A Conditional Multifactor Analysis of Return Momentum

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Abstract

Although the Fama-French three-factor model captures most CAPM anomalies, it still fails to explain return momentum. This paper shows that the incorporation of conditioning information into an asset-pricing model is one way to capture return momentum. Results from the conditional regression with linear exposures in the instruments show clear evidence that both SMB and HML risks are time varying and that momentum and reversal return patterns have different time-varying risk characteristics. The conditional Fama-French regression model seems, however, to remain misspecified. Conversely, when the linearity assumption is relaxed and cross-sectional restrictions are imposed, the conditional pricing model appears to capture both short-term momentum and long-term reversal.

Key words: Conditional Asset Pricing, Conditioning Information, Multifactor Model, Return Momentum, Return Reversal

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1. Introduction

During the late 1970s, evidence started to accumulate against the then-accepted paradigm of market efficiency. However, as argued by Fama (1991), the "abnormal" returns found by many researchers may not be reliable evidence against market efficiency if the equilibrium pricing model adopted in tests—typically the static CAPM by Sharpe (1964), Lintner (1965), and Black (1972)—is incorrect. Confirming Fama's misgivings about the static CAPM, Fama and French (hereafter FF) (1992) demonstrate that there seems to be no relation between the average stock returns and the conventionally estimated beta; in contrast, the market value of the firm's equity and book-to-market ratio do significantly explain average stock returns. In their subsequent work, FF (1993) propose a related three-factor asset pricing model that does seem to describe adequately the average stock excess returns. The FF three factors are the market return in excess of a risk-free rate, or EMR, the average return on small-size firms minus average returns on big-cap firms, or SMB (a factor that is related to size), and the average return on high book-to-market firms minus the average return on low book-to-market firms, or HML (a factor that is related to book-to-market equity).

Using their three-factor model, FF (1996) clear up CAPM anomalies such as size, book-to-market, earnings/price, cash flow/price, and past sales growth.[1] In view of FF's choice of the

[1] These anomalies are documented in Banz (1981), Basu (1983), Rosenberg, Reid, and Lanstern (1985), and Lakonishok, Shleifer, and Vishny (1994), and among others. There are also anomalies related to past returns. DeBondt and Thaler (1985,1987) document the return reversal phenomenon; see also Ball and Kothari (1989), Chopra, Lakonishok, and Ritter (1992), and others for the relevant debate. For momentum, see Jagadeesh and Titman (1993) and Asness (1995).

factor portfolios, it comes as no surprise that their model can absorb the size and book-to-market effects, as well as other effects that bear an obvious relation to size and book-to-market. What makes their findings more appealing is that the same three factors are also able to explain long-term return reversal, namely, past long-term losers (winners) tend to become future winners (losers), a phenomenon that before FF(1996) had been thought to be unconnected to size and book-to-market. However, one anomaly remains unresolved by FF (1996): the three-factor model cannot capture the short-term return continuation (or momentum) phenomenon. As Chan, Jegadeesh, and Lakonishok (1996) put it: “in the absence of an explanation, the evidence on momentum stands out as a major unresolved puzzle.”

The main finding of this paper is that incorporating conditioning information into the FF three factor model is a crucial step to capture return continuation as well as reversal. My motivation for considering a conditional version of the FF model is that, in a dynamic world, risk exposures as well as prices of risks are likely to vary through time and to depend on conditioning information. My emphasis on conditioning information is similar to Ferson and Harvey (1999) but in different ways. Using 25 book-to-market and size-sorted test portfolios, Ferson and Harvey (1999) show that the FF three factors fail in conditional regression tests, similar to the first part of this paper using portfolios sorted on past returns. But I argue that conditional SMB and HML risks do reflect time-varying risk characteristics that may distinguish return momentum and reversal patterns. Ferson and Harvey further show that an additional pricing factor that is based purely on conditioning information (predetermined variables) washes out the FF three factors but alone still cannot explain the cross section of asset returns in the Fama-MacBath (1973) two-pass cross-sectional tests. The second part of this paper is significantly different in this regard as shown below in detail. Accordingly, I proceed in two steps.

