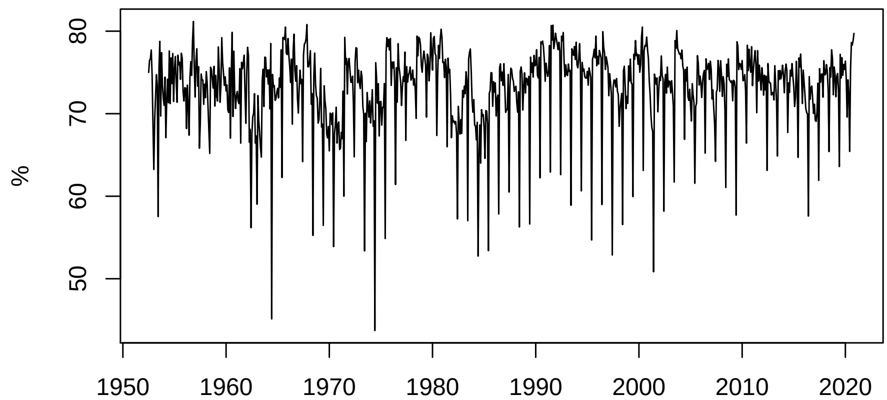
This figure plots the cumulative log-returns of the overlapping and pure factor portfolios in each leg, in comparison to the market portfolio. The sample contains the monthly excess returns from 1952:07 to 2020:12 (822 months). The short portfolios are in solid and the long portfolios are in dashed lines. The pure factor portfolios are in black and overlapping portfolios are in grey.

Figure 3: Proportion of stocks staying in the portfolio next month

(a) *Overlapping portfolio*



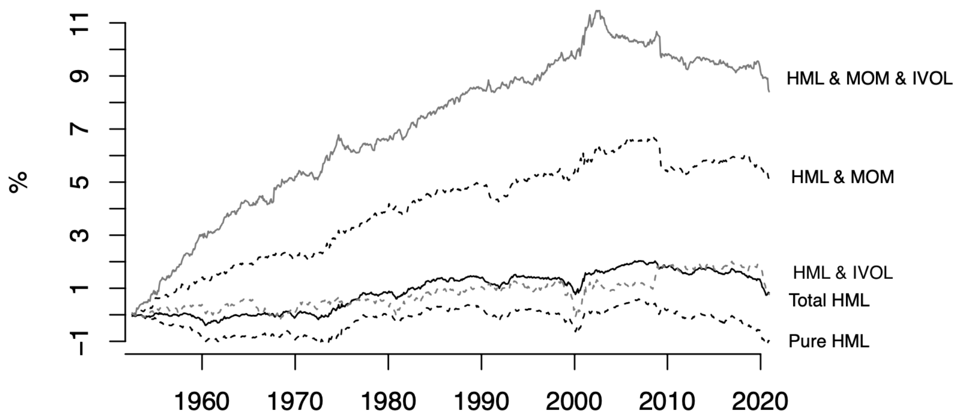
(b) *Pure factor portfolio*



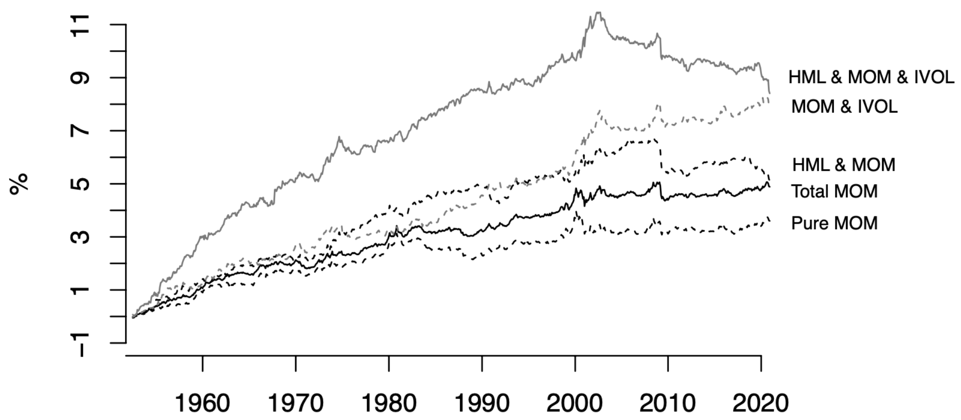
This figure plots the proportions of stocks in the overlapping and the pure factor portfolios that stays in the same portfolio in the following month. The sample contains the monthly excess returns from 1952:07 to 2020:12 (822 months). The portfolio is rebalanced every month.

