Market Risk and the Momentum Mystery

James W. Kolari,* and Wei Liu†

February 7, 2019

Abstract

This paper employs an asset pricing model to show that momentum returns are highly related to market risk arising from return dispersion (RD). Cross-sectional tests show that momentum risk loadings and RD risk loadings are similarly priced in momentum portfolios. Comparative analyses find that zero-investment momentum portfolios and zero-investment return dispersion portfolios earn high returns relative to other risk factors. Further regression tests indicate that zero-investment momentum returns are very significantly related to zero-investment return dispersion returns. We conclude that the momentum mystery is explained by market risk associated with return dispersion for the most part.

*The corresponding author is JP Morgan Chase Professor of Finance, Texas A&M University, Department of Finance, College Station, TX 77843-4218
Office phone: 979-845-4803
Email address: j-kolari@tamu.edu

†Quantitative Risk Analyst Senior, USAA Bank, Chief Risk Office, San Antonio, TX 78288
Office phone: 979-224-7276
Email address: yuna0831@gmail.com

The authors gratefully acknowledge financial support from the Teachers Retirement System of Texas. Helpful discussions and comments have been provided Ali Anari, Will Armstrong, Jaap Bos, Yong Chen, Gjergji Cici, Lammertjan Dam, Paige Fields, Markus Franke, Britt Harris, Hogyu Jhang, Hwagyun Kim, Johan Knif, Anestis Ladas, Scott Lee, Qi Li, Francisco Penaranda, Ralitsa Petkova, Seppo Pynnönen, Katharina Schüller, William Smith, Sorin Sorescu, Mark Westerfield, Jian Yang, Nan Yang, Christopher Yost-Bremm, Jun Zhang, Zhao Xin, and Tony van Zijl.

Market Risk and the Momentum Mystery

1 Introduction

Now famous work by Jegadeesh and Titman (1993) shows that abnormal trading profits can be earned on simple, relative-strength momentum strategies that buy (sell) recent winners (losers). For example, in the period 1965 to 1989, trading profits of about 12 percent per year are produced by constructing zero-investment portfolios with long (short) positions in high (low) return stocks in the past 6 months and holding them for the next 6 months. Numerous studies prove that this momentum effect is persistent in stock returns.[1] As observed by Daniel (2014), momentum has been documented to exist for a wide variety of asset classes, including bonds, commodities, currencies, and exchange-traded funds, and is commonly used by investment managers. Moskowitz, Ooi, and Pedersen (2012) find that momentum profits are pervasive across different futures and forwards contracts that span a broad spectrum of asset classes and markets. Due to its widespread recognition among academics and practitioners, in the context of various anomalous patterns in average stock returns, Fama and French (2008) consider momentum to be the premier puzzle in financial economics. Because momentum is so simple yet enables investors to outperform the general market, Subrahmanyam (2018) considers momentum to be the biggest challenge to the efficient markets hypothesis (see Petruno (2018)). In an attempt to better understand the momentum anomaly, a growing body of research has sought to investigate behavioral theories (e.g., Barberis, Shleifer, and Vishny

[1]The momentum literature is extensive. For example, see studies and citations therein by Conrad and Kaul (1998), Rouwenhorst (1998), Moskowitz and Grinblatt (1999), Grundy and Martin (2001), Jegadeesh and Titman (2001), Chordia and Shivakumar (2002), Lewellen (2002), Griffin, Ji, and Martin (2003), Cooper, Gutierrez, and Hameed (2004), Fama and French (2008), Gutierrez and Kelley (2008), Liu and Zhang (2008), Novy-Marx (2012), Asness, Moskowitz, and Pedersen (2013), Kim and Choi (2014), Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016), Hou, Xue, and Zhang (2017), Chang, Ko, Nakano, and Rhee (2018), Goyal and Jegadeesh (2018), and others. Other contrarian trading strategies investigate short-term reversal in a week or month (e.g., Jegadeesh (1990), Lehman (1990), and Lo and MacKinlay (1990)) among others) as well as long-term reversals in three-to-five years (e.g., DeBondt and Thaler (1985, 1987), Andrei and Cujean (2017), and Conrad and Yavuz (2017)) that can yield significant abnormal investor returns.

(1998), Daniel Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), Brav and Heaton (2002), George and Hwang (2004), Grinblatt and Han (2005), Da, Gurun, and Warachka (2014), Luo, Subrahmanyam, and Titman (2018), and others) as well as rational explanations (e.g., Fama and French (1996), Johnson (2002), Sagi and Seasholes (2007), and others). Subrahmanyam (2018) provides an excellent synthesis of the growing theoretical and empirical research on momentum and concludes that no consensus exists on its root cause. He recommends that future research should focus on empirical tests of potential drivers of momentum that help explain whether it emanates from behavioral versus rational phenomenon.

This paper hypothesizes that momentum profits are rationally explained in large part by market risk as reflected in cross-sectional return dispersion. Recent work by Liu, Kolari, and Huang (2018) develops an asset pricing model dubbed the ZCAPM that posits market risk is comprised of two components: (1) beta risk related to the average return of all assets in the market, and (2) zeta risk associated with the cross-sectional standard deviation of returns, i.e., return dispersion (RD). The authors propose an empirical version of the ZCAPM that takes into account the sensitivity of an asset to return dispersion (or zeta risk) and show that it is highly significant in cross-sectional tests of U.S. stocks returns. Here we apply the ZCAPM to the problem of understanding what explains momentum profits. No previous studies investigate the relation between momentum profits and return dispersion.

To test our momentum hypothesis, we conduct three related tests using U.S. stocks in the sample period 1965 to 2017. First, cross-sectional tests of momentum portfolios find that estimated loadings for RD and momentum returns are very similarly priced. For example, we initially conduct tests based on momentum portfolio returns downloaded from Kenneth French's online data library. Using 25 size-momentum portfolios with equal-weighted returns, the market prices of RD and momentum loadings have t-values of 6.65 and 6.39, respectively. Using value-weighted returns for these portfolios, their t-values are 5.54 and 3.20, respectively. Further analyses with stocks sorted into 25 momentum portfolios and 25 zeta risk portfolios corroborate these findings. Other popular factors, such as size, value, profit, and investment, have lower and less consistent significance in these asset pricing tests. We infer that RD and momentum loadings are similarly priced in the cross-section of stock returns among portfolios constructed from past returns and zeta risk levels. Second, we compare the returns and risks of zero-investment momentum portfolios to those of zero-investment, return dispersion mimicking portfolios based on zeta risk. A 12-month estimation period is used to sort stocks into zeta risk portfolios, and post-formation monthly returns are computed. The zero-investment return dispersion portfolio based on high-decile/low-decile zeta risk returns earns on average 1.50 percent per month, which outperforms the traditional momentum zero-investment portfolio using high-decile/low-decile past returns at 0.94 percent per month. Combining these two zero-invesetment portfolios into a hybrid strategy, average returns in excess of 1.50 percent per month can be earned. Other zero-investment portfolios, including the size, value, profit, and capitial investment factors of Fama and French (1992, 1993, 1995, 2015), earn at most 0.34 percent per month. Third, and last, we regress zero-investment momentum returns on zero-investmern return dispersion returns in addition to the aforementioned multifactors. We find a very close relationship between zero-investment momentum returns and zero-investment return dispersion returns with an estimated t-value on their regression coefficient of 38.02 and adjusted R^2 value of 69 percent, whereas other factors have at most an estimated R^2 of 5 percent. Based on these findings, we conclude that momentum returns are explained by market risk arising from return dispersion for the most part.

The next section overviews the ZCAPM. Section 3 discusses empirical methods. Section 4 presents the empirical results. The last section concludes.

2 Overview of the ZCAPM

An extensive literature exists that theoretically justifies cross-sectional return dispersion (RD) as a risk factor due to its close association with fundamental economic variables, including unemployment rates, economic uncertainty, economic restructuring, business cycles, and market volatility caused by various macroeconomic shocks.[2] Exemplary of these studies, Gomes, Kogan, and Zhang (2003) and Zhang (2005) find significant relationships between RD and macroeconomic states as well as stock returns.[3] Given its importance as a market risk factor, numerous studies incorporate RD in asset pricing models. For example, Jiang (2010) augments the market factor with RD. Demirier and Jategaonkar (2013) find that RD is more significantly priced when market returns are relatively high rather than at other times. Garcia, Mantilla-Garcia, and Martellini (2014) and Chichernea, Holder, and Petkevich (2015) add RD to Fama and French's (1992, 1993, 1995) three-factor model and find that it is significantly priced in cross-sectional tests.

Extending the aforementioned asset pricing studies, Liu, Kolari, and Huang (2018) propose that market risk factor RD can have both positive and negative effects on asset returns. If RD increases, assets with positive (negative) sensitivity will experience increasing (decreasing) returns, and vice versa if RD decreases. Consistent with these asymmetric RD effects, they specify the following time series return generating process for the expected excess return of asset i:

$$E(\widetilde{R}_{it}) - R_{ft} = \beta_i[E(\widetilde{R}_{mt}) - R_{ft}] + Z_i^{\pm}\widetilde{\sigma}_{mt}, \tag{1}$$

where R_{ft} is the riskless rate at time t, beta risk coefficient β_i measures sensitivity to expected excess market returns denoted $E(\widetilde{R}_{mt}) - R_{ft}$, zeta risk coefficient $Z_i^{\pm}$ measures

[2] See Loungani, Rush, and Tave (1990), Christie and Huang (1994), Bekaert and Harvey (1997, 2000), Connolly and Stivers (2003), Stivers (2003), Bansal and Yaron (2004), Pastor and Veronesi (2009), Bansal, Kiku, Shaliastovich, and Yaron (2014), Angelidis, Sakkas, and Tessaromatis (2015), among others.