In the first stage, I test the FF assumption that the exposures are constant. To that aim, the paper investigates four portfolios: the best short-term winners and the worst short-term losers (i.e., the extreme momentum portfolios) and the best long-term winners and the worst long-term losers (i.e., the extreme reversal portfolios). I use a conditional regression model, which explicitly assumes that the risk exposures are linear functions of the information variables. I find overwhelming evidence that the SMB and HML risks are time varying.

A further exploratory investigation reveals an important difference in the time paths of risk patterns between the return momentum and reversal. I show that, like the SMB risks, the HML risks are significantly *negatively* cross-correlated between short-term winners and losers but significantly *positively* cross-correlated between long-term winners and losers. Since time-variation characteristics of risks like this can be important in asset pricing and are missed in the FF unconditional analysis, it is difficult for their unconditional model to accommodate both the opposite return patterns of continuation and reversal with the same set of pricing factors. Therefore, my findings shed more light on the ability of the conditional asset pricing model to capture the time path behavior of risks and hence to explain both momentum and reversal.

However, the conditional regression model still fails to explain average returns even though conditioning information has been taken into consideration (see also Ferson and Harvey, 1999). This failure in itself does not provide sufficient evidence against the conditional FF model. First, the conditional regression model imposes a very specific (i.e., linear) structure on the risk exposures, which can be relaxed in different ways. Second, in the first-pass tests, each portfolio equation is estimated in isolation without cross-sectional constraints. As argued by Kandel and Stambaugh (1995), to assess a model properly, one definitely needs a cross-sectional picture, using the covariance matrix of asset returns, because otherwise the relation between expected returns and estimated risk exposures can vary arbitrarily across equations. For this reason, FF (1996) base their final conclusions on the multivariate test by Gibbons, Ross, and Shanken (hereafter GRS) (1989). In the same spirit, in the second stage of this analysis, I employ parsimonious conditional cross-sectional asset pricing tests, which can be viewed as a conditional analogue to the static GRS test.

In the conditional cross-sectional tests, I first follow the econometric specification of Dumas and Solnik (1995). This approach takes a stand on the functional form of a price of risk (i.e., the reward-to-risk ratio or the expected factor return divided by the variance of the factor). Prices of risks are assumed linearly related to conditioning information variables that to some extent predict future returns but impose no structure on the covariance. With no-arbitrage conditions imposed across test portfolios, the conditional FF model is tested using Hansen's (1982) Generalized Method of Moment (GMM), first on decile portfolios that exhibit continuation and then on decile portfolios that exhibit reversal. As in FF (1996), I cannot reject the hypothesis that the conditional FF model produces zero pricing errors for return reversal portfolios; the interesting, new result, however, is that I can not reject the hypothesis of zero pricing errors for return momentum portfolios.

These tests still have a drawback in that they are conducted on two separate sets of portfolios —one constructed to show return momentum, the other to exhibit reversal. Thus, the estimated prices of risks depend on which test portfolios are to be examined. However, if the law of one price holds, one vector of prices of risks should price both the momentum and reversal portfolios. Tests that ignore these constraints may lack the power to assess a model because they leave too many degrees of freedom in econometrically fitting separate data sets.

To mitigate these problems, I also run the Dumas-Solnik pricing tests on ten portfolios, five of which now exhibit momentum, and the other five reversal. A related important issue, which Jagannathan and Wang (1996) point out in the concluding section of their paper, is that there is no consensus on a common set of test portfolios, which is desired for general asset pricing, particularly for the robust comparison among models. A particular set of test portfolios may favor one model but not another. When a model is rejected, one could raise reasonable doubt by arguing that the test portfolios on which the rejection is based may contain too little dispersion in the risks that the model in question emphasizes. This issue is, however, less central to the tests of this paper, because I focus on the ability of a specific model to price different portfolios rather than run a horse race with different models. In contrast, I need a good set of test portfolios that characterize all portfolios in question just because it can provide sharper tests of the particular model (other things being equal).