Figure 4: Cumulative returns of decomposed factor portfolios

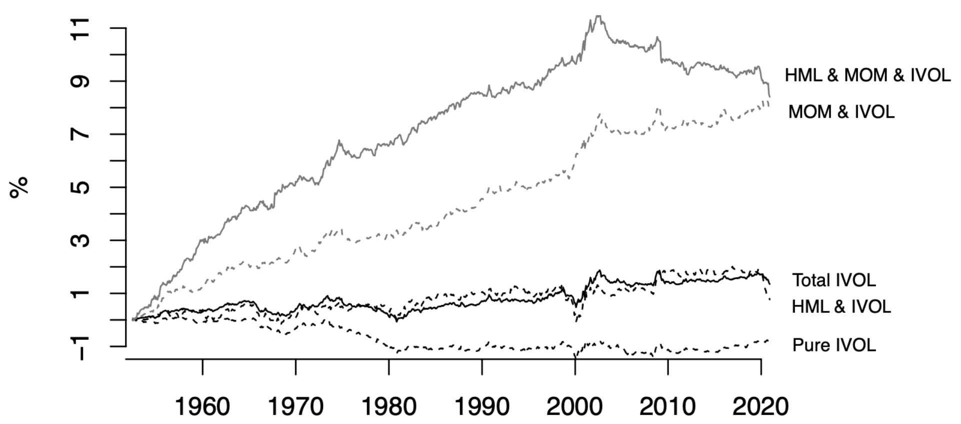
(a) *HML*



(b) *MOM*

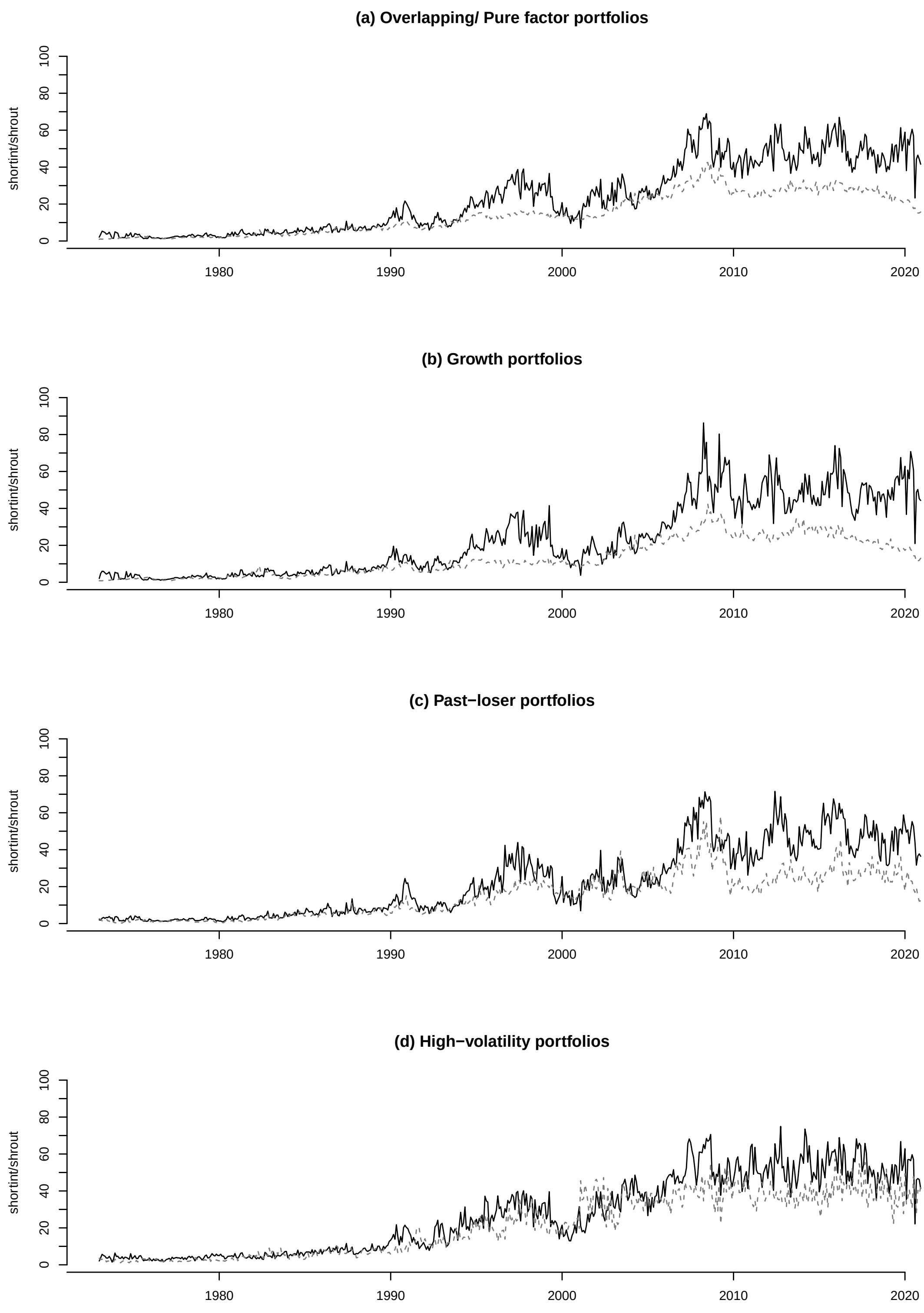


(c) *IVOL*



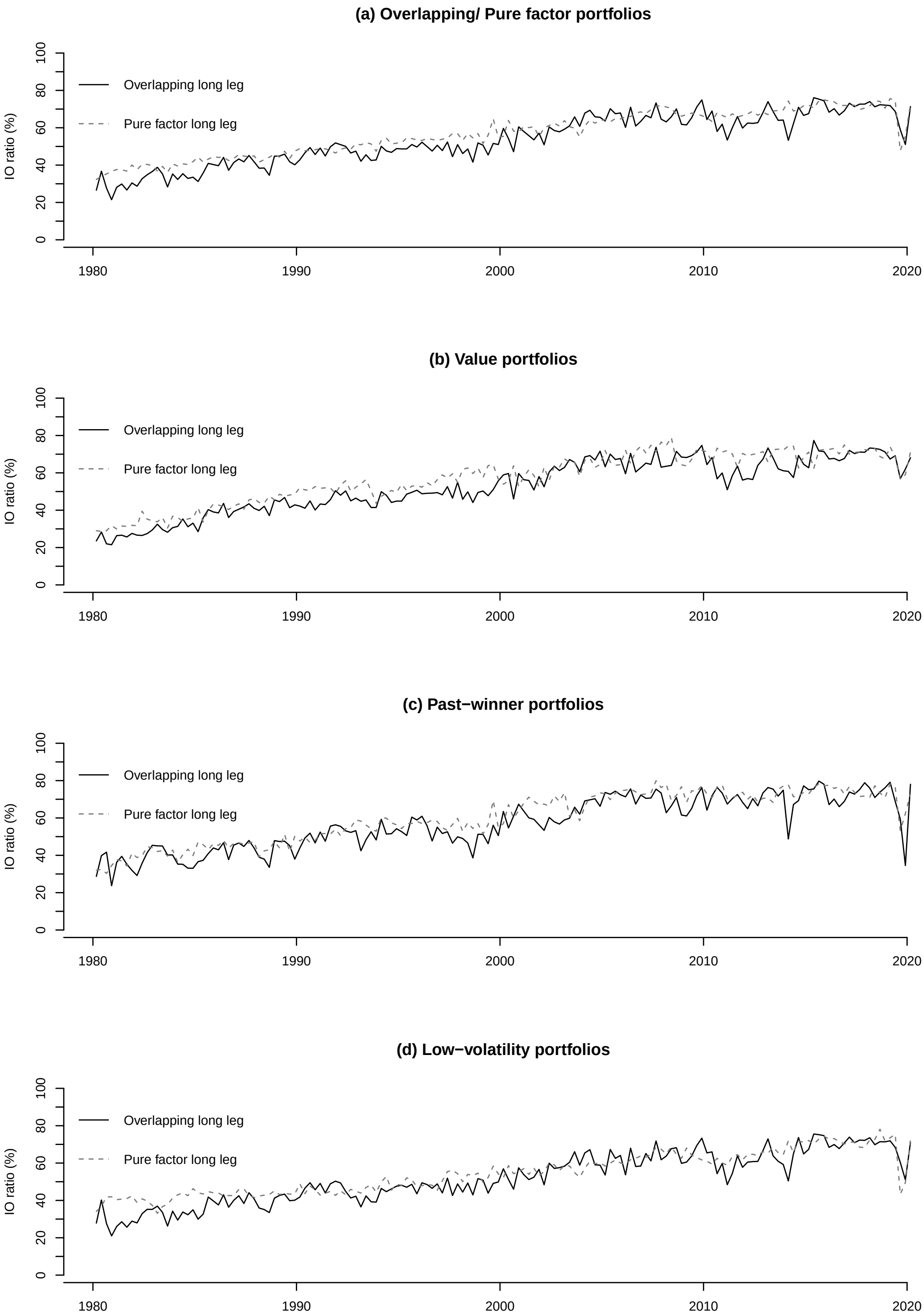
This figure plots the cumulative logreturns of long-short portfolios in each factor: HML (Panel A), MOM (Panel B), and IVOL (Panel C). The sample contains the monthly excess returns from 1952:07 to 2020:12 (822 months)

Figure 5: Short interest in the short legs (value-weighted)



This figure plots the value-weighted short interest divided by shares outstanding in the short leg of multiple portfolios. I obtain short interest for each stock from Compustat Supplementary Short Interest File. The sample is from 1978:01 to 2020:12.

Figure 6: Institutional ownership ratio in the long legs (value-weighted)



This figure plots the value-weighted institutional ownership ratio in the long leg of several factor portfolios. The IO ratio, in percentage, is the total institutional ownership divided by the total shares outstanding (adjusted). I obtain the total IO from SEC 13F and the adjusted total shares outstanding from CRSP. I keep data at quarter dates end. The sample is from 1980:03 to 2020:03.

Table 1: Fraction of pure factor stocks and overlapping stocks

	Long leg	Short leg	Benchmark
Panel A: In the universe of stocks			
Pure factor	0.392	0.304	0.384
Pure HML	0.123	0.109	0.128
Pure MOM	0.135	0.099	0.128
Pure IVOL	0.134	0.096	0.128
Overlapping	0.099	0.132	0.104
HML & MOM	0.032	0.028	0.032
HML & IVOL	0.033	0.030	0.032
MOM & IVOL	0.026	0.053	0.032
HML & MOM & IVOL	0.007	0.021	0.008
Panel B: In each factor portfolio			
HML	1.000	1.000	1.000
Pure HML	0.628	0.579	0.640
Overlapping HML	0.372	0.421	0.360
HML & MOM	0.165	0.148	0.160
HML & IVOL	0.171	0.159	0.160
HML & MOM & IVOL	0.036	0.114	0.040
MOM	1.000	1.000	1.000
Pure MOM	0.674	0.491	0.640
Overlapping MOM	0.326	0.509	0.360
HML & MOM	0.161	0.140	0.160
MOM & IVOL	0.130	0.262	0.160
HML & MOM & & IVOL	0.035	0.107	0.040
IVOL	1.000	1.000	1.000
Pure IVOL	0.669	0.481	0.640
Overlapping IVOL	0.331	0.519	0.360
HML & IVOL	0.166	0.150	0.160
MOM & IVOL	0.130	0.262	0.160
HML & MOM & IVOL	0.035	0.107	0.040

This table reports the average fraction of pure factor/ overlapping stocks in the data versus the benchmark fraction in the strategy that invests equally in HML, MOM, and IVOL. The benchmark fractions are given by $f_S(k) = \binom{S}{k}\left(\frac{1}{5}\right)^k\left(\frac{4}{5}\right)^{S-k}, k = 0, \ldots, S$ for $S = 3$. The benchmark is the same for the long leg and the short leg. The empirical fractions are the average of fractions in each month per portfolio.

Table 2: Portfolio performance of the HML-MOM-IVOL strategy

	Return				Sharpe	Distribution				CAPM		Average characteristic			
Portfolio	Mean (%)	Min. (%)	Max. (%)	Volatility (%)	ratio	Positive (%)	Negative (%)	Skewness	Kurtorsis	$\hat{\alpha}$	$\hat{\beta}_{MKT}$	Log-mkt. cap	B/M	Prior-ret (%)	Resid. vol. (%)
Market	0.651	-22.883	16.530	4.288	0.152	60.827	39.173	-0.485	1.881			4.880	0.538	17.696	1.304
Overlapping portfolio															
Long	0.954	-20.860	14.176	4.141	0.230	61.922	38.078	-0.565	2.229	0.401***	0.848***	4.989	0.780	33.685	1.105
Short	0.298	-27.080	30.384	6.547	0.045	52.190	47.810	0.000	2.418	-0.595***	1.372***	4.371	0.429	4.980	1.899
Long–Short	0.656	-31.374	25.001	4.712	0.139	58.637	41.363	-0.618	6.672	0.997***	-0.524***	0.618	0.352	28.705	-0.794
Pure factor portfolio (across all factors)															
Long	0.730	-22.175	15.688	4.228	0.173	61.557	38.443	-0.478	1.881	0.104***	0.963***	4.921	0.555	25.058	1.236
Short	0.680	-21.057	19.802	4.595	0.148	59.611	40.389	-0.397	1.553	0.001	1.043***	4.867	0.421	16.842	1.371
Long–Short	0.050	-7.880	11.717	1.443	0.035	49.757	50.243	0.395	8.897	0.102**	-0.081***	0.055	0.133	8.216	-0.135
EW. multi-factor	0.287	-21.225	21.032	2.611	0.110	59.124	40.876	-0.466	14.057	0.462***	-0.268***	0.323	0.216	18.849	-0.417
HML	0.101	-15.148	19.781	3.557	0.028	51.582	48.418	0.168	2.630	0.181	-0.123***	-0.638	0.947	-3.025	-0.078
MOM	0.596	-35.169	25.824	5.033	0.118	58.029	41.971	-0.828	7.718	0.670***	-0.114***	0.710	-0.297	68.153	-0.116
IVOL	0.165	-19.845	26.885	4.264	0.039	52.798	47.202	0.324	5.411	0.534***	-0.566***	0.897	-0.004	-8.580	-1.056

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the summary statistics of overlapping/ pure factor portfolio value-weighted returns, in excess of the risk-free rate, comparing to the market and factor returns. The sample is from 1952:07 to 2020:12 (822 monthly returns). Market is the excess returns of the CRSP U.S. total market index. The risk-free rate is from Kenneth R. French's Data Library. The last four columns present the averages over time of the value-weighted characteristic of stocks in each portfolio. The EW. multi-factor portfolio is the equal-weighted combination of the three factors. Note that the pure factor portfolio contains pure HML, pure MOM, and pure IVOL stocks.

Table 3: Individual factor decomposition

	Total Factor	Pure Factor	Over-lapping	Decomposition of overlapping portfolio: HML & MOM	HML & IVOL	MOM & IVOL	3F
Panel A: HML							
Return (%)							
Long	1.077	0.983	1.205	1.256	1.054		1.387
Short	0.976	1.101	0.708	0.630	0.958		0.313
Long–Short	0.101	-0.118	0.498	0.625	0.095		1.074
Log-market cap							
Long	4.486	4.264	4.865	4.561	5.118		4.941
Short	5.124	5.414	4.732	4.726	5.103		4.159
Long–Short	-0.638	-1.150	0.134	-0.165	0.015		0.781
Avg. weight	1.000	0.598	0.402	0.152	0.180		0.071
Characteristic spreads (Long–Short)							
Book-to-market ratio	0.947	1.068	0.801	0.643	0.947		0.679
Prior 12-to-2 return (%)	-3.025	-17.015	16.730	71.181	-32.460		65.654
Residual volatility (%)	-0.078	0.220	-0.692	0.060	-1.101		-1.200
Panel B: MOM							
Return (%)							
Long	1.328	1.363	1.365	1.256		1.340	1.387
Short	0.732	0.924	0.475	0.630		0.372	0.313
Long–Short	0.596	0.439	0.891	0.625		0.968	1.074
Log-market cap							
Long	5.133	5.231	4.918	4.561		5.371	4.941
Short	4.423	4.724	4.153	4.726		3.822	4.159
Long–Short	0.710	0.507	0.765	-0.165		1.549	0.781
Avg. weight	1.000	0.604	0.396	0.148		0.181	0.069
Characteristic spreads (Long–Short)							
Book-to-market ratio	-0.297	-0.510	0.051	0.643		-0.607	0.679
Prior 12-to-2 return (%)	68.153	68.771	64.789	71.181		60.744	65.654
Residual volatility (%)	-0.116	0.184	-0.604	0.060		-1.018	-1.200
Panel C: IVOL							
Return (%)							
Long	1.021	0.938	1.246		1.054	1.340	1.387
Short	0.856	1.042	0.660		0.958	0.372	0.313
Long–Short	0.165	-0.104	0.585		0.095	0.968	1.074
Log-market cap							
Long	5.213	5.234	5.194		5.118	5.371	4.941
Short	4.316	4.376	4.269		5.103	3.822	4.159
Long–Short	0.897	0.858	0.925		0.015	1.549	0.781
Avg. weight	1.000	0.574	0.426		0.176	0.182	0.069
Characteristic spreads (Long–Short)							
Book-to-market ratio	-0.004	-0.127	0.259		0.947	-0.607	0.679
Prior 12-to-2 return (%)	-8.580	-24.732	13.825		-32.460	60.744	65.654
Residual volatility (%)	-1.056	-0.942	-1.129		-1.101	-1.018	-1.200

We decompose each factor into pure factor stocks and multi-signal stocks. This table reports the summary statistics of decomposed portfolios for each factor: HML (Panel A), MOM (Panel B), and IVOL (Panel C), where 3F denotes HML & MOM & IVOL. The sample is from 1952:07 to 2020:12 (822 monthly returns). Portfolios are value-weighted of stocks returns and rebalanced every month. The characteristic spreads are the long–short averages over time of the value-weighted characteristics of the stocks in each portfolio.