[3] See also Garcia, Mantilla-Garcia, and Martellini (2014), who link stock return dispersion to aggregate idiosyncratic risk.

positive or negative sensitivity to RD, and $\widetilde{\sigma}_{mt}$ is the cross-sectional standard deviation of asset returns (RD) at time t. This relation can be re-written in the form of the ZCAPM asset pricing model as:

$$E(\widetilde{R}_{it}) - R_{ft} = \beta_i[E(\widetilde{R}_{mt}) - R_{ft}] + Z_i\widetilde{\sigma}_{mt} \tag{2}$$

$$E(\widetilde{R}_{it}) - R_{ft} = \beta_i[E(\widetilde{R}_{mt}) - R_{ft}] - Z_i\widetilde{\sigma}_{mt}, \tag{3}$$

where the Z_i coefficient has a positive or negative sign as specified in equations (2) and (3), respectively. A probabilistic mixture model, the ZCAPM has two mixture components wherein each is a two-factor regression model comprised of market and RD factors.

To estimate the zeta risk coefficient, the following novel regression model is employed:

$$\widetilde{R}_{it} - R_{ft} = \alpha_i + \beta_i(\widetilde{R}_{mt} - R_{ft}) + Z_i D_{it}\widetilde{\sigma}_{mt} + \widetilde{u}_{it}, \quad t = 1, \cdots, T \tag{4}$$

where D_{it} is a signal variable taking values 1 and -1 to indicate positive and negative RD effects, respectively, on the ith asset's returns at time t, $\widetilde{u}_{it} \sim$ iid $\mathrm{N}(0, \sigma_i^2)$, and other notation is as before. Because the signal variable D_{it} cannot be observed, D_{it} are assumed to be independent random variables with two-point distributions:

$$D_{it} = \begin{cases} 1 & \text{with probability } p_i \\ -1 & \text{with probability } 1 - p_i, \end{cases} \tag{5}$$

where p_i (or $1 - p_i$) is the probability of a positive (or negative) return dispersion effect, and D_{it} are independent of $\widetilde{u}_{it}$.

Empirical model (4) can be expanded as follows:

$$\widetilde{R}_{it} - R_{ft} = \alpha_1 + \beta_i(\widetilde{R}_{mt} - R_{ft}) + Z_i\widetilde{\sigma}_{mt} + \widetilde{u}_{it}, \quad t = 1, \cdots, T, \tag{6}$$

$$\widetilde{R}_{it} - R_{ft} = \alpha_i + \beta_i(\widetilde{R}_{mt} - R_{ft}) - Z_i\widetilde{\sigma}_{mt} + \widetilde{u}_{it}, \quad t = 1, \cdots, T, \tag{7}$$

where equation (6) has probability p_i, and equation (7) has probability $1 - p_i$. Thus, the ZCAPM is a two-component mixture of two-factor regression models (6) and (7). The hidden binary variable D_{it} determines which regression model to use. The parameters in equations (4) and (5) are $\theta_i = (\alpha_i, \beta_i, Z_i, \sigma_i^2, p_i)$. To estimate these parameters, Liu, Kolari, and Huang utilize an expectation-maximization (EM) regression model (see Dempster, Laird, and Rubin (1977)). In the EM model, the intercept parameter α_i is set to zero to avoid local maximization pitfalls.

Because $E(D_{it}) = 2p_i - 1$, after integrating out the probability distribution of the unobservable signal variable, the marginal form of the ZCAPM mixture becomes:

$$\widetilde{R}_{it} - R_{ft} = \beta_i(\widetilde{R}_{mt} - R_{ft}) + Z_i^* \widetilde{\sigma}_{mt} + \widetilde{u}_{it}, \quad t = 1, \cdots, T \tag{8}$$

where $Z_i^* = Z_i(2p_i - 1)$, and β_i and Z_i^* are beta and zeta risk loadings, respectively. The probability p_i associated with signal variable D_{it} in period $t = 1, \cdots, T$, determines whether the sign of the zeta risk loading Z_i^* is positive or negative. Both Matlab and R versions of the EM algorithm are available from the authors.

The authors implement the following standard Fama and MacBeth (1973) out-of-sample cross-sectional tests:

$$\widetilde{R}_{i,T+1} - R_{fT+1} = \lambda_M \hat{\beta}_{i,T} + \lambda_V \hat{Z}_{i,T}^*, \quad i = 1, ..., N, \tag{9}$$

where $\widetilde{R}_{i,T+1}$ is the realized return on asset i in out-of-sample time period $T+1$ (e.g., one-month-ahead), λ_M and λ_V are the market prices of beta risk and zeta risk, respectively, associated with estimated coefficients $\hat{\beta}_{i,T}$ and $\hat{Z}_{i,T}^*$ using data from prior time period $t = 1, ..., T$, N is the number of assets, and other notation is as before. Empirical tests using a wide variety of test asset portfolios as well as individual stocks show that zeta risk loadings are highly significant in these cross-sectional tests. They obtain t-values associated with λ_V that consistently range from 3 to 6, which exceeds the recently recommended threshold of 3 by Harvey, Liu, and Zhu (2015) for the significance of asset pricing factors. Other factors in the Fama and French (1992, 1993, 1995, 2015) three- and five-factor models in addition to the momentum factor are not as significantly and consistently priced across different test assets.

3 Empirical Methods

Our research hypothesis is that momentum profits are explained in large part by market zeta risk associated with return dispersion. All NYSE, AMEX, and NASDAQ stocks returns from the Center for Research in Security Prices (CRSP) in the sample period January 1965 to December 2017 are used. Small firms with common stock prices below $5 are dropped. As described below, three empirical tests of this hypothesis are conducted.

3.1 Cross-Sectional Asset Pricing Tests

We conduct standard Fama and MacBeth (1973) cross-sectional tests to investigate the relation of RD loadings (i.e., zeta risk) to momentum returns. For purposes of estimating the ZCAPM, mean market returns ($\widetilde{R}_{mt}$) and riskless returns (R_{ft}) are proxied by CRSP value-weighted returns and one-month Treasury bill rates, respectively. The cross-sectional standard deviation of $i = 1, ..., n$ assets' returns (i.e., market volatility) is estimated on day t as follows:

$$\widetilde{\sigma}_{mt} = \sqrt{\frac{n}{n-1}\sum_{i=1}^{n} w_{it-1}(\widetilde{R}_{it} - \widetilde{R}_{mt})^2}, \tag{10}$$

where w_{it} = the market value weight for asset i on day t. Referring to this equation, the following descriptive statistics (in percent terms per month) are obtained in our sample period: (1) the mean daily return (standard deviation) for the value-weighted CRSP index (i.e., $\widetilde{R}_{mt}$) equals 0.91 (4.37) percent, and (2) the mean cross-sectional standard deviation of daily returns (standard deviation) for CRSP stocks (i.e., σ_{mt}) equals 8.17

(3.04) percent. The mean monthly U.S. Treasury bill rate (standard deviation) equals 0.39 (0.27) percent. It is noteworthy that the estimated correlation coefficient between the daily series $\widetilde{R}_{mt}$ and σ_{mt} is only -0.01.

The following sequence of computations is used in cross-sectional tests of the ZCAPM using the monthly rolling approach:

(1) ZCAPM $\hat{\beta}_i$ and $\hat{Z}_i^*$ factor loadings in equation (8) for each portfolio are estimated using EM time series regression methods with daily returns in the 12-month period January 1964 to December 1964.

(1) For each portfolio one-month-ahead excess returns are computed in the out-of-sample month January 1965.

(2) Cross-sectional OLS regression equation (9) is estimated using excess returns in the out-of-sample month January 1965 as the dependent variable for each portfolio and factor loadings (i.e., parameter estimates) from EM time series regressions as the independent variables for the portfolio.[4] The estimated coefficients denoted $\hat{\lambda}_k$ for the kth factor provide estimates of beta and zeta risk factor prices or risk premiums in percent per month.[5]

(3) The above process is rolled forward one month at a time to the end of the analysis period or December 2017 (i.e., the last out-of-sample monthly excess returns for portfolios).

(4) The monthly time series of 636 estimated out-of-sample factor prices of risk $\hat{\lambda}_k$ for

[4]Out-of-sample tests are recommended to mitigate data snooping and other potential model assessment problems (e.g., see Simin (2008) and Ferson, Nallareddy, and Xie (2012)).

[5]It should be noted that beta loadings are benchmarked to one on average for the market portfolio but not zeta loadings. Beta loadings are time invariant in the sense that similar estimated values are obtained using daily versus month returns. By contrast, zeta loadings are affected by the holding period used in their time series regression estimation. Because zeta loadings are estimated in a time series regression with daily returns but one-month excess returns are used as the dependent variable, $\hat{Z}_{i,T}^*$ is rescaled from a daily to monthly basis in cross-sectional regression equation (9) as follows:

$$\widetilde{R}_{i,T+1} - R_{fT+1} = \lambda_M \hat{\beta}_{i,T} + \lambda_V \hat{Z}_{i,T}^* N_{T+1}, i = 1, ..., N,$$

where N_{T+1} is the number of trading days in month $T+1$, $Z_{i,T}^*$ is estimated using daily returns for the ith portfolio in time series regression relation (8), $Z_{i,T}^* N_{T+1}$ is the monthly estimated zeta risk, and λ_V is the monthly risk premium associated with zeta risk. It is important to note that the risk premium $\hat{\lambda}_V$ per unit zeta risk is unchanged by this rescaling. Rescaling $Z_{i,T}^*$ up to a monthly basis enables comparisons to λ_M estimates associated with beta loadings.

the kth factor from January 1965 to December 2017 are used to compute the average values of $\hat{\lambda}_k$ in percent per month and associated t-statistics.[6]

As in Jagannathan and Wang (1996) and Lettau and Ludvigson (2001, footnote 17, p. 1254), the goodness-of-fit of cross-sectional regressions is assessed using the adjusted R^2 statistic from the single regression approach. This approach averages the time series of one-month-ahead stock returns of portfolios and regresses them on their time series averages of factor loadings from the monthly rolling approach

In addition to the ZCAPM, we estimate four popular asset pricing models:

- CAPM market model with the CRSP value-weighted index as the market factor;
- Fama and French's (1992, 1993, 1995) three-factor model based on augmenting the market model with size (viz., small minus large firms' stock returns, or *SMB*) and value (viz., high B/M minus low B/M firms' stock returns, or *HML*) factors;
- Carhart's (1997) four-factor model based on augmenting the three-factor model with a momentum factor (viz., firms with high past return stock returns minus low past stock returns, or *MOM*); and
- Fama and French's (2015) five-factor model based on augmenting their three-factor model with profit (viz., robust operating profitability minus weak operating profitability returns, or *RMW*) and capital investment (viz., conservative investment minus aggressive investment returns, or *CMA*) factors.