Lastly, to check for robustness, I also subject this pooled portfolio set to the asset pricing test used by Harvey (1989). Prices of risks in this test are also assumed linearly related to instruments, much as in Dumas-Solnik's approach, but Harvey's approach examines moment conditions consisting of nonlinear functions. Despite the differences in these two approaches, the test results show that one single set of estimated prices of risks tend to price both momentum and reversal portfolios. In fact, the two sets of estimates of the time-varying prices are surprisingly robust: the prices of risks from Dumas-Solnik's approach are nearly perfectly correlated with their counterparts from Harvey's approach (correlation coefficients are above 0.95).

The remainder of the paper is organized as follows. Section 2 presents the data and summary statistics for the portfolios sorted on various past returns as well as for the FF three factors and the information variables that are used as instruments. Section 3 summarizes the basics of the conditional FF three-factor model. Section 4 investigates explicitly the conditional risk exposures to the FF three factors for extreme winners and losers, using the regression version of the conditional FF model. Section 5 describes more general conditional cross-sectional asset pricing tests, and reports the test and estimation results. Section 6 concludes the paper.

2. Data and summary statistics

In this section, I first replicate the continuation and reversal evidence from FF, using a data set that contains both more sample years and more stocks. I then describe the factors and the instrumental variables.

2.1. Portfolios formed on past returns

From the database of the Center for Research in Security Prices (CRSP), I retrieve monthly data on all NYSE and AMEX US common stocks from July 1958 to December 1995. After setting aside five years of data for the purpose of ranking (as described below), my test sample runs from July 1963 to December 1995.

The individual stocks are grouped into equally weighted decile portfolios on the basis of past continuously compounded monthly returns. As in FF (1996), different ranking periods are used to form such deciles. To capture short-term past performance, I focus mainly on the ranking labeled “Past2-12”, i.e., a ranking on the basis of the return between month *t*-11 and *t*-1. (The return in month *t* is omitted to avoid spurious reversal due to the bid-ask bounce.) To capture long-run past performance purged of short-term past returns, I form deciles on the basis of Past13-60, i.e., using returns from *t*-59 to *t*-12. For each decile, I then compute monthly post-formation excess returns, using as the risk-free rate the one-month T-bill holding period return (obtained from the SBBI file in Ibbotson Associates).

Throughout this paper, a monthly return of one means one percent per month. The average monthly excess returns for July 1963 to December 1995 and the *t*-values of the averages are presented in Table 1, Panel A. The phenomenon of return continuation (or momentum) shows up in the decile-classification Past2-12. In this cross-sectional pattern, the worst past losers (decile 1) show an average post-formation excess return of –0.02 percent per month, while the best past winners (decile 10) yield a significant average post-formation excess return of 1.46 percent per month (*t*-value=4.23). Short-term past losers (winners) tend to be future losers (winners) — hence there is return continuation.

In contrast, the row labeled "Past13-60", where ranking is based on earlier long-term performance, shows a pattern of return reversal: in these decile portfolios, the worst past losers produce a significant average post-formation excess return of 1.41 percent per month (*t*-value=3.11), while the best past winners provide an average post-formation excess return of only 0.35 percent per month. The results here are much more pronounced than in FF (1996) with only NYSE stocks and a shorter sample period by two years.[2] Therefore, the patterns of return continuation and return reversal pose a tougher challenge to asset pricing tests.

In Hansen and Richard (1987), unconditionally efficient portfolios are shown to be conditionally efficient too. Accordingly, one may wonder what the point is of adding a conditional test to FF's earlier work, if FF can already explain return reversal without the use of

[2] I also use alternative classifications that start in months *t*-11, *t*-23, *t*-35, *t*-47, or *t*-59, all ending in month *t*-1. Consistent with FF (1996), Past2-24 and Past2-36 also give indications of return momentum, while Past2-60 shows return reversal.

a conditional model. The reason is that Hansen and Richard's claim holds true only when the test portfolios are the same in both unconditional and conditional tests. In the conditional tests that follow, however, the portfolio set (or the strategy space) is extended by conditioning information or trading rules (see e.g., Cochrane, 1994 and Dumas and Solnik, 1995). In other words, the strategy space in my conditional cross sectional test is larger than that which FF use in their unconditional test. Therefore, it is not *a priori* obvious that the pattern of return reversal can be explained by a conditional pricing model.