Table 4: Fama–MacBeth cross-sectional regressions

	(1)	(2)	(3)	(4)	(5)
Panel A: Cross-section of 25 size×value, 25 size×momentum, and 25 size×volatility portfolios					
λ_{MKT}	-1.038***	0.753**	0.354	-0.203	0.559**
	(-6.21)	(2.18)	(1.36)	(-0.94)	(1.97)
λ_{SMB}	0.134***	0.216***	0.165***	0.141***	0.181***
	(2.59)	(3.81)	(3.20)	(2.73)	(3.45)
λ_{HML}		0.248**			
		(2.52)			
λ_{MOM}		0.685***			
		(6.88)			
λ_{IVOL}		0.344***			
		(3.63)			
$\lambda^{3F}_{overlap}$			1.231***		1.525***
			(9.15)		(7.19)
λ^{3F}_{pure}				0.601***	-0.194
				(6.89)	(-0.96)
λ_0	1.748***	-0.117	0.303	0.869***	0.099
	(10.45)	(-0.32)	(1.14)	(3.91)	(0.34)
Adjusted R^2	0.309	0.773	0.694	0.560	0.733
Panel B: Cross-section of 25 size×net share issues and 25 size×accruals portfolios					
λ_{MKT}	-0.704**	0.379	0.269	-0.131	0.167
	(-2.25)	(0.81)	(0.56)	(-0.34)	(0.33)
λ_{SMB}	0.168***	0.111	0.139**	0.086	0.107
	(2.82)	(1.34)	(2.30)	(1.27)	(1.50)
λ_{HML}		0.530**			
		(1.96)			
λ_{MOM}		2.350**			
		(2.49)			
λ_{IVOL}		0.209			
		(0.78)			
$\lambda^{3F}_{overlap}$			1.312***		1.193***
			(3.17)		(2.73)
λ^{3F}_{pure}				0.728***	0.497
				(2.82)	(1.39)
λ_0	1.354***	0.259	0.365	0.769**	0.468
	(4.31)	(0.55)	(0.75)	(2.00)	(0.93)
Adjusted R^2	0.325	0.662	0.511	0.548	0.551

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the second-stage cross-sectional regressions by Fama and MacBeth (1973) on the returns of 75 portfolios formed on size×value, size×momentum, and size×volatility (Panel A) and 50 portfolios formed on size×net share issues and size×accruals (Panel B). Double sorted portfolios are retrieved from Kenneth R. French's data library.

Table 5: Fama–MacBeth cross-sectional regressions on decomposed individual factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Cross-section of 25 size×value portfolios								
λ_{MKT}	-1.237***	-0.656	-0.294	-0.814	-0.135	-0.602	-0.854	-0.065
	(-2.61)	(-1.11)	(-0.39)	(-1.34)	(-0.17)	(-0.94)	(-1.55)	(-0.06)
λ_{SMB}	0.083	0.122	0.133	0.111	0.135	0.123	0.117	0.129
	(1.06)	(1.48)	(1.57)	(1.34)	(1.60)	(1.48)	(1.42)	(1.54)
λ_{HML}		0.275***						
		(2.79)						
$\lambda^{3F}_{overlap}$			1.076***		1.350**			
			(2.67)		(2.10)			
λ^{3F}_{pure}				0.308	-0.021			
				(1.61)	(-0.06)			
$\lambda^{HML}_{overlap}$						0.722***		1.364
						(2.87)		(1.18)
λ^{HML}_{pure}							0.308	-0.183
							(1.35)	(-0.28)
λ_0	1.967***	1.314**	0.951	1.493**	0.797	1.264*	1.518***	0.739
	(4.19)	(2.14)	(1.19)	(2.36)	(0.94)	(1.88)	(2.64)	(0.65)
Adjusted R^2	0.397	0.543	0.531	0.449	0.528	0.508	0.488	0.505
Panel B: Cross-section of 25 size×momentum portfolios								
λ_{MKT}	-1.511***	-0.395	0.629	0.070	1.376*	-0.153	-0.597*	0.547
	(-4.98)	(-1.09)	(1.29)	(0.17)	(1.75)	(-0.39)	(-1.72)	(0.68)
λ_{SMB}	0.190**	0.227**	0.184*	0.132	0.270**	0.202**	0.212**	0.184*
	(2.01)	(2.40)	(1.94)	(1.38)	(2.28)	(2.13)	(2.23)	(1.91)
λ_{MOM}		0.723***						
		(6.95)						
$\lambda^{3F}_{overlap}$			1.188***		1.945***			
			(6.78)		(3.00)			
λ^{3F}_{pure}				0.716***	-0.768			
				(6.33)	(-1.01)			
$\lambda^{MOM}_{overlap}$						1.168***		1.771***
						(7.16)		(2.84)
λ^{MOM}_{pure}							0.984***	0.432
							(5.33)	(1.10)
λ_0	2.208***	1.173***	0.067	0.646	-0.713	0.917**	1.390***	0.162
	(6.99)	(3.21)	(0.14)	(1.51)	(-0.88)	(2.34)	(3.97)	(0.19)
Adjusted R^2	0.375	0.879	0.874	0.833	0.893	0.859	0.834	0.870
Panel C: Cross-section of 25 size×volatility portfolios								
λ_{MKT}	-0.702***	0.931**	0.690	0.391	0.616	0.721	0.424	0.689
	(-2.81)	(2.05)	(1.61)	(0.91)	(1.41)	(1.62)	(0.98)	(1.55)
λ_{SMB}	0.080	0.158	0.224**	0.224**	0.198*	0.183*	0.065	0.370**
	(0.77)	(1.50)	(2.04)	(1.97)	(1.74)	(1.71)	(0.62)	(2.50)
λ_{IVOL}		0.398***						
		(3.66)						
$\lambda^{3F}_{overlap}$			1.693***		1.658***			
			(4.72)		(4.58)			
λ^{3F}_{pure}				1.352***	-0.419			
				(3.28)	(-0.53)			
$\lambda^{IVOL}_{overlap}$						1.249***		2.753***
						(4.80)		(3.20)
λ^{IVOL}_{pure}							0.993***	-1.443
							(3.72)	(-1.64)
λ_0	1.428***	-0.355	-0.097	0.211	-0.006	-0.113	0.221	-0.101
	(5.90)	(-0.74)	(-0.22)	(0.46)	(-0.01)	(-0.24)	(0.49)	(-0.22)
Adjusted R^2	0.150	0.683	0.608	0.416	0.612	0.575	0.419	0.665

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the second-stage cross-sectional regressions by Fama and MacBeth (1973) on the returns of 25 portfolios formed on size×value (Panel A), size×momentum (Panel B), and size×volatility (Panel C). Double sorted portfolios are retrieved from Kenneth R. French's data library.

Table 6: Portfolio spanning tests

	HML & MOM & IVOL		HML		MOM		IVOL	
Panel A: Dependent variable = returns to the overlapping portfolio								
	FF2	FF2 + pure factor	FF2	FF2 + pure HML	FF2	FF2 + pure MOM	FF2	FF2 + pure IVOL
α	1.003***	0.895***	0.819***	0.885***	1.147***	0.888***	1.040***	0.948***
	(7.11)	(6.84)	(5.25)	(6.15)	(6.31)	(6.48)	(7.24)	(7.04)
Panel B: Dependent variable = returns to the pure factor portfolio								
	FF2	FF2 + overlapping	FF2	FF2 + overlapping HML	FF2	FF2 + overlapping MOM	FF2	FF2 + overlapping IVOL
α	0.100**	-0.033	-0.153	-0.437***	0.398**	-0.368***	0.194*	-0.081
	(2.03)	(-0.70)	(-1.10)	(-3.35)	(2.16)	(-2.59)	(1.80)	(-0.78)

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the spanning test alphas and the corresponding t-statistics. Panel A shows the time-series regressions of the returns to the overlapping portfolios on the market, size factor (MKT + SMB := FF2), and the pure factor portfolios. Panel B shows the regressions of the returns to the pure factor portfolios on the FF2 and the overlapping portfolios. The sample is from 1952:07 to 2020:12 (822 monthly returns).

Table 7: Economic risk exposures

	Long		Short		Long–short	
	Overlapping	Pure factor	Overlapping	Pure factor	Overlapping	Pure factor
Panel A: Consumption risk and other macroeconomic risk exposures						
CG_t	0.464**	0.147	0.281	0.220	0.183	-0.073
	(2.04)	(0.62)	(0.74)	(0.85)	(0.67)	(-0.88)
$I_{Recession,t}$	-1.171**	-1.187**	-1.100	-1.269**	-0.070	0.082
	(-2.25)	(-2.18)	(-1.27)	(-2.15)	(-0.11)	(0.44)
$TERM_t$	0.143	0.227	0.101	0.189	0.043	0.038
	(1.08)	(1.63)	(0.46)	(1.25)	(0.27)	(0.78)
DEF_t	0.216	0.496	0.904	0.787*	-0.688	-0.291*
	(0.53)	(1.15)	(1.33)	(1.69)	(-1.40)	(-1.96)
a	0.492	-0.044	-0.676	-0.327	1.168**	0.284*
	(1.17)	(-0.10)	(-0.97)	(-0.69)	(2.33)	(1.87)
Observations	701	701	701	701	701	701
Adjusted R^2	0.012	0.009	-0.000	0.008	-0.001	0.001
Panel B: Liquidity measures						
LIQ_t	6.053*	8.061	6.738**	6.124*	-2.009	0.614
	(1.89)	(1.39)	(1.97)	(1.65)	(-0.43)	(0.47)
VIX_t	-0.183***	-0.195***	-0.186***	-0.182***	0.012	-0.004
	(-6.92)	(-4.07)	(-6.62)	(-5.98)	(0.33)	(-0.36)
TED_t	-0.271	-1.085	-0.184	-0.237	0.813	0.052
	(-0.56)	(-1.23)	(-0.35)	(-0.42)	(1.16)	(0.26)
a	4.932***	5.282***	4.875***	4.770***	-0.350	0.105
	(9.64)	(5.68)	(8.93)	(8.07)	(-0.47)	(0.50)
Observations	419	419	419	419	419	419
Adjusted R^2	0.177	0.083	0.164	0.136	-0.000	-0.006
Panel C: Exposures to investor sentiment						
S_{t-1}	-0.117	-0.149	-0.624**	-0.252	0.507***	0.103*
	(-0.72)	(-0.87)	(-2.34)	(-1.35)	(2.60)	(1.71)
a	0.767***	0.600***	0.116	0.533***	0.651***	0.067
	(4.75)	(3.51)	(0.44)	(2.86)	(3.34)	(1.11)
Observations	641	641	641	641	641	641
Adjusted R^2	-0.001	-0.000	0.007	0.001	0.009	0.003

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the estimated risk exposures to several variables. In all panels, the dependent variable R_t is the excess returns of the overlapping/ pure factor portfolios. In panel A, we regress the monthly excess returns on per capita real consumption growth (CG), NBER's recession dummy variable, term spread measured by 10Y government bond minus 3M Treasury Bills, and default premium measured by BAA minus AAA rated corporate bonds, from 1962:08 to 2020:12

$$R_t = a + bCG_t + cI_{recession,t} + dTERM_t + eDEF_t + \epsilon_t.$$

In panel B, we regress the monthly excess returns on Stambaugh et al. (2012)'s liquidity factor (LIQ), the implied market volatility (VIX), and funding liquidity (TED spread), from 1986:02 to 2020:12

$$R_t = a + bLIQ_t + cVIX_t + dTED_t + \epsilon_t.$$

In panel C, we regress the monthly portfolio excess returns on the Baker and Wurgler (2007)'s investor sentiment index, lagged by one month, from 1965:07 to 2018:12

$$R_t = a + bS_{t-1} + \epsilon_t.$$

Table 8: Decomposing individual factor portfolios (CMA, RMW, and IVOL)