Factor return series for these models are downloaded from Kenneth French's website. The same Fama-MacBeth two-stage regression procedure for cross-sectional tests described above for the ZCAPM is applied to these models. We conjecture that factor loadings on the momentum factor and return dispersion are similarly priced and diverge considerably from the market pricing of other factors' loadings.

[6] Under the monthly rolling approach, the t-statistics are corrected for cross-sectional correlation of residual errors (see Cochrane (2005, pp. 250–251).

3.2 Comparative Returns

In further comparative analyses of the relationship between momentum and return dispersion, we construct zero-investment momentum portfolios and zero-investment return dispersion mimicking portfolios. We build momentum portfolios by ranking holding period returns in previous 12-month estimation periods that start with the period January to December 1964. Stocks are placed into deciles, and high-to-low return portfolios are denoted denoted $M10$ to $M1$. Following convention, we use equal weights to compute average monthly returns in the post-formation month January 1965. This process is rolled forward one month at a time to develop time series of one-month-ahead holding period returns for $M10$ to 1 from January 1965 to December 2017. Next, momentum return series are computed for the following zero-investment portfolios: $M10 - M1$, $M9 - M2$, $M8 - M3$, $M7 - M4$, and $M6 - M5$. Like Jegadeesh and Titman (1993), we compute results for momentum portfolios using a 1-week lag (i.e., the last week of the 12-month period) between the estimation period and post-formation holding period.[7]

Zero-investment return dispersion portfolios are constructed by means of the ZCAPM. We estimate times-series regressions for the empirical ZCAPM in equation (8) with daily returns for 12-month prior estimation periods that start with the period January to December 1964. All stocks are ranked in terms of their estimated zeta coefficient, or $\hat{Z}_i^*$. Stocks are placed in deciles and denoted $Z10$ to $Z1$. Using a 1-week lag between the estimation period and post-formation period, equal-weighted post-formation returns for these portfolios are computed in the next month January 1965. The process is rolled forward one month at a time to rebalance the portfolios until the last post-formation holding period return is computed in December 2017. Like the momentum return series, return dispersion zero-investment returns are computed for the following portfolios: $Z10-Z1$, $Z9-Z2$, $Z8-Z3$, $Z7-Z4$, and $Z6-Z5$. We conjecture that zero-investment returns on momentum portfolios and return disperson portfolios are similar to one another and

[7] We also computed post-formation returns using a 1-month lag to explore lag effects on momentum profits. However, because the 1-week lag profits were higher than those using a 1-month lag, to conserve space we only report the 1-week lag results.

diverge considerably from those of other zero-investment portfolios.

3.3 Regression Tests

We conduct regression tests to investigate the relationship between the returns from zero-investment momentum and zero-investment return dispersion strategies. The following OLS regression is estimated:

$$MOM_T = \alpha_{MOM} + \beta_{MOM} FACTOR_T + \varepsilon_T, \tag{11}$$

where MOM_T is the momentum return, and $FACTOR_T$ is the factor return in month T. We test alternative dependent variable MOM factors defined as: $M10-M1$, $M9-M2$, $M8-M3$, $M7-M4$, and $M6-M5$. Independent variable $FACTOR$ is alternatively defined as: $Z10-Z1$, $Z9-Z2$, $Z8-Z3$, $Z7-Z4$, and $Z6-Z5$ in addition to SMB, HML, RMW, and CMA. We conjecture that a highly significant relationship exists between zero-investment momentum returns and zero-investment return dispersion returns, which well exceeds its relationship with the returns of other zero-investment factors.

4 Empirical Results

This section presents the empirical results of cross-sectional tests of momentum portfolios, return comparisons of zero-investment momentum and zero-investment return dispersion mimicking portfolios, and regression analyses of zero-investment momentum returns and zero-investment return dispersion mimicking portfolio returns.

4.1 Cross-Sectional Test Results

Are momentum portfolio returns priced similarly by momentum and return dispersion factor loadings? To answer this question, we conduct cross-sectional tests using different momentum portfolios and zeta risk portfolios as test assets. We begin with momentum portfolios' returns available from Kenneth French's data library. These portfolios use quintiles of size and quintiles of past returns in the previous year (excluding the last month). The test results are summarized in Table 1. Panels A and B show the results for 25 size-momentum portfolios using value- and equal-weighted returns, respectively. Not surprisingly, size and momentum are significantly priced in models containing these factors. Size is more significantly priced in the Panel B with equal-weighted returns, which place more emphasis on small stocks, than in Panel A with value-weighted returns. The value (HML) and capital investment (CMA) factors are significant in some models but not the profit (RMW) factor. The market factor (M) is not priced using value-weighted returns but for equal-weighted returns is highly significant at the one percent or lower levels across different models, with the exception of the ZCAPM. Unfortunately, it is negatively priced which is difficult to interpret. Turning to the main focus of the present paper, momentum is similarly priced for both value- and equal-weighted returns with $\hat{\lambda}_{MOM} = 0.56$ percent per month ($t = 3.20$) and $\hat{\lambda}_{MOM} = 0.54$ percent per month ($t = 2.93$), both significant at the one percent level. Importantly, for the ZCAPM in Panels A and B, the return dispersion (RD) factor is highly significant with $\hat{\lambda}_{RD} = 0.61$ percent per month ($t = 5.54$) and $\hat{\lambda}_{RD} = 0.74$ percent per month ($t = 6.70$). Hence, RD has noticeably higher t-values[8] than the momentum factor, and RD and momentum factors have similar magnitudes for the market prices of their respective risk loadings.

Next we constructed equal-weighted returns for 25 momentum portfolios sorted on past returns. These portfolios are formed by sorting all CRSP stocks on their past holding period returns in a 12-month period (e.g., January 1964 to December 1964 excluding the last week). One-month-ahead returns are computed for portfolios in January 1965. This process is rolled forward monthly to construct time series of part return portfolios' returns from January 1965 to December 2017. In Panel C of Table 1, we see that return dispersion and momentum loadings are significantly priced: $\hat{\lambda}_{RD} = 0.60$ percent ($t =$

[8]As cited in the introduction section, Harvey, Liu, and Zhu (2015) document evidence that factors should have t-values of 3.0 or more to be recognized as statistically significant.

3.83) and $\hat{\lambda}_{MOM} = 1.01$ percent ($t = 3.20$), respectively. Market factor loadings are significantly priced in most of models, but size loadings are not priced. Adjusted R^2 values equal 82 percent for both the ZCAPM and four-factor model with momentum, whereas other models have lower estimated values around 50 percent.

To examine size effects, we reform the 25 momentum portfolios using the 60 percent largest and 40 percent smallest stocks by market capitalization. Panels D and E in Table 1 display the results. The most consistently significant loadings correspond to return dispersion (i.e., $t = 7.14$ and $t = 4.71$ in Panels D and E, respectively). Momentum loadings are highly significant for larger stocks in Panel D (i.e., $t = 6.43$) but not for smaller stocks in Panel E. Size and profit loadings exhibit some significance also but are negatively signed. A notable difference related to size is that the adjusted R^2 values for all but the CAPM are markedly higher for larger stocks compared to smaller stocks, with the highest values coincident with the ZCAPM.

Since we hypothesize that momentum and zeta risk are related to one another, we formed 25 portfolios sorted by zeta coefficients from the ZCAPM estimated in the prior year using daily returns. Again results are provided for all stocks as well as largest 60 percent and smallest 40 percent of stocks by market capitalization. In Panel A of Table 2 for all stocks, the results for return dispersion and momentum loadings are both very significant: $\hat{\lambda}_{RD} = 0.69$ percent ($t = 5.01$) and $\hat{\lambda}_{MOM} = 1.42$ percent ($t = 4.16$), respectively. In some models the market factor and value factor loadings are significantly priced but value loadings negatively so. In Panels B and C return dispersion and momentum loadings are the most significant and consistently priced factors. And, like momentum sorted portfolios in Panels D and E of Table 1, estimated R^2 values are generally higher for larger stocks than smaller stocks.

Lastly, we combined the equal-weighted returns for the 25 size-momentum, 25 momentum, and 25 zeta risk portfolios (i.e., 75 test asset portfolios). The results in Table 3 again show that return dispersion and momentum loadings are highly significant (i.e., i.e., $t = 5.01$ and $t = 4.00$, respectively). Also, market and size factor loadings are signficant in most cases. For this larger set of test assets, the adjusted R^2 estimate for the ZCAPM at 88 percent is substantially higher than those for other models, which range from 37 percent to 47 percent. This goodness-of-fit is illustrated in Figures 1 and 2. These figures plot the 75 portfolios' one-month-ahead predicted excess returns (using the cross-sectional regression model estimates) and realized excess returns. Predicted and realized excess returns are averages of 636 cross-sectional monthly values. The graphs for three-, four-, and five-factor models are similar due to comparable R^2 values in Table 3. Compared to these models, the ZCAPM in Panel A of Figure 1 has noticeably higher goodness-of-fit. With the exception of two portfolios[9], most portfolios lie very close to the 45-degree line describing a perfect relation between predicted and realized returns. Relevant to our research hypothesis, this graph shows that momentum and zeta risk portfolios are similarly priced by the ZCAPM.

In sum, our cross-sectional test results support the notion that momentum and return dispersion loadings are similarly priced using test asset portfolios related to momentum returns, including momentum and zeta risk portfolios. This evidence strongly suggests that momentum is closely related to market risk associated with return dispersion.

4.2 Comparative Analysis Results

Are zero-investment momention and zero-investment return dispersion returns similar? Descriptive return statistics for these comparative returns are shown in Table 4. Here we focus attention on the decile 10 minus decile 1 and decile 9 minus decile 2 strategies. The highest momentum return is the traditional $M10 - M1$ strategy at 0.94 percent per month. Returns drop off markedly for the $M9 - M2$ strategy at 0.59 percent month. As the average return gap between winners and losers narrow further, momentum returns largely dissipate.