In the above, the ranking produces either reversal or momentum. I also generate a group of ten test portfolios, of which five exhibit reversal and the other five continuation. To obtain this set, the NYSE and AMEX US firms are randomly separated into two subsets. In the first subset, quintiles are then formed on the basis of short-term performance (portfolios Past2-12q), while in the second subset the ranking and grouping are ordered on the basis of more long-run and distant returns (Past13-60q). As shown in Table 1, Panel B, the return continuation pattern still shows up, with the worst short-term losers (quintile 1) producing an average excess return of 0.20 (t-value=0.52) and the best short-term winners (quintile 5) achieving a stunning average excess return of 1.38 (t-value=4.32). Also, the return reversal pattern is still evident: the worst long-term losers (quintile 1) turn out to be the best winners with a significant average excess return of 1.14 (t-value=2.99), while the best long-term winners (quintile 5) become the worst losers with a much inferior performance of 0.47 (t-value=1.60).

2.2. Factors and instrumental variables

The three pricing factors—excess market return (EMR), SMB and HML—were kindly provided by Eugene Fama and are detailed in FF (1993, 1995, 1996). To get a feel for the factors, the average excess market return is 0.48 percent per month, and the average returns of the two mimicking portfolios, SMB and HML, are equal to 0.25 and 0.44 percent per month for July 1963 through December 1995.

As for the instruments, I need market-wide financial variables that carry information on the state of the economy that are useful in predicting asset returns. For the selection of factors, I rely on previous work where the information variables have been extensively screened on their predictive power (see e.g., Ferson, 1994, for a summary). Thus, although my strategy space differs from that used by others, my instruments are the ones that are widely used in conditional asset pricing.[3] I use five instruments, which are similar to those used in Harvey (1989) and Ferson and Harvey (1991): (a) the one-month lagged (NYSE, AMEX, and Nasdaq) value-weighted market excess return, EMR(–1) (from Fama); (b) the one-month US T-bill rate observed at the beginning of the return period, TB1 (from the Fama file in CRSP); (c) the yield spread between three- and one-month US T-bills, TB31 (the three-month T-bill rate observed at the beginning of the return period also from the Fama file); (d) the yield spread between Corporate Baa- and Aaa-bonds observable prior to the beginning of the return period, JUNK (from the Federal Reserve Bulletin); and (e) the one-month lagged spread between a dividend yield and the one-month T-bill return, DIV(–1).[4]

[3] This selection method does not necessarily bend our tests in favor of accepting a conditional model. For example, the conditional CAPM in Harvey (1989) is rejected using a similar set of instruments.

[4] The monthly 12-month-accumulated dividend yields are computed as follows (see also Campbell and Ammer, 1993, and Campbell, 1996). I take the differences between the monthly S&P stock returns with and without dividends (from Ibbotson Associates) to generate a monthly dividend yield series and then convert these dividend yields into a 12-month (including current month) backward moving average of dividends divided by the end-of-current-month index price. The use of a moving average eliminates the strong (quarterly) seasonality of dividend payments, but results in a time series with high autocorrelations. As a partial remedy, following Dumas and Solnik (1995) and others, the one-month T-bill return is subtracted from the dividend yield.