	Total Factor	Pure Factor	Over-lapping	Decomposition of overlapping portfolio			
				CMA & RMW	CMA & IVOL	RMW & IVOL	3F
Panel A: CMA							
Return (%)							
Long	1.071	1.046	1.074	1.146	0.991		1.248
Short	0.951	1.092	0.692	0.885	0.707		0.291
Long–short	0.120	-0.047	0.381	0.260	0.284		0.957
Log-market cap							
Long	4.566	4.351	5.231	5.151	5.274		5.660
Short	4.969	5.034	4.864	4.979	4.978		4.365
Long–short	-0.403	-0.683	0.368	0.172	0.296		1.295
Avg. weight	1.000	0.681	0.319	0.114	0.154		0.050
Characteristic spreads (long–short)							
Change in total assets	-0.496	-0.426	-0.665	-0.716	-0.489		-1.023
Operating profitability	-0.002	-0.263	0.431	1.189	-0.216		1.291
Residual volatility (%)	-0.179	0.141	-0.767	-0.013	-1.072		-1.394
Panel B: RMW							
Return (%)							
Long	1.095	1.114	1.093	1.146		1.033	1.248
Short	0.797	0.867	0.724	0.885		0.753	0.291
Long–short	0.299	0.247	0.369	0.260		0.279	0.957
Log-market cap							
Long	5.129	5.076	5.227	5.151		5.223	5.660
Short	4.504	4.861	4.102	4.979		3.693	4.365
Long–short	0.625	0.214	1.125	0.172		1.530	1.295
Avg. weight	1.000	0.620	0.380	0.116		0.214	0.051
Characteristic spreads (long–short)							
Change in total assets	-0.079	0.141	-0.420	-0.716		0.100	-1.023
Operating profitability	1.064	1.076	1.020	1.189		0.921	1.291
Residual volatility (%)	-0.214	0.154	-0.854	-0.013		-1.268	-1.394
Panel C: IVOL							
Return (%)							
Long	1.021	1.016	1.028		0.991	1.033	1.248
Short	0.856	1.055	0.649		0.707	0.753	0.291
Long–short	0.165	-0.040	0.379		0.284	0.279	0.957
Log-market cap							
Long	5.213	5.209	5.231		5.274	5.223	5.660
Short	4.316	4.407	4.231		4.978	3.693	4.365
Long–short	0.897	0.801	0.999		0.296	1.530	1.295
Avg. weight	1.000	0.582	0.418		0.155	0.213	0.050
Characteristic spreads (long–short)							
Change in total assets	-0.142	0.051	-0.362		-0.489	0.100	-1.023
Operating profitability	0.076	-0.162	0.446		-0.216	0.921	1.291
Residual volatility (%)	-1.056	-0.929	-1.186		-1.072	-1.268	-1.394

We decompose each factor into a portfolio containing pure factor stocks and a portfolio containing overlapping stocks. This table reports the summary statistics of decomposed portfolios for each factor: CMA (Panel A), RMW (Panel B), and IVOL (Panel C), where 3F denotes CMA & RMW & IVOL. The sample is from 1952:07 to 2020:12 (822 monthly returns). Portfolios are value-weighted of stocks returns and rebalanced every month. The characteristic spreads are the long–short averages over time of the value-weighted characteristics of the stocks in each portfolio.

Table 9: Fama–MacBeth cross-sectional regressions on alternative factors (CMA, RMW, and IVOL)

Dependent variable: Cross-section of 25 size×investment, 25 size×profitability, and 25 size×volatility portfolios					
	(1)	(2)	(3)	(4)	(5)
λ_{MKT}	-0.759***	0.452	0.545	-0.246	0.534
	(-4.13)	(1.07)	(1.58)	(-0.88)	(1.55)
λ_{SMB}	0.126**	0.145**	0.151***	0.122**	0.159***
	(2.29)	(2.39)	(2.73)	(2.21)	(2.85)
λ_{CMA}		0.132			
		(1.25)			
λ_{RMW}		0.197*			
		(1.85)			
λ_{IVOL}		0.329***			
		(3.10)			
$\lambda_{overlap}^{3F}$			1.446***		1.489***
			(5.50)		(5.58)
λ_{pure}^{3F}				0.538***	-0.031
				(2.71)	(-0.13)
λ_0	1.445***	0.143	0.060	0.882***	0.082
	(7.91)	(0.33)	(0.17)	(2.98)	(0.23)
Adjusted R^2	0.283	0.642	0.599	0.369	0.610

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the second-stage cross-sectional regressions by Fama and MacBeth (1973) on the returns of 75 portfolios formed on size×investment, size×profitability, and size×volatility. Double sorted portfolios are retrieved from Kenneth R. French's data library.

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Online Appendices

A1 Pricing decile portfolios

I regress the returns of decile portfolios sorted on book-to-market, prior 12-to-2 returns, and residual volatility against fmy different asset pricing models: CAPM with SMB (denoted as FF2), FF2 with each factor (HML, MOM, or IVOL), FF2 with returns on the overlapping factor portfolio (overlapping HML, overlapping MOM, or overlapping IVOL respectively), and FF2 with returns on the pure factor portfolio (pure HML, pure MOM, or pure IVOL respectively). Table A2 reports the mean excess returns, estimates for alphas and factor loadings in the top and bottom decile portfolios.

[Table A2 about here.]

On average, the long-short strategy earns positive excess returns. With portfolios sorted on book-to-market, the high-minus-low portfolio yields an average return of 0.29% per month. With portfolios sorted on prior returns, the loser portfolio generates an insignificant negative return of −0.01% per month. The winner portfolio generates a significant positive return of 1.22% per month. Thus, the winner-minus-loser portfolio earns an average return of 1.24% per month. With portfolios sorted on residual volatility, the difference between the low-volatility and high-volatility portfolios is 0.54% per month.

Adding each factor to the benchmark model (FF2 + Factor) significantly reduces the alpha. With portfolios sorted on book-to-market, the estimated alpha for the high-minus-low strategy reduces from 0.23% to −0.24%. The average absolute alpha over ten portfolios reduces from 11.6 to 8.3 basis points. With portfolios sorted on prior returns, the estimated alpha of the winner-minus-loser strategy reduces from 1.44% to 0.27% and the average absolute alpha reduces from 36.4 to 13.4 basis points. With portfolios sorted on residual volatility, the estimated alpha of the lowvol-minus-highvol strategy reduces from 1.14% to 0.35% and the average absolute alpha reduces from 23.0 to 14.3 basis points.

Consistently, adding the overlapping factor performance to the benchmark (FF2 + overlapping) improves pricing the decile portfolios. In the HML strategy, alpha becomes insignificant and reduces from 0.23 to −0.21. In the MOM strategy, alpha is less significant and it reduces by more than half of the benchmark $(1-0.28/1.44)$. In the IVOL strategy, alpha also reduces by more than half of the benchmark $(1-0.49/1.14)$. These results imply that less returns remain unexplained in the model after including the overlapping factor portfolio as a factor. I find that including the overlapping factor performance improves the alpha of the long-short strategy just as well as including each individual factor.

[Figure A1 about here.]

I also find that the overlapping factor portfolio prices each individual portfolio more modestly than the factor itself. Figure A1 plots the mean return and the estimated alpha of each decile portfolio. Across the deciles, the alpha in the FF2 + overlapping model closely follows the alpha in the FF2 + Factor model. Yet there is less overshooting in the intermediate portfolios, especially from Decile 2 to Decile 4 of prior return and residual volatility portfolios. I also find that FF2 + overlapping only yields significant alphas in the long and short portfolios and not in any intermediate decile portfolio.

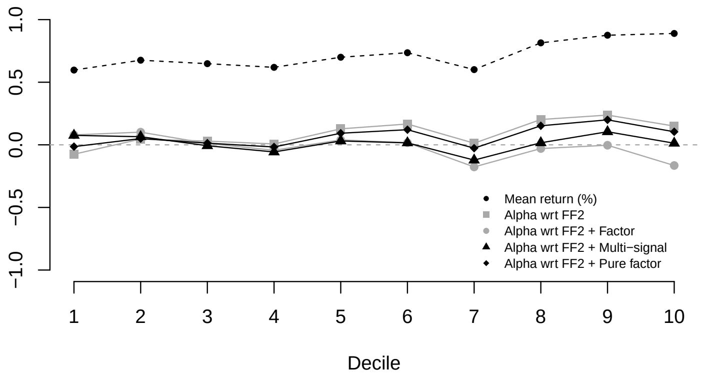
Formally, Table A2 reports the test for joint significance of alphas, introduced by Gibbons, Ross, and Shanken (1989). In all panels, I find that the GRS F-statistic to test the null hypothesis that alphas across all decile portfolios are zero remain low. Therefore, including the overlapping factor performance in the benchmark model reduces the significance of alpha across decile portfolios.

I find opposite conclusions when including the pure factor performance in the benchmark (FF2 + Pure factor). Adding this portfolio as a factor does not improve pricing the decile portfolios. Although the estimated betas of the pure factor strategy are significantly large in all three panels, the estimated alphas are not much different from the benchmark. The average absolute alphas and the GRS-test statistics are also just similar to the benchmark. Therefore, adding the pure factor returns as a factor to the benchmark model has no contribution in pricing the characteristic-sorted portfolios.

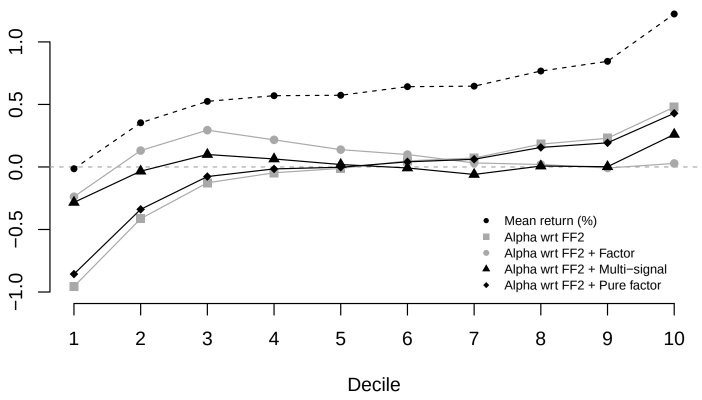
So far, I find that the overlapping factor portfolio is powerful in pricing single-sorted portfolios and it outperforms the factor in pricing intermediate portfolios. In contrast, the pure factor portfolio contributes no benefit to the cross-sectional multi-factor strategies, in comparison to the benchmark. The overlapping factor portfolio contains fewer stocks than the total factor portfolios, but this portfolio has approximately the same explanatory power as all three factors when included as a priced risk factor. The pure factor portfolio that contains stocks sorted only to that factor does not perform differently than the benchmark.