[9]These two portfolios have the most extreme negative past returns among the 25 momentum portfolios. In one-month-ahead returns after the formation period, these portfolios sometimes have return reversals that account for their higher than predicted returns. Using the 60 percent highest market capitalization stocks, all 25 portfolios lie close to the 45-degree line.

Zero-investment return dispersion portfolios outperform their momentum counterparts. For example, the $Z10 - Z1$ strategy earns 1.50 percent per month or almost 60 percent more than the traditional $M10 - M1$ portfolio. Also, $Z9 - Z2$ does quite well at 0.85 percent per month or about 44 percent more than $M9 - M2$. Given the smaller standard deviation of the $Z9-Z2$ portfolio compared to the $M10-M1$ portfolio (i.e., 3.56 percent versus 6.24 percent, respectively), this performance is very good on a risk-adjusted basis.

It should be noted that higher returns for return dispersion portfolios cannot be attributed to higher total risk. The standard deviations of returns are similar between $M10-M1$ and $Z10-Z1$ as well as $M9-M2$ and $Z9-Z2$. Also, since their minimum returns are similar but maximum returns are higher for these return dispersion strategies, it is upside gains rather than downside losses that explains the higher gains from return dispersion relative to momentum.

An obvious return disparity in Table 4 is the much higher gains from return dispersion and momentum compared to the average monthly returns for popular size (SMB), value (HML), profit (RMW), and investment (CMA) factors. The latter factors have much lower average returns in the range of 0.27 percent to 0.34 percent per month. Their total risk as measured by the standard deviation of returns is about 50 percent less than the $M10-M1$ and $Z10-Z1$ portfolios but not much less than the $M9-M2$ and $Z9-Z2$ portfolios. Hence, the latter portfolios are clearly superior in return/risk terms compared to these popular factors.

The relatively high returns of momentum strategies compared to other zero-investment factors has led many authors to infer that they are anomalous. As discussed in the introduction section, in the absence of a market-risk-based explanation of momentum, controversy has surrounded this factor. The debate has led Fama and French (2008) to tag momentum as the premier unsolved finance puzzle, and Subrahmanyam (2018) to label it the biggest challenge to the efficient market hypothesis. Because our zero-investment return dispersion portfolios likewise outperform popular factors by a wide margin, they could be considered another anomaly. However, rather than being two separate anomalies, another possible explanation is that these two anomalies are closely related to one another via their common link with market risk as manifested by return dispersion.

Assuming momentum and return dispersion have a common market risk link, we should be able to combine them into a hybrid zero-investment portfolio strategy. Tables 5 and 6 report the performance results of hybrid momentum-zeta-risk portfolios without and with risk management, respectively. In these analyses, we drop small stocks due to potential short-term reversals and use only the 80 percent largest stocks by market capitalization. Hybrid portfolios are formed by taking the intersection of stocks in the $M10$ and $Z10$ portfolios as well as the intersection of stocks in the $M1$ and $Z1$ portfolios. The equal-weighted hybrid zero-investment portfolio is denoted $MZ10 - MZ1$. We also weighted individual stocks based on their $|Z^*|$ proportions to form hybrid portfolio $MZ10^* - MZ1^*$. Without risk management, due to dropping small stocks, Table 5 shows that the average return of the momentum portfolio $M10 - M1$ is boosted from 0.94 percent (in Table 4) to 1.74 percent per month. The hybrid portfolios $MZ10 - MZ1$ and $MZ10^* - MZ1^*$ further boost average returns to 1.81 percent and 1.91 percent per month, respectively. We infer that zeta risk more accurately captures market risk associated with return dispersion than the momentum strategy and, therefore, enhances momentum returns.

In Table 6 we repeat the analyses in Table 5 but implement risk management. In any month, if the average zeta risk span between the $Z10$ and $Z1$ portfolios is within the smallest quintile of all previous months in the sample period, then the zero-investment portfolio is replaced by market portfolio $CRSP - R_f$ for monthly rebalancing purposes. As shown in Table 6, the resultant risk-managed portfolios earn yet higher average monthly returns: $M10 - M1$ from 1.74 (in Table 5) to 1.87 percent; $MZ10 - MZ1$ from 1.87 percent (in Table 5) to 1.95 percent; and $MZ10^* - MZ1^*$ from 1.91 percent (in Table 5) to 2.03 percent. These results further support our hypothesis that momentum-based portfolio returns are related to zeta risk.

4.3 Regression Test Results

How closely related to one another are the returns of zero-investment momentum and zero-investment return dispersion strategies? The regression results in Table 5 strongly support this relationship. In Panel A using $M10 - M1$ as the dependent variable, independent variable $Z10 - Z1$ has a t-value of 38.02 and adjusted R^2 value of 69 percent, which far exceeds the statistical significance and goodness-of-fit associated with popular SMB, HML, RMW, and CMA factors. Not surprisingly, there is a high stimated correlation coefficient between $M10 - M1$ and $Z10 - Z1$ at 0.78. The Panel B results using $M9 - M2$ as the dependent variable are similar, with a t-value of 34.00 associated with $Z9 - Z2$ and adjusted R^2 value of 65 percent (i.e., estimated correlation coefficient of 0.73); by contrast, other factors have almost no explanatory power. Even the results in Panel C for $M8 - M3$ and $Z8 - Z3$ exhibit a very strong relationship with t-value equal to 24.21 and adjusted R^2 of 48 percent (i.e., estimated correlation coefficient of 0.69). This relationship drops off in Panels D and E for portfolios with smaller return spreads.

The very close relationship between momentum and return dispersion returns in Table 5 suggests that, as discusssed in the previous subsection, these two phenomenon are attributable to a single underlying anomaly, rather than two separate anomalies. In this regard, as discussed in the previous section, a large body of literature has shown that return dispersion is related to economic fundamentals indicative of general market risk. Thus, by transitive logic, we infer that momentum is associated with general market risk also. Consistent with this inference, Chordia and Shivakumar (2002) find that momentum profits adjusted for macroeconomic variables are much smaller than unadjusted profits.[10]

[10] However, Griffin, Ji,, and Martin (2003) find that momentum profits and the business cyle are only weakly related in international markets.

5 Conclusion

This paper has sought to provide empirical evidence on the mystery of what explains momentum profits. We hypothesized that a large portion of momentum profits arise rationally from market risk associated with cross-sectional market volatility. Recent work by Liu, Kolari, and Huang (2012) develops a special case of the zero-beta CAPM dubbed the ZCAPM that posits market risk has two components: (1) beta risk related to average market returns, and (2) zeta risk associated with cross-sectional market volatility (denoted RD). It is well known that momentum profits are not explained by market risk arising from the market factor but no previous studies consider their relation to market risk stemming from cross-sectional market volatility.

For U.S. stocks in the sample period 1965 to 2017, we conducted three different analyses of the relation between return dispersion and momentum returns: (1) cross-sectional asset pricing tests, (2) comparative historical returns, and (3) regression analyses. For cross-sectional tests, we estimated the ZCAPM via the expectation-maximization (EM) regression method. Based on test assets sorted on momentum, we found that the market prices of both return dispersion and momentum loadings were highly significant and more consistently priced than the loadings of other popular risk factors, including size, value, profit, and investment. Similar results are obtained for test assets sorted on zeta risk levels (i.e., sensitivity to return dispersion). Comparatively, in our analysis period, zero-investment return dispersion portfolios based on high-decile/low-decile zeta risk averaged approximately 1.50 percent compared to 0.94 percent for high-decile/low-decile zero-investment momentum portfolios. And, average monthly returns greater than 1.50 percent were possible by combining zero-investment momentum and return dispersion strategies. Other popular zero-investment factors earned at most 0.34 percent per month. Regression analyses indicated that zero-investment momentum returns are very significantly related to zero-investment return dispersion returns with higher t-statistics and adjusted R^2 values compared to other factors. In view of this evidence, we conclude that market risk related to return dispersion explains momentum profits for the most part.

A number of possible areas of research are suggested by our findings. For example, future research is recommended to examine momentum profits and return dispersion in other asset classes, such as bonds, commoities, currencies, etc. Another area of interest is whether other anomalous patterns in average returns, including (for example) net stock issues, accruals, asset growth, etc., are largely captured by return dispersion. Most anomalies are measured with zero-investment portfolio returns which themselves proxy return dispersion. Finally, research is recommended on the relation between business cyle and macroeconomic variables and both zero-investment momentum profits and zero-investment return dispersion profits.

References

[1] Angelidis, T., A. Sakkas, and N. Tessaromatis, 2015, Stock market dispersion, the business cycle and expected factor returns, *Journal of Banking and Finance* 59, 256–279.

[2] Asness, C., T. Moskowitz, and L. Pedersen, 2013, Value and momentum everywhere, *Journal of Finance* 68, 929–985.

[3] Bansal, R., D. Kiku, I. Shaliastovich, and A. Yaron, 2014, Volatility, the macroeconomy, and asset prices, *Journal of Finance* 69, 2471–2511.

[4] Bansal, R., and A. Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481–1509.

[5] Bekaert, G., and C. Harvey, 2000, Foreign speculators and emerging equity markets, *Journal of Finance* 55, 565–513.

[6] Barberis, M., A. Shleifer, and R. Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

[7] Barroso, P., and P. Santa-Clara, 2015, Momentum has its moments, *Journal of Financial Economics* 116, 111120.

[8] Black, F., 1972, Capital market equilibrium with restricted borrowing, *Journal of Business* 45, 444–454.

[9] Brav, A., and J. B. Heaton, 2002, Competing theories of financial anomalies, *Review of Financial Studies* 15, 575–606.

[10] Chang, R., K. Ko, S. Nakano, and G. Rhee, 2018, Residual momentum in Japan, *Journal of Empirical Finance* 45, 283–299.

[11] Chichernea, D. C., A. D. Holder, and A. Petkevich, 2015, Does return dispersion explain the accrual and investment anomalies?, *Journal of Accounting and Economics* 60, 133–148.

[12] Chordia, T., and L. Shivakumar, 2002, Momentum, business cycle, and time-varying expected returns, *Journal of Finance* 57, 985–1019.

[13] Christie, W., and R. Huang, 1994, The changing functional relation between stock returns and dividend yields, *Journal of Empirical Finance* 1, 161–191.