Table 2 provides summary statistics for the instruments. The major concern about Hansen's (1982) GMM test, which this paper employs later, is that some instruments come close to non-stationarity. Specifically, the autocorrelation coefficients of the one-month risk-free rate, TB1, and of the yield spread between Baa- and Aaa-bonds, JUNK, are high at lag 1 (0.95 and 0.97) and do not entirely die out even after 36 months (0.21 and 0.19). This could violate the strict stationarity assumption that underpins the theoretical asymptotic properties of the GMM. However, simulation tests with finite sample by Ferson and Foerster (1994) suggest that the GMM coefficient estimators and test statistics still conform well to some of the theoretical asymptotic properties even when some instruments are nearly non-stationary.

3. Basics of the conditional FF three-factor model

In the spirit of Merton's (1973) Intertemporal Capital Asset Pricing Model and Ross' (1976) Arbitrage Pricing Theory, FF (1993) propose a multifactor model with three factors: the market return in excess of a risk-free rate, EMR, and two mimicking portfolio returns: SMB (small minus big) and HML (high minus low).[5]

Using these three pricing factors, FF (1996) succeed in resolving most of the well-known CAPM anomalies except short-term return continuation. FF (1996) cannot explain both continuation and reversal at the same time, because they find that the exposure patterns of losers versus winners is the same whether past performance is defined as short- or long-term. That is,

[5] Although FF(1995) demonstrate that both firm size and book-to-market, which are used to construct SMB and HML respectively, have strong empirical links to firms' economic fundamentals (profitability), controversy remains over whether SMB and HML are really risk-based, rational asset pricing factors (see, e.g., Ferson and Harvey, 1999). This paper does not intend to join the debate on the rationality issue. However, since the paper has a clear focus within the framework of the FF model, I preserve the consistency of FF's logic throughout the paper.

relative to short-term winners, short-term losers on average load more on SMB as well as on HML, which is the same pattern as observed for long-term losers relative to long-term winners. As a result, in the FF tests, the high loadings for short-term losers incorrectly predict the same pattern as for long-term losers, namely reversal rather than continuation.

FF obtain the above results in an unconditional setting. However, there is no strong *a priori* reason to believe that prices of risks and degrees of risks stay constant through time. In an attempt to explain the unresolved cross-sectional patterns of return continuation, I investigate whether it helps to take market-wide conditioning information into consideration. The conditional version of the FF three-factor asset pricing model can be written as

$$E[r_{i,t+1}|\Omega_t] = \beta_{mt}\, E[\mathrm{EMR}_{t+1}|\Omega_t] + \beta_{st}\, E[\mathrm{SMB}_{t+1}|\Omega_t] + \beta_{ht}\, E\,[\mathrm{HML}_{t+1}|\Omega_t] \qquad (1)$$

where $r_{i,t+1}$ is the return of asset i from time t to t+1 in excess of a risk-free rate; EMR_{t+1} is the return on the market portfolio in excess of a risk-free rate; SMB_{t+1} is the mimicking portfolio return used to capture the size effect; HML_{t+1} is the mimicking portfolio return to explain relative distress; Ω_t is the information set that investors rely upon to balance their portfolios through time; $E[.|\Omega_t]$ is the expectation conditioned on information at time t; β_{mt} is the market risk; β_{st} is the state risk arising from investors' special hedging concerns associated with size; and β_{ht} is the risk arising from special hedging concerns related to relative distress. In a conditional setting, risk measures as well as risk premiums are supposed to vary through time; and time-varying risks are explicitly specified in Section 4.

Alternatively, the conditional version of the FF three-factor pricing model can take the following form:

$$E[r_{i,t+1}|\Omega_t]=\lambda_{mt}\,\mathrm{cov}[r_{i,t+1},\mathrm{EMR}_{t+1}|\Omega_t] + \lambda_{st}\,\mathrm{cov}[r_{i,t+1},\mathrm{SMB}_{t+1}|\Omega_t] + \lambda_{ht}\,\mathrm{cov}[r_{i,t+1},\mathrm{HML}_{t+1}|\Omega_t] \quad (2)$$

where λ_{mt} is the price of the market risk (reward to covariability with the market); λ_{st} is the price of the state risk that is associated with size (reward to covariability with SMB_{t+1}); and λ_{ht} is the price of the state risk that is associated with relative distress (reward to covariability with HML_{t+1}). In a conditional setting, the covariances and prices of risks are supposed to vary through time; and conditional prices of risks are explicitly specified in Section 5.