Figure A1: Time-series alphas in decile portfolios

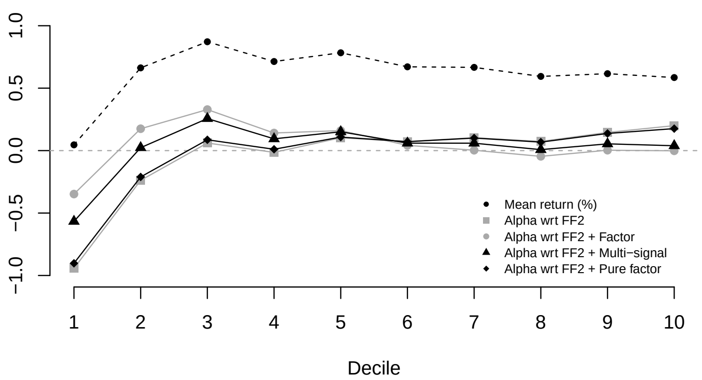
(a) *Book-to-market portfolios (Factor = HML)*



(b) *12-to-2 return portfolios (Factor = MOM)*

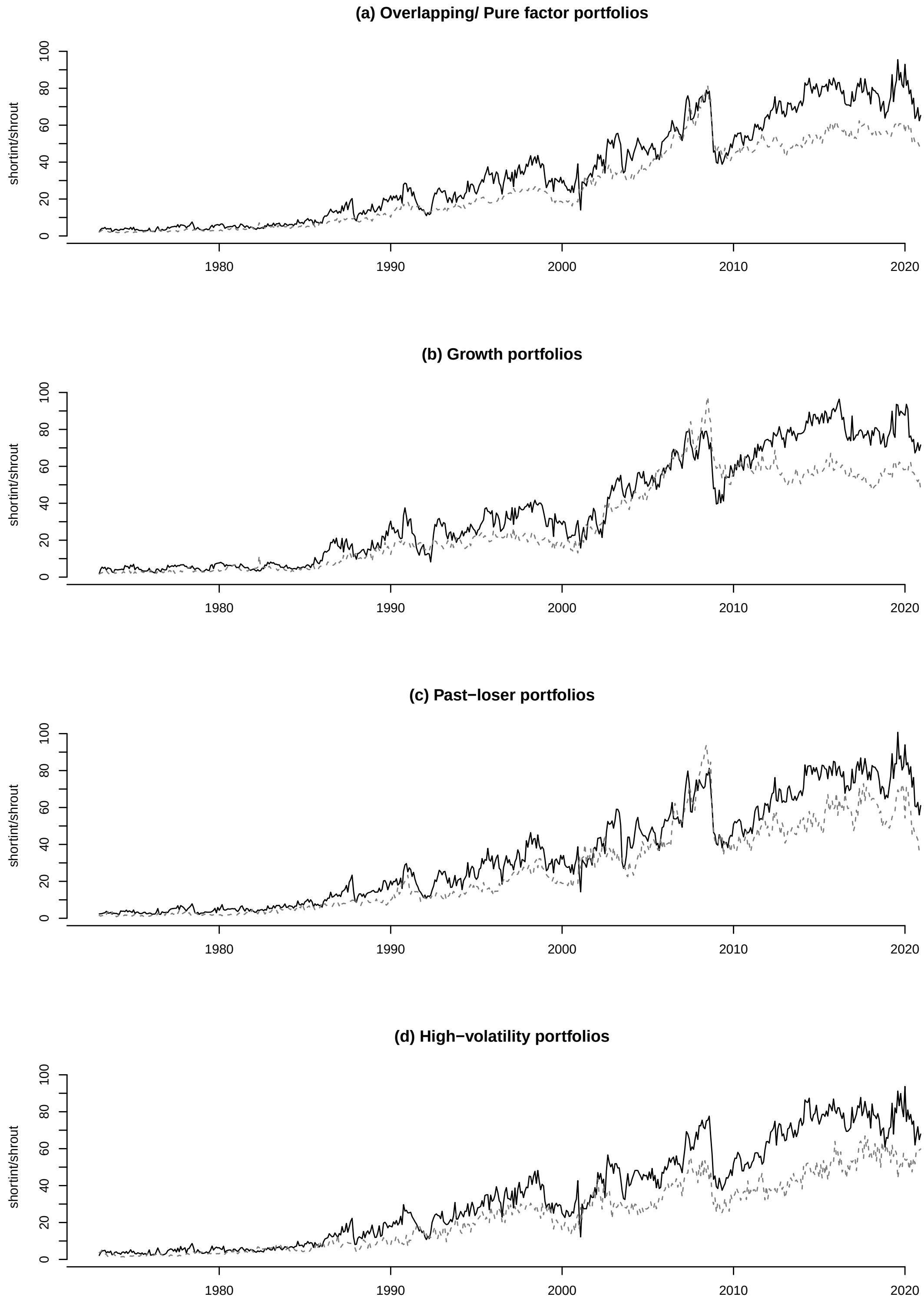


(c) *Residual volatility portfolios (Factor = IVOL)*



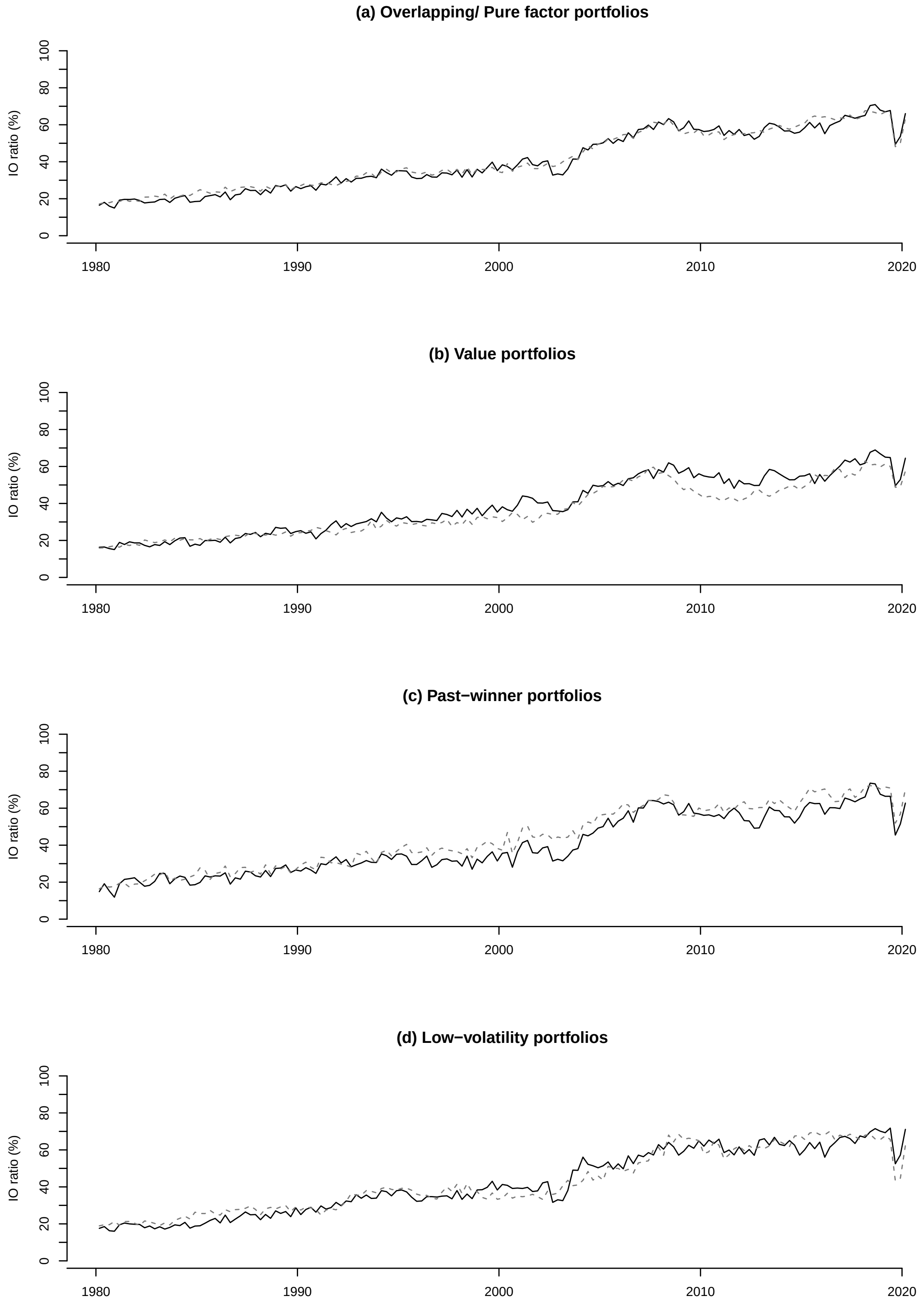
This figure plots the mean returns and time-series alphas of decile portfolios formed on HML (Panel A), MOM (Panel B), and IVOL (Panel C). The time-series regressions of each set of decile portfolios are on CAPM with size (FF2 := CAPM + SMB), FF2 with factor returns, FF2 with returns on the overlapping factor portfolio, and FF2 with returns on the pure factor portfolio. The sample is from 1952:07 to 2020:12 (822 monthly returns).

Figure A2: Short interest in the short legs (equal-weighted)



This figure plots the equal-weighted short interest divided by shares outstanding in the short leg of multiple portfolios. I obtain short interest for each stock from Compustat Supplementary Short Interest File. The sample is from 1952:07 to 2020:12 (822 monthly returns).

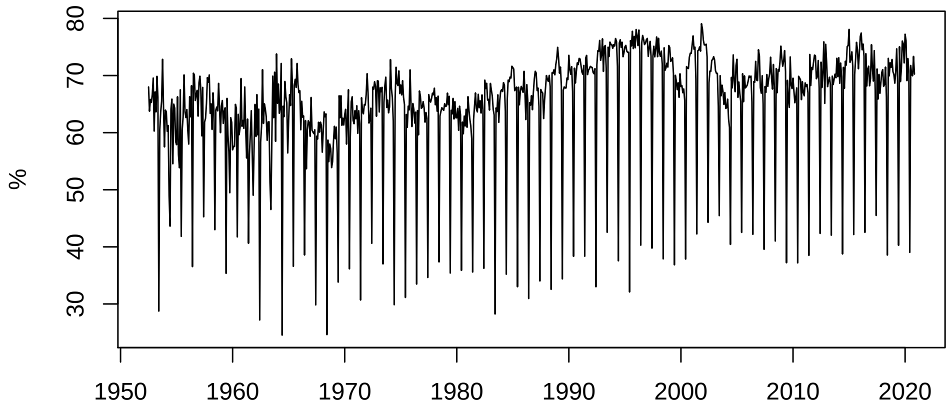
Figure A3: Institutional ownership ratio in the long legs (equal-weighted)



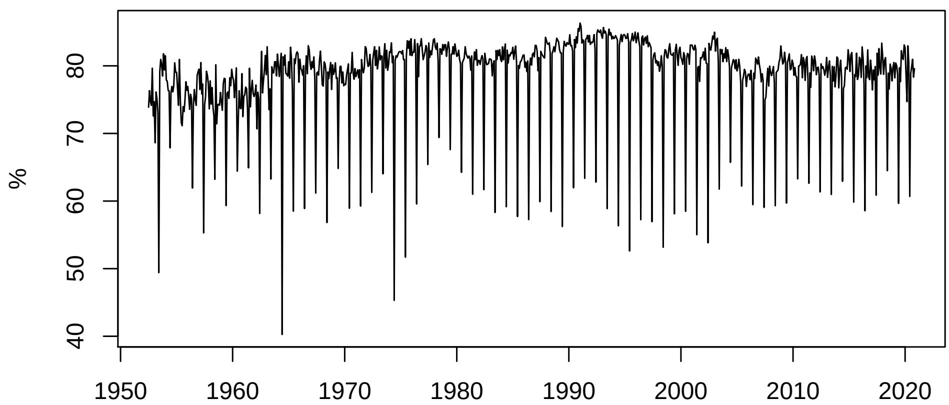
This figure plots the equal-weighted institutional ownership ratio in the long leg of multiple factor portfolios. The IO ratio, in percentage, is the total institutional ownership divided by the total shares outstanding (adjusted). I obtain the total IO from SEC 13F and the adjusted total shares outstanding from CRSP. I keep data at quarter dates end. The sample is from 1980:03 to 2020:03.