[14] Connolly, R., and C. Stivers, 2003, Momentum and reversals in equity index returns during periods of abnormal turnover and return dispersion, *Journal of Finance* 58, 1521–1556.

[15] Conrad, J., and G. Kaul, 1998, An anatomy of trading strategies, *Review of Financial Studies* 11, 489–519.

[16] Conrad, J., and D. Yavuz, 2017, Momentum and reversal: Does what goes up always come down?, *Review of Finance* 21, 555–581.

[17] Cooper, M. J., R. C. Gutierrez Jr., and A. Hameed, 2004, Market states and momentum, *Journal of Finance* 59, 1345–1365.

[18] Da, Z., U. Gurun, and M. Warachka, 2014, Frog in the pan: Continuous information and momentum, *Review of Financial Studies* 27, 2171–2218.

[19] Daniel, K., 2014, Momentum crashes, Working paper, Columbia University.

[20] Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, *Journal of Finance* 53, 1839–1885.

[21] Daniel, K., and T. J. Moskowitz, 2016, Momentum crashes, *Journal of Financial Economics* 12, 221247.

[22] De Bondt, W. F. M., and R. Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793–805.

[23] DeBondt, W. F. M., and R. Thaler, 1987, Further evidence of stock market overreaction and seasonality, *Journal of Finance* 42, 557–581.

[24] Demirer, R. and S. P. Jategaonkar, 2013, The conditional relation between dispersion and return, *Review of Financial Economics* 22, 125–134.

[25] Fama, E. F., and K. R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

[26] Fama, E. F., and K. R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

[27] Fama, E. F., and K. R. French, 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, 131–156.

[28] Fama, E. F., and K. R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

[29] Fama, E. F., and K. R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

[30] Fama, E. F., and K. R. French, 2008, Dissecting anomalies, *Journal of Finance* 63, 1653–1678.

[31] Garcia, R., D. Mantilla-Garcia, and L. Martellini, 2014, A model-free measure of aggregate idiosyncractic volatility and the prediction of market returns, *Journal of Financial and Quantitative Analysis* 49, 1133–1165.

[32] George, T. J., and C.-Y. Hwang, 2004, The 52-week high and momentum investing, *Journal of Finance* 59, 2145–2176.

[33] Gomes, J., L. Kogan, and L. Zhang, 2003, Equilibrium cross section of returns, *Journal of Political Economy* 111, 693–732.

[34] Goyal, A., and N. Jegadeesh, 2018, Cross-sectional and time-series tests of return predictability: What is the difference?, *Review of Financial Studies* 31, 1784–1824.

[35] Griffin, J. M., X. Ji, and J. S. Martin, 2003, Momentum investing and business cycle risk: Evidence from pole to pole, *Journal of Finance* 58, 2515–2547.

[36] Grinblatt, M., and B. Han, 2005, Prospect theory, mental accounting and momentum, *Journal of Financial Economics* 78, 311–339.

[37] Grundy, B. D., and J. S. Martin, 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies* 14, 29–78.

[38] Gutierrez, R. C., and E. K. Kelly, 2008, The long-lasting momentum in weekly returns, *Journal of Finance* 63, 415–447.

[39] Hong, H., and J. C. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance* 54, 2143–2184.

[40] Hou, K., C. Xue, and L. Zhang, 2017, Replicating anomalies, Working paper no. WP 2017-10, Ohio State University.

[41] Jagannathan, R. and T. Ma, 2003, Risk reduction in large portfolios: A role for portfolio weight constraints, *Journal of Finance* 58, 1651–1684.

[42] Jegadeesh N., 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881–898.

[43] Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

[44] Jegadeesh, N., and S. Titman, 2001, Profitability of momentum strategies: An evaluation of alternative explanations *Journal of Finance* 56, 699–720.

[45] Jiang, X., 2010, Return dispersion and expected returns, *Financial Markets and Portfolio Management* 24, 107–135.

[46] Johnson, T. C., 2002, Rational momentum effects, *Journal of Finance* 57, 585–608.

[47] Kallberg, J. G., and W. T. Ziemba, 1983, Comparison of alternative utility functions in portfolio selection problems, *Management Science* 29, 1257–1276.

[48] Kim, H., and S. M. Choi, 2014, Momentum effect as part of a market equilibrium, *Journal of Financial and Quantitative Analysis* 49, 107–130.

[49] Lehmann, B. N., 1990, Fads, martingales, and market efficiency, *Quarterly Journal of Economics* 105, 1–28.

[50] Liu, W., J. Kolari, and J. Huang, 2018, Return dispersion and the cross-section of stock returns, Working paper, Texas A&M University. Available on SSRN at http://ssrn.com/abstract=3200095.

[51] Liu, L. X., and L. Zhang, 2008, Momentum profits, factor pricing, and macroeconomic risk, *Review of Financial Studies* 21, 2417–2448.

[52] Lewellen, J., 2002, Momentum and autocorrelation in stock returns, *Review of Financial Studies* 15, 533–563.

[53] Lo, A. W., and A. C. MacKinlay, 1990, When are contrarian profits due to stock market overreaction?, *Review of Financial Studies* 3, 175–205.

[54] Loungani, P., M. Rush, and W. Tave, 1990, Stock market dispersion and unemployment, *Journal of Monetary Economics* 25, 367–388.

[55] Luo, J., A. Subrahmanyam, and S. Titman, 2018, Stock price patterns when overconfident traders underestimate their competition, Working Paper, University of Texas. at Austin.

[56] Markowitz, H. M., 1959, *Portfolio Selection: Efficient Diversification of Investments* (John Wiley & Sons, New York, NY).

[57] Moskowitz, T. J., and M. Grinblatt, 1999, Do industries explain momentum?, *Journal of Finance* 54, 1249–1290.

[58] Moskowitz, T. J., Y. H. Ooi, and L. H. Pedersen, 2012, Time series momentum, *Journal of Financial Economics* 104, 228–250.

[59] Novy-Marx, R., 2012, Is momentum really momentum?, *Journal of Financial Economics* 103, 429–453.

[60] Pastor, L., and P. Veronesi, 2009, Technological revolutions and stock prices, *American Economic Review* 99, 1451–1483.

[61] Petruno, T., 2018, Momentum investing: It works, but buy?, —it UCLA Anderson Review, Featured research by Avanidhar Subrahmanyam, October 31.

[62] Pulley, L. B., 1981, General mean-variance approximation to expected utility for short holding periods, *Journal of Financial and Quantitative Analysis* 16, 361–373.

[63] Rouwenhorst, K. G., 1998, International momentum strategies, *Journal of Finance* 53, 267–284.

[64] Sagi, J. S., and M. S. Seasholes, 2007, Firm-specific attributes and the cross-section of momentum, *Journal of Financial Economics* 84, 389–434.

[65] Stivers, C., 2003, Firm-level return dispersion and the future volatility of aggregate stock market returns, *Journal of Financial Markets* 6, 389–411.

[66] Subrahmanyam, A., 2018, Equity market equilibrium: A synthesis of the literature and suggestions for future work, *Pacific-Basin Finance Journal* 51, 291–296.

[67] Zhang, L., 2005, The value premium, *Journal of Finance* 60, 67–103.

Table 1: Fama-MacBeth cross-sectional regression tests of momentum portfolios: January 1965 to December 2017

This table reports cross-sectional asset pricing tests based on the Fama-MacBeth monthly rolling approach. The following models are tested:

- CAPM market model with the CRSP value-weighted index as the market factor (M);
- ZCAPM with market return (M) and cross-sectional return dispersion (RD) factors proxied by the CRSP value-weighted index;
- Fama and French's (1992, 1993, 1995) three-factor model with market (M), size (SMB), and value (HML) factors;
- Carhart's (1997) four-factor model with market (M), size (SMB), value (HML), and momentum (MOM) factors; and
- Fama and French's (2015) five-factor model with market (M), size (SMB), value (HML), profit (RMW), and capital investment (CMA) factors.

Most factor return series and one-month Treasury bill rates are downloaded from Kenneth French's online data library. The RD factor is computed as the daily cross-sectional standard deviation of CRSP value-weighted stock returns. The following two-step procedure is used: (1) time series regressions of the respective factor model are fitted using daily returns in a 12-month period to estimate factor loadings for test asset portfolios; and (2) in the subsequent out-of-sample month, a cross-sectional regression is run using one-month-ahead portfolio returns to estimate the out-of-sample factor prices of risk denoted λ_k for the kth factor (in monthly percent return terms). The analyses are rolled forward one month at a time to enable cross-sectional regressions in each month from Jauary 1965 to December 2017. The time series average of $t = 1, \cdots, 636$ estimated factor prices for the kth factor is denoted $\hat{\lambda}_k$ (t-statistics in parentheses). Following Jagannathan and Wang (1996) and Lettau and Ludwigson (2001, footnote 17, p. 1254), adjusted R^2 values are estimated from a single equation cross-sectional regression (i.e., the time series average of one-month-ahead excess returns for all portfolios is regressed on the time series average loadings of factors for portfolios). Results are shown for the following test asset portfolios downloaded from French's data library: (Panel A) 25 size-momentum value-weighted portfolios, and (Panel B) 25 size-momentum equal-weighted portfolios. Further results are based on the following test asset momentum portfolios constructed from past returns by the present authors: (Panel C) 25 momentum equal-weighted portfolios using all stocks, (Panel D) 25 momentum equal-weighted portfolios using the 60% largest market capitalization stocks, and (Panel E) 25 momentum equal-weighted portfolios using the 40% smallest market capitalization stocks. All test asset portfolio returns are computed in the one-month-ahead post-formation period.