4. Exploring conditional risk exposures

One potential reason that the FF tests fail to accommodate short-term momentum may be that assets' exposures to the SMB and HML factors are indeed time-varying and that time-variation characteristics of different assets, which are missed by the unconditional FF tests, may play an important role in asset pricing. In this section, I try to model explicitly conditional risk loadings and show evidence that they are time-varying indeed and that different assets have different time-variation characteristics of risks.

Consistent with the conditional version of the FF model in (1), I postulate that the risk loadings are linear functions of a set of conditioning information and run a conditional regression as follows: [6]

$$r_{i,t+1} = \alpha + \boldsymbol{Z}_t\boldsymbol{\beta}_m\,\mathrm{EMR}_{t+1} + \boldsymbol{Z}_t\boldsymbol{\beta}_s\,\mathrm{SMB}_{t+1} + \boldsymbol{Z}_t\boldsymbol{\beta}_h\,\mathrm{HML}_{t+1} + \eta_{i,t+1} \quad (3)$$

[6] This is similar to Ferson and Harvey (1999). Conditional regressions have become widely used in empirical finance. For example, Ferson and Schadt (1996) use them to re-evaluate fund performance.

where $r_{i,t+1}$ is the excess return (total return) on portfolio (arbitraging portfolio) i and EMR_{t+1} is the excess return on market; SMB_{t+1} and HML_{t+1} are returns on the mimicking portfolios that reflect premiums on size effect and relative distress effect, respectively; $\boldsymbol{Z}_t$ is a row vector of the six instruments including a constant; and α, $\boldsymbol{\beta}_m$, $\boldsymbol{\beta}_s$, and $\boldsymbol{\beta}_h$ are constant weights to be estimated. Thus, $\mathbf{Z}_t\boldsymbol{\beta}_m$, $\mathbf{Z}_t\boldsymbol{\beta}_s$, and $\mathbf{Z}_t\boldsymbol{\beta}_h$ are conditional risk loadings on EMR, SMB, and HML, respectively. The intercept, α, is usually interpreted as the abnormal return.

With little loss of generality, I focus on four extreme portfolios: the worst and best performers in ranking Past2-12 (denoted as SL and SW, respectively), and the worst and best performers in ranking Past13-60 (LL and LW, respectively). I am particularly curious as to whether the risk exposures for these portfolios vary through time in relation with conditioning information, whether and how conditional risk exposures for different assets behave differently, and whether conditioning information helps the model to explain return momentum and reversal.

In Table 3, each of $\boldsymbol{\beta}_m$, $\boldsymbol{\beta}_s$, and $\boldsymbol{\beta}_h$ shows the weights on $\boldsymbol{Z}_t$ in the corresponding exposures. Using heteroskedasticity-consistent Wald tests, I first test the null hypothesis that, in each vector, the slopes (excluding the constant term) are jointly zero. For the market risks, the Wald test rejects the hypothesis of constant exposure only in one case, namely for LL (χ^2 statistic = 15.23, p-value=0.01). In contrast, there is overwhelming evidence that the exposures to SMB and HML tend to be time-varying; only the constant SMB risk for LW is not rejected (χ^2 statistic = 5.29, p-value=0.38) at the 10% level.

Second, if the FF three-factor model is correctly specified, abnormal returns should be close to zero. However, this is not the case in view of the evidence from the conditional regression with linear risk exposures in the instruments. The estimates of α, are in general significantly different from zero, with LL being the only portfolio with an insignificant α value (-0.33, *t*-value=-1.49).

The less-than-perfect performance of the linear-exposure model, however, does not mean that a conditional regression model is useless. It is a long tradition that researchers use the market model to control for the market risk for an asset or portfolio regardless of whether this asset or portfolio is over- or under-priced by this one-factor model. In other words, it is widely accepted that the risk loading suggested by a return generating process bears useful information about the risk for the asset or portfolio in question. In the same spirit, I simply use the linear-exposure model to discover the prime characteristics of the conditional risk exposures even though it is known that the linear model does not capture the whole picture.