Figure A4: Proportion of stocks staying in the portfolio next month in the CMA-RMW-IVOL strategy

(a) *Overlapping portfolio*



(b) *Pure factor portfolio*



This figure plots the proportions of stocks in the overlapping and the pure factor portfolios that stays in the same portfolio in the following month. The sample is from 1952:07 to 2020:12 (822 monthly returns). The portfolio is rebalanced every month.

Table A1: Correlations of firm characteristics and factor returns

Panel A: Correlations between characteristics

	Mkt. cap	B/M	Op. prof.	Δ total assets	12-to-2 return	Resid vol.
Mkt. cap	1.00					
B/M	-0.09	1.00				
Op. prof.	0.02	-0.07	1.00			
Δ total assets	-0.00	-0.09	0.04	1.00		
12-to-2 return	0.03	-0.25	0.02	-0.02	1.00	
Resid vol.	-0.15	0.18	-0.08	0.02	-0.10	1.00

Panel B: Correlations between factor returns

	MKT	HML	RMW	CMA	MOM	IVOL
MKT	1.00					
HML	-0.14	1.00				
RMW	-0.20	-0.28	1.00			
CMA	-0.34	0.65	-0.06	1.00		
MOM	-0.10	-0.22	0.17	-0.08	1.00	
IVOL	-0.57	0.25	0.36	0.48	0.13	1.00

This table shows the correlations between stock characteristics and between the factor returns from 1952:07 to 2020:12 (822 months). We construct each factor using five value-weighted portfolios from characteristic, controlling for size. The monthly size breakpoints are the 30th and 70th NYSE percentile. Stocks are equally divided into quintiles of characteristics. Panel A reports the average correlation between stock characteristics over time. Panel B shows the correlation between factor portfolio returns over time. Factor returns are the returns of the long-short portfolio (Q5-Q1).

Table A2: Pricing decile portfolios

Portfolio	Mean return	FF2 $\hat{\alpha}$	FF2 + Factor $\hat{\alpha}$	FF2 + Factor $\hat{\beta}_{Factor}$	FF2 + Overlapping $\hat{\alpha}$	FF2 + Overlapping $\hat{\beta}^{Factor}_{overlap}$	FF2 + Pure factor $\hat{\alpha}$	FF2 + Pure factor $\hat{\beta}^{Factor}_{pure}$
Panel A: Decile book-to-market portfolios (Factor = HML)								
High	0.889***	0.150	-0.165**	0.909***	-0.094	0.297***	0.232***	0.542***
	(4.26)	(1.35)	(-2.35)	(35.10)	(-0.92)	(13.20)	(2.88)	(26.78)
Low	0.597***	-0.075	0.079*	-0.446***	0.112**	-0.229***	-0.128***	-0.348***
	(3.46)	(-1.23)	(1.76)	(-26.89)	(2.21)	(-20.43)	(-3.41)	(-36.86)
High–Low	0.292*	0.225	-0.244***	1.355***	-0.206	0.526***	0.361***	0.890***
	(1.86)	(1.48)	(-2.95)	(44.52)	(-1.58)	(18.35)	(4.11)	(40.52)
Average $\lvert\hat{\alpha}\rvert$		0.116	0.083		0.076		0.116	
GRS F-stat		2.376	2.980		1.884		5.938	
GRS p-value		0.009	0.001		0.044		0.000	
Panel B: Decile 12-to-2 return portfolios (Factor = MOM)								
Up	1.224***	0.479***	0.028	0.591***	0.081	0.347***	0.298***	0.456***
	(5.94)	(4.63)	(0.43)	(36.27)	(0.96)	(21.96)	(4.89)	(39.49)
Down	-0.014	-0.956***	-0.238**	-0.940***	-0.200*	-0.659***	-0.729***	-0.569***
	(-0.05)	(-5.89)	(-2.38)	(-37.70)	(-1.78)	(-31.22)	(-5.86)	(-24.15)
Up–Down	1.238***	1.435***	0.266***	1.530***	0.281*	1.006***	1.027***	1.025***
	(5.26)	(6.16)	(2.62)	(60.48)	(1.90)	(36.17)	(7.48)	(39.41)
Average $\lvert\hat{\alpha}\rvert$		0.364	0.134		0.121		0.258	
GRS F-stat		5.939	4.366		3.171		6.713	
GRS p-value		0.000	0.000		0.001		0.000	
Panel C: Decile idiosyncratic volatility portfolios (Factor = IVOL)								
Lowvol	0.585***	0.200***	-0.002	0.342***	0.012	0.204***	0.145***	0.281***
	(4.22)	(3.65)	(-0.04)	(20.68)	(0.28)	(19.36)	(3.37)	(20.70)
Highvol	0.046	-0.943***	-0.348***	-1.009***	-0.479***	-0.503***	-0.852***	-0.463***
	(0.14)	(-7.19)	(-4.01)	(-31.01)	(-4.52)	(-20.36)	(-7.17)	(-12.36)
Lowvol–Highvol	0.539**	1.143***	0.346***	1.351***	0.492***	0.707***	0.997***	0.744***
	(1.98)	(7.16)	(3.91)	(40.69)	(4.26)	(26.31)	(7.55)	(17.87)
Average $\lvert\hat{\alpha}\rvert$		0.230	0.143		0.165		0.251	
GRS F-stat		8.006	5.274		5.459		7.874	
GRS p-value		0.000	0.000		0.000		0.000	
Observations		822	822		822		822	

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the time-series regressions of each set of the long and the short characteristic-sorted portfolios on CAPM with size (FF2 := CAPM + SMB), FF2 with factor returns, FF2 with returns on the long–short overlapping portfolio within the factor, and FF2 with returns on the long–short pure factor portfolio within the factor. The sample is 1952:07 to 2020:12 (822 monthly returns). Decile portfolios are retrieved from Kenneth R. French's data library. The first column displays the mean excess return of each portfolio.

Table A3: Consumption risk exposures

	Long		Short		Long–short	
	Overlapping	Pure factor	Overlapping	Pure factor	Overlapping	Pure factor
Panel A: Exposure to quarterly real consumption growth						
CG	0.159	-0.007	0.101	-0.011	0.166	0.112
	(0.59)	(-0.02)	(0.40)	(-0.04)	(0.63)	(1.29)
Constant	0.876***	-0.434	0.510**	0.374	1.310***	0.136
	(3.14)	(-1.12)	(1.99)	(1.34)	(4.85)	(1.53)
Observations	274	274	274	274	274	274
Adjusted R^2	-0.002	-0.004	-0.003	-0.004	-0.002	0.002
Panel B: Exposure to ultimate consumption risk						
UC	-0.032	-0.077	-0.058	-0.058	0.046	-0.000
	(-0.41)	(-0.70)	(-0.80)	(-0.72)	(0.58)	(-0.01)
Constant	1.220**	-0.011	0.973**	0.727	1.231**	0.247
	(2.41)	(-0.02)	(2.04)	(1.38)	(2.36)	(1.46)
Observations	262	262	262	262	262	262
Adjusted R^2	-0.003	-0.002	-0.001	-0.002	-0.003	-0.004
Panel C: Exposure to ultimate consumption risk and consumption growth rate on durable goods						
UC	-0.082	-0.143	-0.094	-0.108	0.061	0.014
	(-1.05)	(-1.27)	(-1.26)	(-1.32)	(0.75)	(0.53)
CG (DG)	1.254***	1.638**	0.879*	1.234**	-0.384	-0.355**
	(2.63)	(2.40)	(1.95)	(2.49)	(-0.78)	(-2.23)
Constant	0.864*	-0.475	0.724	0.377	1.340**	0.347**
	(1.67)	(-0.64)	(1.47)	(0.70)	(2.48)	(2.00)
Observations	262	262	262	262	262	262
Adjusted R^2	0.019	0.016	0.009	0.018	-0.004	0.011
Panel D: Exposure to unfiltered NIPA consumption (nondurables and services)						
Unf. NIPA (NG&S)	0.137	0.229	0.110	0.152	-0.093	-0.042
	(1.28)	(1.52)	(1.09)	(1.37)	(-0.85)	(-1.18)
Constant	0.711**	-0.927**	0.371	0.060	1.637***	0.311***
	(2.25)	(-2.07)	(1.24)	(0.18)	(5.09)	(2.97)
Observations	266	266	266	266	266	266
Adjusted R^2	0.002	0.005	0.001	0.003	-0.001	0.001
Panel E: Exposure to unfiltered NIPA consumption (nondurables only)						
Unf. NIPA (NG)	0.137	0.229	0.110	0.152	-0.093	-0.042
	(1.28)	(1.52)	(1.09)	(1.37)	(-0.85)	(-1.18)
Constant	0.711**	-0.927**	0.371	0.060	1.637***	0.311***
	(2.25)	(-2.07)	(1.24)	(0.18)	(5.09)	(2.97)
Observations	266	266	266	266	266	266
Adjusted R^2	0.002	0.005	0.001	0.003	-0.001	0.001

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the estimated risk exposures to several variables. In all panels, the dependent variable is the excess returns of the overlapping/ pure factor portfolios. CG is the quarterly real consumption growth rate on nodurables and services. UC is the Parker and Julliard (2005)'s quarterly ultimate consumption risk. CG (DG) is the quarterly real consumption growth rate on durable goods. Unfiltered NIPA consumption measured are obtained from Kroencke (2017). The sample is from 1952:Q3 to 2020:Q4.

Table A4: Portfolio performance on different subsample periods

	Return				Sharpe	Distribution				CAPM		Average characteristic			
Portfolio	Mean (%)	Min. (%)	Max. (%)	Volatility (%)	ratio	Positive (%)	Negative (%)	Skewness	Kurtorsis	$\hat{\alpha}$	$\hat{\beta}_{MKT}$	Log-mkt cap	Value	Momentum (%)	Resid. vol. (%)
Panel A: Subsample 1952:07 - 1980:12															
Market	0.583	-12.685	16.530	4.099	0.142	58.772	41.228	-0.210	1.097			4.297	0.608	14.890	1.129
Overlapping portfolio															
Long	0.937	-18.341	14.176	4.183	0.224	60.819	39.181	-0.251	1.335	0.403***	0.915***	4.390	0.836	30.835	1.021
Short	0.151	-17.907	23.175	5.613	0.027	50.292	49.708	0.117	1.472	-0.587***	1.265***	4.086	0.443	1.712	1.534
Long–short	0.786	-14.331	10.492	3.525	0.223	59.649	40.351	-0.324	1.243	0.990***	-0.350***	0.304	0.392	29.123	-0.513
Pure factor portfolio (across all factors)															
Long	0.625	-13.652	12.623	3.953	0.158	60.526	39.474	-0.395	0.843	0.072*	0.949***	4.327	0.616	18.706	1.044
Short	0.562	-15.807	19.802	4.395	0.128	57.018	42.982	-0.216	1.444	-0.044	1.040***	4.302	0.473	14.067	1.163
Long–short	0.063	-7.853	4.169	1.279	0.049	51.170	48.830	-0.764	5.373	0.116*	-0.091***	0.025	0.143	4.639	-0.119
EW. multi-factor	0.383	-8.508	6.381	1.819	0.210	64.327	35.673	-0.489	3.910	0.491***	-0.186***	0.128	0.245	16.675	-0.277
HML	0.176	-13.505	12.394	3.247	0.054	54.094	45.906	0.066	1.740	0.239*	-0.107**	-0.581	1.015	0.905	0.059
MOM	0.969	-14.128	19.642	3.941	0.246	62.573	37.427	-0.182	2.410	0.963***	0.403	-0.259	57.056	-0.029	
IVOL	0.002	-13.661	11.557	3.272	0.001	53.801	46.199	-0.170	1.643	0.271	-0.461***	0.564	-0.023	-7.936	-0.860