Panel A: 25 size-momentum value-weighted portfolios									
Model	$\hat{\alpha}$	$\hat{\lambda}_M$	$\hat{\lambda}_{RD}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	$\hat{\lambda}_{RMW}$	$\hat{\lambda}_{CMA}$	Adj R^2
CAPM	0.61	0.10							-0.01
	(2.61)	(0.41)							
ZCAPM	0.41	0.22	0.61						0.98
	(1.86)	(0.99)	(5.54)						
Three-factor	0.56	0.03		0.33	-0.05				0.51
	(2.16)	(0.12)		(2.39)	(-0.28)				
Four-factor	1.01	-0.41		0.32	-0.19	0.56			0.70
	(4.94)	(-1.83)		(2.32)	(-1.15)	(3.20)			
Five-factor	0.40	0.20		0.32	-0.35		0.27	-0.07	0.50
	(1.71)	(0.81)		(2.51)	(-1.83)		(1.55)	(-0.42)	

Table 1, continued

Panel B: 25 size-momentum equal-weighted portfolios									
Model	$\hat{\alpha}$	$\hat{\lambda}_M$	$\hat{\lambda}_{RD}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	$\hat{\lambda}_{RMW}$	$\hat{\lambda}_{CMA}$	Adj R^2
CAPM	1.47	-0.70							0.32
	(6.91)	(-3.34)							
ZCAPM	0.85	-0.19	0.74						0.96
	(4.14)	(-0.95)	(6.70)						
Three-factor	1.79	-1.22		0.72	-0.17				0.74
	(8.07)	(-5.69)		(4.86)	(-0.17)				
Four-factor	1.95	-1.39		0.64	-0.20	0.54			0.77
	(9.35)	(-6.79)		(4.35)	(-0.96)	(2.93)			
Five-factor	1.52	-0.95		0.51	-0.46		-0.28	0.47	0.82
	(7.35)	(-4.43)		(3.76)	(-2.11)		(-1.23)	(2.52)	

Panel C: 25 momentum equal-weighted portfolios using all stocks									
Model	$\hat{\alpha}$	$\hat{\lambda}_M$	$\hat{\lambda}_{RD}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	$\hat{\lambda}_{RMW}$	$\hat{\lambda}_{CMA}$	Adj R^2
CAPM	-0.29	1.62							0.48
	(-1.06)	(3.40)							
ZCAPM	-0.17	1.26	0.60						0.82
	(-0.68)	(3.11)	(3.83)						
Three-factor	-0.21	1.75		-0.61	0.16				0.51
	(-0.72)	(3.27)		(-1.39)	(0.42)				
Four-factor	0.19	0.75		-0.14	0.13	1.01			0.82
	(0.68)	(1.46)		(-0.35)	(0.47)	(3.20)			
Five-factor	-0.18	1.65		-0.61	-0.25		0.34	-0.38	0.50
	(-0.74)	(3.29)		(-1.64)	(-0.80)		(0.98)	(-1.25)	

Table 1, continued

Panel D: 25 momentum equal-weighted portfolios using 60% largest market capitalization stocks									
Model	$\hat{\alpha}$	$\hat{\lambda}_M$	$\hat{\lambda}_{RD}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	$\hat{\lambda}_{RMW}$	$\hat{\lambda}_{CMA}$	Adj R^2
CAPM	0.37	0.27							-0.01
	(1.77)	(0.80)							
ZCAPM	0.22	0.36	0.92						0.99
	(0.97)	(1.14)	(7.14)						
Three-factor	0.33	1.39		-1.32	-0.29				0.77
	(1.36)	(2.76)		(-3.15)	(-1.10)				
Four-factor	0.56	0.44		-0.60	0.45	1.41			0.97
	(2.49)	(1.12)		(-2.06)	(2.08)	(6.43)			
Five-factor	0.21	1.16		-0.92	-0.06		0.36	0.01	0.98
	(0.90)	(2.53)		(-2.57)	(-0.21)		(1.66)	(0.06)	
Panel E: 25 momentum equal-weighted portfolios using 40% smallest market capitalization stocks									
Model	$\hat{\alpha}$	$\hat{\lambda}_M$	$\hat{\lambda}_{RD}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	$\hat{\lambda}_{RMW}$	$\hat{\lambda}_{CMA}$	Adj R^2
CAPM	0.09	2.30							0.38
	(0.39)	(2.30)							
ZCAPM	0.03	1.93	0.65						0.76
	(0.14)	(3.61)	(4.71)						
Three-factor	0.41	1.40		-0.53	0.27				0.28
	(1.95)	(2.48)		(-1.48)	(0.54)				
Four-factor	0.41	1.22		-0.55	0.01	0.15			0.27
	(2.10)	(2.40)		(-1.63)	(0.01)	(0.37)			
Five-factor	0.48	1.35		-0.74	-0.11		-0.04	-0.28	0.34
	(2.32)	(2.48)		(-2.00)	(-0.26)		(-0.12)	(-0.91)	

Table 2: Fama-MacBeth cross-sectional regression tests of zeta risk portfolios: January 1965 to December 2017

This table reports cross-sectional asset pricing tests based on the Fama-MacBeth monthly rolling approach. The following models are tested:

- CAPM market model with the CRSP value-weighted index as the market factor (M);
- ZCAPM with market return (M) and cross-sectional return dispersion (RD) factors proxied by the CRSP value-weighted index;
- Fama and French's (1992, 1993, 1995) three-factor model with market (M), size (SMB), and value (HML) factors;
- Carhart's (1997) four-factor model with market (M), size (SMB), value (HML), and momentum (MOM) factors; and
- Fama and French's (2015) five-factor model with market (M), size (SMB), value (HML), profit (RMW), and capital investment (CMA) factors.

Most factor return series and one-month Treasury bill rates are downloaded from Kenneth French's online data library. The RD factor is computed as the daily cross-sectional standard deviation of CRSP value-weighted stock returns. The following two-step procedure is used: (1) time series regressions of the respective factor model are fitted using daily returns in a 12-month period to estimate factor loadings for test asset portfolios; and (2) in the subsequent out-of-sample month, a cross-sectional regression is run using one-month-ahead portfolio returns to estimate the out-of-sample factor prices of risk denoted λ_k for the kth factor (in monthly percent return terms). The analyses are rolled forward one month at a time to enable cross-sectional regressions in each month from Jauary 1965 to December 2017. The time series average of $t = 1, \cdots, 636$ estimated factor prices for the kth factor is denoted $\hat{\lambda}_k$ (t-statistics in parentheses). Following Jagannathan and Wang (1996) and Lettau and Ludwigson (2001, footnote 17, p. 1254), adjusted R^2 values are estimated from a single equation cross-sectional regression (i.e., the time series average of one-month-ahead excess returns for all portfolios is regressed on the time series average loadings of factors for portfolios). Results are shown for the following test asset portfolios formed by sorting stocks by zeta coefficients estimated by the ZCAPM with 12-months of daily returns: (Panel A) 25 zeta risk equal-weighted portfolios using all stocks, (Panel B) 25 zeta risk equal-weighted portfolios using the 60% largest market capitalization stocks, and (Panel C) 25 zeta risk equal-weighted portfolios using 40% smallest market capitalization stocks. All test asset portfolio returns are computed in the one-month-ahead post-formation period.

Panel A: 25 zeta risk equal-weighted portfolios using all stocks									
Model	$\hat{\alpha}$	$\hat{\lambda}_M$	$\hat{\lambda}_{RD}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	$\hat{\lambda}_{RMW}$	$\hat{\lambda}_{CMA}$	Adj R^2
CAPM	0.58	0.52							0.23
	(2.14)	(1.08)							
ZCAPM	0.16	0.71	0.69						0.95
	(0.76)	(2.01)	(5.01)						
Three-factor	0.44	0.29		0.18	-0.16				0.77
	(2.02)	(0.66)		(0.50)	(-0.42)				
Four-factor	0.17	0.57		0.35	-0.45	1.42			0.96
	(0.96)	(1.68)		(1.08)	(-1.81)	(4.16)			
Five-factor	0.05	0.77		0.21	-0.77		0.40	-0.54	0.83
	(0.24)	(1.97)		(0.66)	(-2.62)		(1.41)	(1.64)	

Table 2, continued

Panel B: 25 zeta risk equal-weighted portfolios using 60% largest market capitalization stocks									
Model	$\hat{\alpha}$	$\hat{\lambda}_M$	$\hat{\lambda}_{RD}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	$\hat{\lambda}_{RMW}$	$\hat{\lambda}_{CMA}$	Adj R^2
CAPM	0.71	-0.12							-0.03
	(3.16)	(-0.33)							
ZCAPM	0.31	0.22	0.92						1.00
	(1.66)	(0.78)	(7.55)						
Three-factor	0.55	0.35		-0.38	-0.05				0.80
	(2.62)	(0.94)		(-1.23)	(-0.20)				
Four-factor	0.37	0.90		-0.74	-0.15	1.40			0.98
	(2.09)	(3.06)		(-2.99)	(-0.77)	(5.85)			
Five-factor	0.14	0.84		-0.24	-0.52		0.60	0.07	0.98
	(0.71)	(2.55)		(-0.88)	(-2.04)		(2.92)	(0.31)	

Panel C: 25 zeta risk equal-weighted portfolios using 40% smallest market capitalization stocks									
Model	$\hat{\alpha}$	$\hat{\lambda}_M$	$\hat{\lambda}_{RD}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	$\hat{\lambda}_{RMW}$	$\hat{\lambda}_{CMA}$	Adj R^2
CAPM	0.59	1.08							0.25
	(2.77)	(1.69)							
ZCAPM	0.42	0.89	0.57						0.93
	(1.86)	(1.72)	(4.37)						
Three-factor	0.52	-0.58		0.93	0.42				0.36
	(2.57)	(-1.10)		(3.12)	(0.87)				
Four-factor	0.50	-0.37		0.84	0.13	0.84			0.68
	(2.69)	(-0.85)		(2.82)	(0.44)	(2.08)			
Five-factor	0.66	-0.89		0.64	0.19		-0.38	0.08	0.65
	(3.38)	(-1.92)		(2.15)	(0.53)		(-1.13)	(0.25)	

Table 3: Fama-MacBeth cross-sectional regression tests of momentum and zeta risk portfolios: January 1965 to December 2017

This table reports cross-sectional asset pricing tests based on the Fama-MacBeth monthly rolling approach. The following models are tested:

- CAPM market model with the CRSP value-weighted index as the market factor (M);
- ZCAPM with market return (M) and cross-sectional return dispersion (RD) factors proxied by the CRSP value-weighted index;
- Fama and French's (1992, 1993, 1995) three-factor model with market (M), size (SMB), and value (HML) factors;
- Carhart's (1997) four-factor model with market (M), size (SMB), value (HML), and momentum (MOM) factors; and
- Fama and French's (2015) five-factor model with market (M), size (SMB), value (HML), profit (RMW), and capital investment (CMA) factors.