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Portfolio statistics on different subsample periods (continued)

	Return				Sharpe	Distribution				CAPM		Average characteristic			
Portfolio	Mean (%)	Min. (%)	Max. (%)	Volatility (%)	ratio	Positive (%)	Negative (%)	Skewness	Kurtorsis	$\hat{\alpha}$	$\hat{\beta}_{MKT}$	Log-mkt cap	Value	Momentum (%)	Resid. vol. (%)
Panel B: Subsample 1981:01 - 2000:12															
Market	0.751	-22.883	12.524	4.371	0.172	60.417	39.583	-0.779	3.516			4.458	0.557	25.067	1.555
Overlapping portfolio															
Long	1.210	-20.860	12.566	4.023	0.301	63.750	36.250	-0.655	3.493	0.611***	0.797***	4.486	0.826	38.909	1.233
Short	0.206	-27.080	15.882	6.226	0.033	52.500	47.500	-0.397	1.510	-0.761***	1.288***	3.746	0.409	15.744	2.305
Long–short	1.004	-8.892	19.650	4.411	0.228	60.833	39.167	0.334	1.193	1.372***	-0.490***	0.740	0.417	23.164	-1.071
Pure factor portfolio (across all factors)															
Long	0.957	-22.175	12.507	4.544	0.211	61.250	38.750	-0.610	2.801	0.200***	1.008***	4.513	0.569	38.001	1.504
Short	0.843	-21.057	12.478	4.692	0.180	60.000	40.000	-0.506	1.657	0.059	1.044***	4.380	0.443	24.933	1.650
Long–short	0.114	-3.025	7.968	1.480	0.077	48.750	51.250	1.036	3.386	0.142	-0.036*	0.133	0.126	13.068	-0.146
EW. multi-factor	0.420	-5.729	7.993	2.284	0.184	60.000	40.000	0.096	0.688	0.583***	-0.217***	0.450	0.240	19.415	-0.549
HML	0.316	-15.148	13.736	3.902	0.081	53.750	46.250	0.105	1.518	0.569**	-0.337***	-0.620	0.935	-8.975	-0.268
MOM	0.498	-15.502	25.824	5.083	0.098	56.667	43.333	0.363	4.312	0.343	0.207***	0.956	-0.316	81.215	-0.130
IVOL	0.446	-15.752	25.139	4.366	0.102	57.083	42.917	0.527	4.746	0.836***	-0.519***	1.012	0.100	-13.996	-1.251

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Portfolio statistics on different subsample periods (continued)

Portfolio	Return				Sharpe	Distribution				CAPM		Average characteristic			
	Mean (%)	Min. (%)	Max. (%)	Volatility (%)	ratio	Positive (%)	Negative (%)	Skewness	Kurtosis	$\hat{\alpha}$	$\hat{\beta}_{MKT}$	Log-mkt cap	Value	Momentum (%)	Resid. vol. (%)
Panel C: Subsample 2001:01 - 2020:12															
Market	0.647	-17.174	13.660	4.480	0.145	64.167	35.833	-0.517	1.154			6.132	0.419	14.323	1.302
Overlapping portfolio															
Long	0.721	-19.639	11.730	4.201	0.172	61.667	38.333	-0.919	2.362	0.193	0.817^{***}	6.345	0.655	32.522	1.095
Short	0.599	-25.000	30.384	7.964	0.075	54.583	45.417	0.078	2.240	-0.425^{*}	1.581^{***}	5.401	0.428	-1.130	2.013
Long–short	0.122	-31.374	25.001	6.217	0.020	55.000	45.000	-0.816	5.952	0.617^{*}	-0.764^{***}	0.944	0.228	33.652	-0.917
Pure factor portfolio (across all factors)															
Short	0.653	-17.076	15.688	4.289	0.152	63.333	36.667	-0.443	1.667	0.048	0.934^{***}	6.177	0.453	21.169	1.242
Short	0.686	-19.194	15.692	4.785	0.143	62.917	37.083	-0.505	1.545	0.009	1.045^{***}	6.157	0.326	12.708	1.389
Long–short	-0.033	-7.880	11.717	1.616	-0.020	48.750	51.250	0.743	13.851	0.039	-0.111^{***}	0.020	0.127	8.461	-0.147
EW. multi-factor	0.019	-21.225	21.032	3.657	0.005	50.833	49.167	-0.370	10.959	0.288	-0.415^{***}	0.474	0.150	21.382	-0.483
HML	-0.221	-14.939	19.781	3.610	-0.061	45.833	54.167	0.337	4.686	-0.260	0.060	-0.736	0.861	-2.675	-0.082
MOM	0.162	-35.169	16.686	6.216	0.026	52.917	47.083	-1.506	7.924	0.528	-0.565^{***}	0.901	-0.330	70.903	-0.226
IVOL	0.116	-19.845	26.885	5.291	0.022	47.083	52.917	0.315	4.587	0.595^{**}	-0.740^{***}	1.258	-0.081	-4.082	-1.141

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the summary statistics of overlapping/ pure factor portfolio value-weighted returns, in excess of the risk-free rate, comparing to the market and factor returns. Market is the excess returns of the CRSP U.S. total market index. The risk-free rate is from Kenneth R. French's Data Library. The last four columns present the averages over time of the value-weighted characteristic of stocks in each portfolio. The EW. multi-factor portfolio is the equal-weighted combination of the three factors. Note that the pure factor portfolio contains pure HML, pure MOM, and pure IVOL stocks.

Table A5: Fraction of pure factor and overlapping stocks based on NYSE breakpoints

	Long leg	Short leg
Panel A: In the universe of stocks		
Pure factor	0.381	0.346
Pure HML	0.105	0.137
Pure MOM	0.156	0.082
Pure IVOL	0.120	0.127
Overlapping	0.087	0.204
HML & MOM	0.031	0.034
HML & IVOL	0.024	0.061
MOM & IVOL	0.026	0.065
HML & MOM & IVOL	0.006	0.044
Panel B: In each factor portfolio		
HML	1.000	1.000
Pure HML	0.634	0.495
Overlapping HML	0.366	0.505
HML & MOM	0.188	0.122
HML & IVOL	0.145	0.222
HML & MOM & IVOL	0.033	0.161
MOM	1.000	1.000
Pure MOM	0.713	0.365
Overlapping MOM	0.287	0.635
HML & MOM	0.142	0.149
MOM & IVOL	0.120	0.289
HML & MOM & IVOL	0.025	0.197
IVOL	1.000	1.000
Pure IVOL	0.683	0.426
Overlapping IVOL	0.317	0.574
HML & IVOL	0.137	0.206
MOM & IVOL	0.149	0.219
HML & MOM & IVOL	0.031	0.149

This table reports the average fraction of pure factor/ overlapping stocks in the data versus the benchmark fraction in the strategy that invests equally in HML, MOM, and IVOL. The benchmark fractions are given by $f_S(k) = \binom{S}{k}\left(\frac{1}{5}\right)^k\left(\frac{4}{5}\right)^{S-k}, k = 0, \ldots, S$ for $S = 3$. The benchmark is the same for the long leg and the short leg. The empirical fractions are the average of fractions in each month per portfolio.

Table A6: Portfolio performance with sorting based on NYSE breakpoints

	Return				Sharpe	Distribution				CAPM		Average characteristic			
Portfolio	Mean (%)	Min. (%)	Max. (%)	Volatility (%)	ratio	Positive (%)	Negative (%)	Skewness	Kurtosis	$\hat{\alpha}$	$\hat{\beta}_{MKT}$	Log-mkt cap	B/M	Prior-ret (%)	Resid. vol. (%)
Market	0.651	-22.883	16.530	4.288	0.152	60.827	39.173	-0.485	1.881			4.880	0.538	17.696	1.304
Overlapping portfolio															
Long	0.944	-20.900	13.934	4.173	0.226	61.922	38.078	-0.521	2.123	0.389***	0.853***	5.035	0.770	34.108	1.094
Short	0.325	-27.572	29.855	6.291	0.052	52.068	47.932	-0.010	2.139	-0.547***	1.340***	4.273	0.428	6.662	1.895
Long–short	0.619	-28.638	23.481	4.435	0.140	58.516	41.484	-0.582	5.420	0.936***	-0.487***	0.762	0.342	27.446	-0.800
Pure factor portfolio (across all factors)															
Long	0.734	-22.879	15.179	4.244	0.173	61.436	38.564	-0.537	1.997	0.107***	0.965***	4.959	0.551	25.797	1.240
Short	0.728	-21.602	20.093	4.481	0.162	59.854	40.146	-0.386	1.599	0.065*	1.018***	4.866	0.418	17.890	1.340
Long–short	0.007	-8.107	9.995	1.317	0.005	50.000	50.000	0.115	6.647	0.042	-0.054***	0.093	0.133	7.906	-0.101
EW. multi-factor	0.276	-18.610	16.991	2.453	0.112	60.097	39.903	-0.742	10.404	0.441***	-0.254***	0.479	0.219	18.295	-0.423
HML	0.094	-15.486	16.656	3.446	0.027	52.068	47.932	0.046	2.311	0.165	-0.109***	-0.461	0.958	-2.658	-0.085
MOM	0.580	-34.247	20.597	4.691	0.124	58.637	41.363	-0.827	6.531	0.650***	-0.109***	0.754	-0.293	65.780	-0.124
IVOL	0.154	-19.823	21.667	4.076	0.038	53.406	46.594	0.023	4.013	0.508***	-0.544***	1.144	-0.008	-8.237	-1.060

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the summary statistics of overlapping/ pure factor portfolio value-weighted returns, in excess of the risk-free rate, comparing to the market and factor returns. The sample is from 1952:07 to 2020:12 (822 monthly returns). Market is the excess returns of the CRSP U.S. total market index. The risk-free rate is from Kenneth R. French's Data Library. The last four columns present the averages over time of the value-weighted characteristic of stocks in each portfolio. The EW. multi-factor portfolio is the equal-weighted combination of the three factors. Note that the uni-signal portfolio contains the total set of pure HML, pure MOM, and pure IVOL stocks.