Most factor return series and the one-month Treasury bill rates are downloaded from Kenneth French's website. The RD factor is computed as the daily cross-sectional standard deviation of CRSP value-weighted stock returns. The following two-step procedure is used: (1) time series regressions of the respective factor model are fitted using daily returns in a 12-month period to estimate factor loadings for test asset portfolios; and (2) in the subsequent out-of-sample month, a cross-sectional regression is run using one-month-ahead portfolio returns to estimate the out-of-sample factor prices of risk denoted λ_k for the kth factor (in monthly percent return terms). The analyses are rolled forward one month at a time to enable cross-sectional regressions in each month from Jauary 1965 to December 2017. The time series average of $t = 1, \cdots, 636$ estimated factor prices for the kth factor is denoted $\hat{\lambda}_k$ (t-statistics in parentheses). Following Jagannathan and Wang (1996) and Lettau and Ludwigson (2001, footnote 17, p. 1254), adjusted R^2 values are estimated from a single equation cross-sectional regression (i.e., the time series average of one-month-ahead excess returns for all portfolios is regressed on the time series average loadings of factors for portfolios). Results are shown for equal-weighted returns using the combination of 25 size-momentum, 25 momentum, and 25 zeta risk portfolios. All test asset portfolio returns are computed in the one-month-ahead post-formation period.

25 size-momentum + 25 momentum + 25 zeta risk portfolios									
Model	$\hat{\alpha}$	$\hat{\lambda}_M$	$\hat{\lambda}_{RD}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{MOM}$	$\hat{\lambda}_{RMW}$	$\hat{\lambda}_{CMA}$	Adj R^2
CAPM	0.68	0.14							-0.01
	(3.43)	(0.62)							
ZCAPM	0.35	0.33	0.73						0.88
	(0.76)	(2.01)	(5.01)						
Three-factor	0.76	-0.28		0.57	-0.12				0.37
	(3.89)	(-1.43)		(3.25)	(-0.44)				
Four-factor	0.83	-0.33		0.55	-0.17	0.85			0.47
	(5.35)	(-1.95)		(3.04)	(-0.82)	(4.00)			
Five-factor	0.54	-0.02		0.48	-0.47		0.10	-0.01	0.41
	(3.26)	(-0.11)		(3.25)	(-2.19)		(0.41)	(-0.08)	

Table 4: Descriptive return statistics for zero-investment momentum and zero-return return dispersion portfolios

This tables provides decriptive statistics for the returns on zero-investment momentum and zero-investment return dispersion portfolios. Momentum portfolios are formed by ranking holding period returns in previous 12-month estimation periods that start with the period January to December 1964. Stocks are placed into deciles, and high-to-low return portfolios are denoted denoted $M10$ to $M1$. Using a 1-week lag between between the estimation period and post-formation holding period, equal-weighted average monthly returns are computed in the post-formation month January 1965. This process is rolled forward one month at a time to develop time series of one-month-ahead holding period returns for $M10$ to $MOM1$ from January 1965 to December 2017. These portfolios' returns are used to compute the returns for the following zero-investment portfolios: $M10-M1$, $M9-M2$, $M8-M3$, $M7-M4$, and $M6-M5$. Zero-investment return dispersion portfolios are constructed by estimating times-series regressions for the empirical ZCAPM in equation (8) with daily returns for 12-month prior estimation periods that start with the period January to December 1964. All stocks are ranked in terms of their estimated zeta coefficient, or $\hat{Z}_i^*$. Stocks are placed in deciles and denoted $Z10$ to $Z1$. Using a 1-week lag between the estimation period and post-formation period, equal-weighted average monthly returns are computed in the post-formation month January 1965. The process is rolled forward one month at a time to rebalance the portfolios until the last post-formation holding period return is computed in December 2017. Like momentum return series, these return series are used to compute the following zero-investment portfolio returns: $Z10-Z1$, $Z9-Z2$, $Z8-Z3$, $Z7-Z4$, and $Z6-Z5$.

Zero-Investment Factor	Mean	Std Dev	Min	Max	Max Loss
$M10-M1$	0.94	6.24	-59.95	19.30	-82.24
$M9-M2$	0.59	3.61	-28.78	13.69	-57.38
$M8-M3$	0.32	2.50	-18.63	9.95	-40.67
$M7-M4$	0.20	1.61	-8.42	4.91	-24.94
$M6-M5$	0.03	1.01	-4.87	2.89	-18.04
$Z10-Z1$	1.48	6.08	-42.57	52.14	-61.04
$Z9-Z2$	0.80	3.56	-17.54	30.27	-37.84
$Z8-Z3$	0.39	2.28	-9.55	15.38	-23.68
$Z7-Z4$	0.21	1.44	-5.93	6.75	-14.23
$Z6-Z5$	0.05	0.92	-2.96	3.54	-21.93
SMB	0.27	3.07	-14.94	18.38	-57.05
HML	0.34	2.84	-11.10	12.90	-40.89
RMW	0.26	2.19	-17.99	12.83	-38.99
CMA	0.29	2.02	-6.88	9.58	-17.30

Table 5: Hybrid zero-investment portfolios formed by combining momentum and zeta risk strategies

This table shows the monthly returns performance of zero-investment portfolios formed by combining momentum and zeta risk strategies. Small stocks are dropped in these analyses due to potential short-term reversal among small stocks. The formation period is one year excluding the last week in the year. One-month-ahead, post-formation returns are computed for each zero-investment portfolio. Zeta coefficients are estimated for the ZCAPM using EM regression with one year of daily returns. Zero-investment momentum and CRSP excess returns over the Treasury bill are shown for comparison purposes. Zero-investment portfolios are formed as follows:

- $M10 - M1$: Form 10 past return equal-weighted portfolios using the 80% largest market capitalization stocks with high-to-low return portfolios denoted $M10$ to $M1$. The momentum portfolio is formed by longing the winner portfolio $M10$ and shorting the loser portfolio $M1$.

- $MZ10 - MZ1$: Form 10 zeta risk equal-weighted portfolios using the 80% largest market capitalization stocks with high-to-low zeta risk portfolios denoted $Z10$ to $Z1$. The hybrid momentum-zeta-risk portfolio is formed by longing the intersection of stocks in the $M10$ and $Z10$ portfolios and shorting the intersection of stocks in the $M1$ and $Z1$ portfolios.

- $MZ10^* - MZ1^*$: Form portfolio $MZ10 - MZ1$ with weights for individual stocks based on their $|Z^*|$ proportions, rather than equal weights.

Zero-Investment Portfolio	Mean	Std Dev	Min	Max	Max Loss
$CRSP - R_f$	0.52	4,44	-23.24	16.10	-55.68
$M10 - M1$	1.74	7.18	-59.39	41.83	-76.47
$MZ10 - MZ1$	1.81	7.35	-62.07	46.82	-78.25
$MZ10^* - MZ1^*$	1.91	7.82	-67.62	50.04	-80.20

Table 6: Risk-managed hybrid zero-investment portfolios formed by combining momentum and zeta risk strategies

This table shows the monthly returns performance of zero-investment portfolios formed by combining momentum and zeta risk strategies. Small stocks are dropped in these analyses due to potential short-term reversal among small stocks. The formation period is one year excluding the last week in the year. One-month-ahead, post-formation returns are computed for each zero-investment portfolio. Zeta coefficients are estimated for the ZCAPM using EM regression with one year of daily returns. Zero-investment momentum and CRSP excess returns over the Treasury bill are shown for comparison purposes. Zero-investment portfolios are formed as follows:

- $M10 - M1$: Form 10 past return equal-weighted portfolios using the 80% largest market capitalization stocks with high-to-low return portfolios denoted $M10$ to $M1$. The momentum portfolio is formed by longing the winner portfolio $M10$ and shorting the loser portfolio $M1$.
- $MZ10 - MZ1$: Form 10 zeta risk equal-weighted portfolios using the 80% largest market capitalization stocks with high-to-low zeta risk portfolios denoted $Z10$ to $Z1$. The hybrid momentum-zeta-risk portfolio is formed by longing the intersection of stocks in the $M10$ and $Z10$ portfolios and shorting the intersection of stocks in the $M1$ and $Z1$ portfolios.
- $MZ10^* - MZ1^*$: Form portfolio $MZ10 - MZ1$ with weights for individual stocks based on their $|Z^*|$ proportions, rather than equal weights.

We apply risk management to zero-investment portfolios. In any month, if the average zeta risk span between the $Z10$ and $Z1$ portfolios is within the smallest quintile of all previous months in the sample period, then the zero-investment portfolio is replaced by market portfolio $CRSP - R_f$ for monthly rebalancing purposes.

Zero-Investment Portfolio	Mean	Std Dev	Min	Max	Max Loss
$CRSP - R_f$	0.52	4,44	-23.24	16.10	-55.68
$M10 - M1$	1.87	6.48	-59.39	41.83	-63.47
$MZ10 - MZ1$	1.94	6.71	-62.07	46.82	-65.88
$MZ10^* - MZ1^*$	2.03	7.22	-67.62	50.04	-70.88

Table 7: Time series OLS regression tests

This table reports OLS regressions on the return relationship between zero-investment momentum and zero-investment return dispersion strategies. The following OLS regression is estimated:

$$MOM_T = \alpha_{MOM} + \beta_{MOM} FACTOR_T + \varepsilon_T, \tag{12}$$

where MOM_T is the momentum return in month T, and $FACTOR_T$ is the factor return. The dependent variable MOM is variously defined as: $M10-M1$, $M9-M2$, $M8-M3$, $M7-M4$, and $M6-M5$. The independent variable $FACTOR$ is defined as: $Z10-Z1$, $Z9-Z2$, $Z8-Z3$, $Z7-Z4$, and $Z6-Z5$ in addition to SMB, HML, RMW, and CMA. All returns are equal-weighted for different investment portfolios.

Panel A: Momentum portfolio $M10-M1$					
Factors	α	t-value	β	$t$value	adj R^2
$Z10-Z1$	-0.25	-1.57	0.80	31.76	0.61
SMB	1.03	4.20	-0.34	-4.29	0.03
HML	1.02	4.14	-0.25	-2.92	0.01
RMW	0.78	3.19	0.62	5.62	0.05
CMA	0.92	3.69	0.05	0.44	-0.00
Panel B: Momentum portfolio $M9-M2$					
Factors	α	t-value	β	t-value	adj R^2
$Z9-Z2$	-0.00	-0.04	0.74	27.03	0.53
SMB	0.64	4.54	-0.20	-4.41	0.03
HML	0.62	4.35	-0.11	-2.15	0.01
RMW	0.49	3.50	0.36	4.12	0.05
CMA	0.57	3.92	0.08	1.11	0.00
Panel C: Momentum portfolio $M8-M3$					
Factors	α	t-value	β	t-value	adj R^2
$Z8-Z3$	0.02	0.31	0.76	24.21	0.48
SMB	0.35	3.60	-0.14	-4.24	0.03
HML	0.36	3.60	-0.11	-3.27	0.02
RMW	0.27	2.73	0.18	4.12	0.02
CMA	0.31	3.10	0.03	0.52	-0.00
Panel D: Momentum portfolio $M7-M4$					
Factors	α	t-value	β	t-value	adj R^2
$Z7-Z4$	0.09	1.54	0.52	13.28	0.22
SMB	0.22	3.40	-0.06	-3.02	0.01
HML	0.21	3.28	-0.03	-1.42	0.00
RMW	0.17	2.69	0.11	3.82	0.02
CMA	0.19	2.99	0.02	0.76	0.00
Panel E: Momentum portfolio $M6-M5$					
Factors	α	t-value	β	t-value	adj R^2
$Z6-Z5$	0.02	0.41	0.16	3.74	0.02
SMB	0.04	0.88	-0.04	-3.04	0.01
HML	0.03	0.77	-0.02	-1.27	0.00
RMW	0.01	0.27	0.05	2.98	0.01
CMA	0.02	0.43	0.03	1.28	0.00

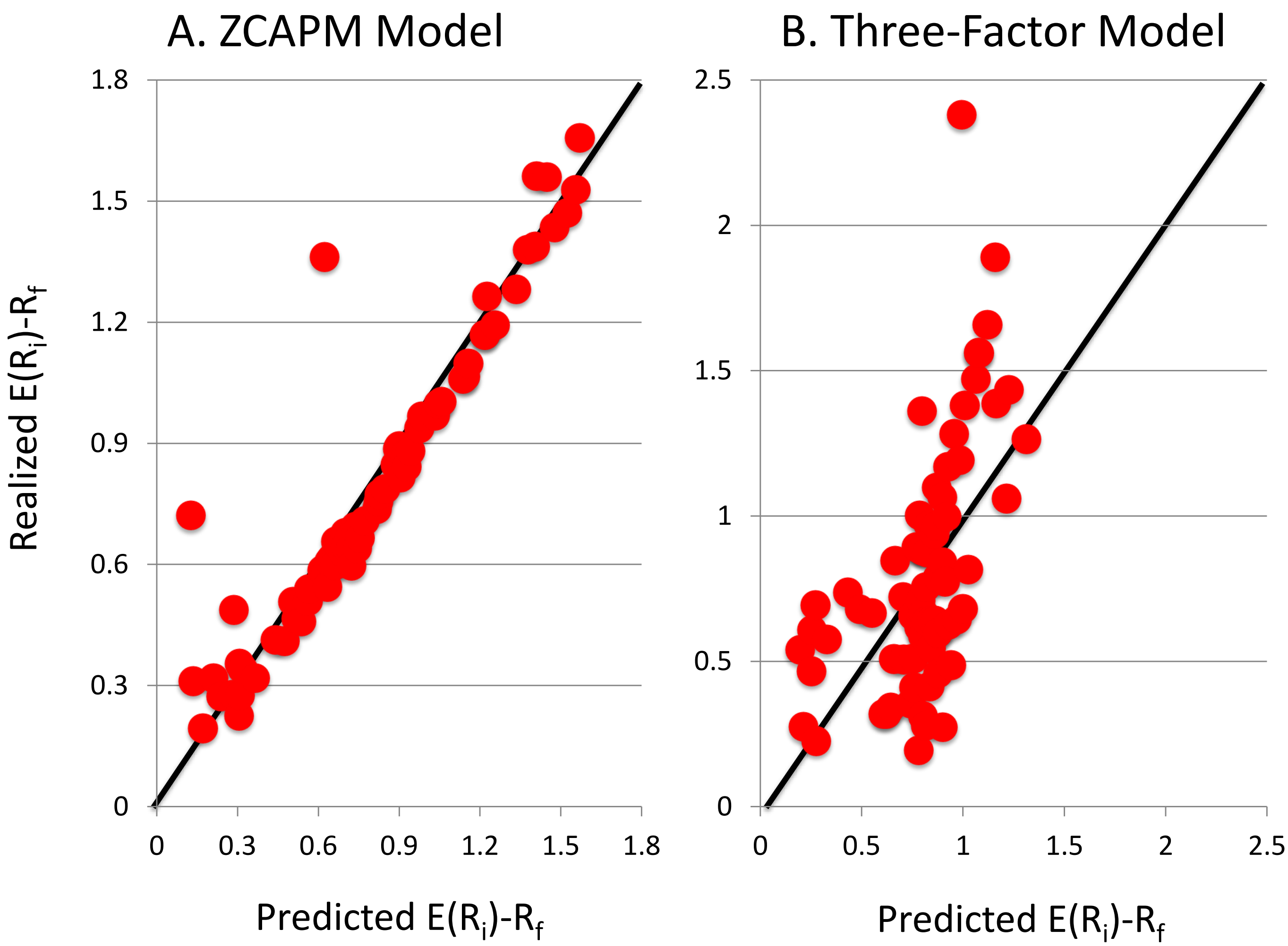

Figure 1: Out-of-sample cross-sectional relationship between average one-month-ahead realized excess returns in percent and average one-month-ahead predicted excess returns in percent for 25 size-momentum, 25 momentum, and 25 zeta risk portfolios: ZCAPM model in Panel A and Fama and French three-factor model in Panel B.

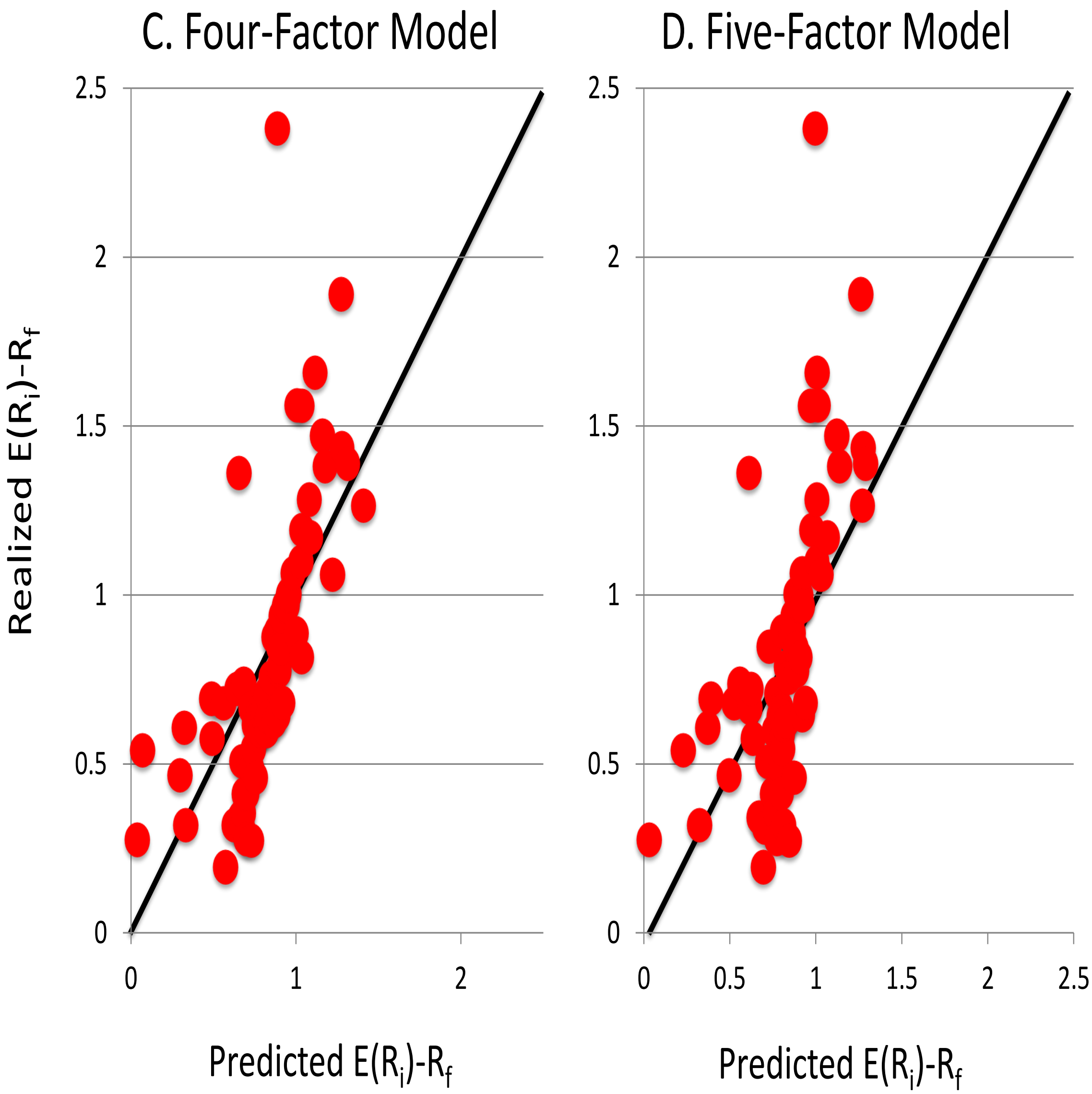

Figure 2: Out-of-sample cross-sectional relationship between average one-month-ahead realized excess returns in percent and average one-month-ahead predicted excess returns in percent for 25 size-momentum, 25 momentum, and 25 zeta risk portfolios: Carhart four-factor model in Panel A and Fama and French five-factor model in Panel B.