Table A7: Fama–MacBeth cross-sectional regressions with sorting by NYSE breakpoints

	(1)	(2)	(3)	(4)	(5)
Panel A: Cross-section of 25 size×value, 25 size×momentum, and 25 size×volatility portfolios					
λ_{MKT}	-1.038***	0.753**	0.365	-0.646***	0.476*
	(-6.21)	(2.18)	(1.40)	(-3.43)	(1.75)
λ_{SMB}	0.134***	0.216***	0.167***	0.118**	0.182***
	(2.59)	(3.81)	(3.23)	(2.28)	(3.44)
λ_{HML}		0.248**			
		(2.52)			
λ_{MOM}		0.685***			
		(6.88)			
λ_{IVOL}		0.344***			
		(3.63)			
$\lambda^{3F}_{overlap}$			1.151***		1.255***
			(9.01)		(8.34)
λ^{3F}_{pure}				0.492***	-0.101
				(5.06)	(-0.72)
λ_0	1.748***	-0.117	0.279	1.374***	0.146
	(10.45)	(-0.32)	(1.04)	(7.35)	(0.51)
Adjusted R^2	0.309	0.772	0.698	0.422	0.724
Panel B: Cross-section of 25 size×net share issues and 25 size×accruals portfolios					
λ_{MKT}	-0.704**	0.379	0.183	-0.607*	0.202
	(-2.25)	(0.81)	(0.38)	(-1.89)	(0.42)
λ_{SMB}	0.168***	0.111	0.147**	0.117*	0.109
	(2.82)	(1.34)	(2.43)	(1.65)	(1.55)
λ_{HML}		0.530**			
		(1.96)			
λ_{MOM}		2.350**			
		(2.49)			
λ_{IVOL}		0.209			
		(0.78)			
$\lambda^{3F}_{overlap}$			1.093***		1.227***
			(2.95)		(3.12)
λ^{3F}_{pure}				0.458	0.402
				(1.49)	(1.30)
λ_0	1.354***	0.259	0.447	1.277***	0.444
	(4.31)	(0.55)	(0.92)	(4.00)	(0.92)
Adjusted R^2	0.325	0.662	0.486	0.380	0.525

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the second-stage cross-sectional regressions by Fama and MacBeth (1973) on the returns of 75 portfolios formed on size×value, size×momentum, and size×volatility (Panel A) and 50 portfolios formed on size×net share issues and size×accruals (Panel B). Double sorted portfolios are retrieved from Kenneth R. French's data library.

Table A8: Fama–MacBeth cross-sectional regressions on individual factors with sorting by NYSE breakpoints

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Cross-section of 25 size×value portfolios								
λ_{MKT}	-1.237***	-0.656	-0.367	-1.108**	-0.307	-0.621	-0.886	0.028
	(-2.61)	(-1.11)	(-0.51)	(-2.06)	(-0.42)	(-0.99)	(-1.62)	(0.03)
λ_{SMB}	0.083	0.122	0.133	0.090	0.137	0.124	0.114	0.139
	(1.06)	(1.48)	(1.57)	(1.13)	(1.61)	(1.49)	(1.39)	(1.63)
λ_{HML}		0.275***						
		(2.79)						
$\lambda^{3F}_{overlap}$			0.927***		1.039***			
			(2.70)		(2.67)			
λ^{3F}_{pure}				0.182	-0.091			
				(0.80)	(-0.32)			
$\lambda^{HML}_{overlap}$						0.655***		1.399
						(2.85)		(1.63)
λ^{HML}_{pure}							0.267	-0.358
							(1.14)	(-0.61)
λ_0	1.967***	1.314**	1.023	1.826***	0.959	1.281*	1.554***	0.638
	(4.19)	(2.14)	(1.35)	(3.34)	(1.26)	(1.95)	(2.74)	(0.66)
Adjusted R^2	0.397	0.543	0.534	0.384	0.537	0.512	0.477	0.543
Panel B: Cross-section of 25 size×momentum portfolios								
λ_{MKT}	-1.511***	-0.395	0.629	-0.387	0.680	-0.170	-0.636*	0.310
	(-4.98)	(-1.09)	(1.28)	(-1.05)	(0.80)	(-0.44)	(-1.85)	(0.42)
λ_{SMB}	0.190**	0.227**	0.179*	0.099	0.184	0.202**	0.207**	0.196**
	(2.01)	(2.40)	(1.89)	(1.03)	(1.62)	(2.13)	(2.18)	(2.06)
λ_{MOM}		0.723***						
		(6.95)						
$\lambda^{3F}_{overlap}$			1.153***		1.186**			
			(6.72)		(2.48)			
λ^{3F}_{pure}				0.750***	0.037			
				(6.02)	(0.07)			
$\lambda^{MOM}_{overlap}$						1.097***		1.527***
						(6.98)		(2.61)
λ^{MOM}_{pure}							0.918***	0.450
							(5.18)	(1.22)
λ_0	2.208***	1.173***	0.058	1.168***	0.002	0.931**	1.434***	0.406
	(6.99)	(3.21)	(0.12)	(3.16)	(0.00)	(2.38)	(4.13)	(0.51)
Adjusted R^2	0.375	0.878	0.865	0.833	0.859	0.855	0.829	0.857
Panel C: Cross-section of 25 size×volatility portfolios								
λ_{MKT}	-0.702***	0.931**	0.692	-1.148***	0.234	0.757*	0.433	0.377
	(-2.81)	(2.05)	(1.64)	(-3.99)	(0.42)	(1.71)	(0.89)	(0.77)
λ_{SMB}	0.080	0.158	0.207*	-0.031	0.132	0.197*	0.053	0.353***
	(0.77)	(1.50)	(1.91)	(-0.28)	(1.08)	(1.83)	(0.51)	(2.61)
λ_{IVOL}		0.398***						
		(3.66)						
$\lambda^{3F}_{overlap}$			1.521***		0.908			
			(4.79)		(1.58)			
λ^{3F}_{pure}				-1.654***	-0.688			
				(-3.08)	(-1.09)			
$\lambda^{IVOL}_{overlap}$						1.161***		2.226***
						(4.86)		(3.66)
λ^{IVOL}_{pure}							1.057***	-1.531*
							(3.12)	(-1.87)
λ_0	1.428***	-0.355	-0.108	1.777***	0.329	-0.150	0.257	0.173
	(5.90)	(-0.74)	(-0.24)	(6.67)	(0.59)	(-0.32)	(0.52)	(0.35)
Adjusted R^2	0.150	0.697	0.630	0.416	0.665	0.600	0.339	0.699

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the second-stage cross-sectional regressions by Fama and MacBeth (1973) on the returns of 25 portfolios formed on size×value (Panel A), size×momentum (Panel B), and size×volatility (Panel C). Double sorted portfolios are retrieved from Kenneth R. French's data library.

Table A9: Portfolio performance of the HML-MOM-IVOL strategy (quarterly rebalancing)

	Return (percentage per quarter)				Sharpe	Distribution				CAPM		Average characteristic			
Portfolio	Mean (%)	Min. (%)	Max. (%)	Volatility (%)	ratio	Positive (%)	Negative (%)	Skewness	Kurtosis	$\hat{\alpha}$	$\hat{\beta}_{MKT}$	Log-mkt. cap	B/M	Prior-ret (%)	Resid. vol. (%)
Makret	0.387	-12.887	10.745	3.857	0.100	59.489	40.511	-0.592	0.990			4.891	0.541	18.029	1.274
Overlapping portfolio															
Long	0.949	-19.639	13.550	4.134	0.230	63.869	36.131	-0.842	3.436	0.611^{***}	0.936^{***}	5.007	0.775	34.454	1.085
Short	-0.437	-22.622	20.505	5.743	-0.076	47.810	52.190	-0.488	2.152	-0.922^{***}	1.344^{***}	4.380	0.443	4.536	1.876
Long–Short	1.386	-16.181	16.024	4.000	0.346	63.869	36.131	0.453	2.765	1.533^{***}	-0.408^{***}	0.627	0.332	29.918	-0.791
Pure factor portfolio (across all factors)															
Long	0.556	-13.652	12.455	3.791	0.147	60.219	39.781	-0.381	1.374	0.213^{***}	0.952^{***}	4.942	0.554	25.273	1.201
Short	0.369	-15.807	11.622	4.138	0.089	56.569	43.431	-0.528	0.902	-0.003	1.030^{***}	4.867	0.419	17.242	1.340
Long–Short	0.188	-4.259	4.325	1.325	0.142	50.730	49.270	0.407	0.948	0.216^{***}	-0.078^{***}	0.075	0.135	8.032	-0.138
EW. multi-factor	0.746	-7.460	11.777	2.158	0.346	65.693	34.307	1.056	4.501	0.828^{***}	-0.227^{***}	0.338	0.210	19.155	-0.423
HML	0.151	-15.148	13.736	3.488	0.043	53.650	46.350	-0.050	3.187	0.174	-0.064	-0.641	0.941	-2.072	-0.067
MOM	1.480	-14.122	21.489	4.384	0.338	66.788	33.212	0.475	3.223	1.507^{***}	-0.074	0.757	-0.297	68.584	-0.157
IVOL	0.607	-12.885	17.680	3.709	0.164	58.029	41.971	0.726	3.939	0.802^{***}	-0.542^{***}	0.897	-0.014	-9.045	-1.045

This table reports the summary statistics of overlapping/ pure factor portfolio value-weighted returns, in excess of the risk-free rate, comparing to the market and factor returns. The sample is from 1952:Q3 to 2020:Q4 (274 quaterly returns). Market is the excess returns of the CRSP U.S. total market index. The risk-free rate is from Kenneth R. French's Data Library. The last four columns present the averages over time of the value-weighted characteristic of stocks in each portfolio. The EW. multi-factor portfolio is the equal-weighted combination of the three factors. Portfolios are rebalanced every quarter, using the characteristic scores at quarter ends. Note that the pure factor portfolio contains pure HML, pure MOM, and pure IVOL stocks.

Table A10: Fama–MacBeth cross-sectional regressions (quarterly rebalancing)

	(1)	(2)	(3)	(4)	(5)
Panel A: Cross-section of 25 size×value, 25 size×momentum, and 25 size×volatility portfolios					
λ_{MKT}	-1.884***	1.338**	-0.160	-0.894***	-0.206
	(-7.40)	(2.43)	(-0.46)	(-3.05)	(-0.57)
λ_{SMB}	0.314***	0.414***	0.296***	0.281***	0.292***
	(3.73)	(4.65)	(3.54)	(3.34)	(3.48)
λ_{HML}		0.114			
		(0.74)			
λ_{MOM}		1.406***			
		(9.10)			
λ_{IVOL}		0.797***			
		(5.25)			
$\lambda^{3F}_{overlap}$			2.244***		2.156***
			(9.55)		(7.26)
λ^{3F}_{pure}				1.073***	0.397*
				(7.72)	(1.68)
λ_0	2.338***	-0.944*	0.410	1.263***	0.466
	(8.96)	(-1.67)	(1.12)	(4.15)	(1.21)
Adjusted R^2	0.409	0.919	0.736	0.693	0.738
Panel B: Cross-section of 25 size×net share issues and 25 size×accruals portfolios					
λ_{MKT}	-0.628	0.554	0.284	-0.507	0.254
	(-1.33)	(0.87)	(0.52)	(-1.07)	(0.44)
λ_{SMB}	0.399***	0.421***	0.324***	0.362***	0.324***
	(4.17)	(3.87)	(3.30)	(3.73)	(3.30)
λ_{HML}		0.383			
		(1.25)			
λ_{MOM}		1.730*			
		(1.74)			
λ_{IVOL}		0.408			
		(1.25)			
$\lambda^{3F}_{overlap}$			1.584***		1.576***
			(3.39)		(3.36)
λ^{3F}_{pure}				0.641**	0.268
				(2.49)	(0.89)
λ_0	1.068**	-0.128	0.115	0.917*	0.144
	(2.22)	(-0.20)	(0.21)	(1.89)	(0.25)
Adjusted R^2	0.513	0.752	0.697	0.624	0.699

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table reports the second-stage cross-sectional regressions by Fama and MacBeth (1973) on the returns of 75 portfolios formed on size×value, size×momentum, and size×volatility (Panel A) and 50 portfolios formed on size×net share issues and size×accruals (Panel B). Double sorted portfolios are retrieved from Kenneth R. French's data library. The sample is from 1963:Q3 to 2020:Q4.