Table 4 reports some key aspects of conditional risk exposures. In Panel A, the time-series means of conditional SMB and HML risks for momentum and reversal portfolios show similar risk patterns found in the unconditional FF (1996) tests, that is, regardless of being short- or long-term, losers load more on SMB and HML than winners do.[7] Such risk patterns are also observed in terms of other location measures reported in Panel A (such as median, the first and third quartile, minimal and maximal values).

In Panel B of Table 4, the time-varying SMB risks for both short- and long-term winners show a pattern of some long memory with significant autocorrelations hovering at a similar level in each case up to at least lag 6. In contrast, positive autocorrelations of the SMB risks for both short- and long-term losers tend to die out after the first lag. In short, there is a strong parallel

[7] Short-term (long-term) losers show an average SMB risk of 1.67 (1.74) and an average HML risk of 0.55 (0.94) while short-term (long-term) winners have, on average, a SMB risk of 1.04 (0.71) and a HML risk of 0.11 (-0.19).

between return momentum and reversal patterns regarding their SMB risks. However, close scrutiny tends to indicate that the HML risk for LL behaves like LW, unlike their short-term counterparts.

Further evidence that apparently breaks the similar risk patterns between return momentum and reversal comes from Panel C of Table 4. Exposures to the two mimicking portfolio factors for short- and long-term pairs finally exhibit a clear asymmetry: for the short-term winners and losers, the SMB risks as well as the HML risks are significantly *negatively* cross-correlated (corrrelation = -0.22 and -0.47, respectively), but these risks for the long-term winners and losers are significantly *positively* cross-correlated (correlation = 0.30 and 0.46, respectively). Thus, the different time-variations in the SMB and HML risks are the empirical fact that clearly distinguishes the short-term winners/losers from the long-term winners/losers.

As a result, it becomes possible that short-term performance is characterized by momentum while long-term performance exhibits reversal. In light of this, the failure of the unconditional asset pricing tests in FF (1996) to accommodate for the opposite return patterns of continuation and reversal with the same unconditional FF three factors now appears less puzzling.

Still, the conditional regression model fails to price assets correctly. However, this failure in itself does not warrant rejection of the role of conditioning information. First and foremost, the conditional regression in (3) imposes a very specific (i.e., linear) structure on the exposures. Second, each portfolio equation is tested in isolation, without cross-sectional constraints. For this reason, FF (1996) base their final conclusions on the multivariate test by GRS (1989). In the same spirit, the next section employs parsimonious conditional cross-sectional pricing tests, which can be viewed as a conditional analogue to the static GRS test.

5. Conditional cross-sectional asset pricing tests

I first use the method by Dumas and Solnik (1995) and then the method by Harvey (1989) to check for robustness. Both methods need just one-shot estimation, which is significantly different from the two-pass approach used in Ferson and Harvey (1999). Also, both methods expand the test portfolios into a much larger strategy space based on conditioning information.

5.1. Econometric test using Dumas-Solnik's approach

Dumas and Solnik (1995) test conditional international asset pricing models with a world market factor and some foreign exchange risk factors. From, for instance, Ross (1976) or Hansen and Jagannathan (1991), if the law of one price prevails, there will be at least some random variable M_{t+1} such that

$$E[M_{t+1}(1+\rho_t)|\Omega_t] = 1, \tag{4a}$$

$$E[M_{t+1}r_{i,t+1}|\Omega_t] = 0 \tag{4b}$$

where M_{t+1} is a stochastic discount factor or a pricing kernel, which can be taken, as a solution, to be equal to the representative investors' intertemporal marginal rate of substitution; ρ_t is a conditional risk-free rate; and $r_{i,t+1}$ is the excess return on a portfolio or the total return on an arbitrage portfolio. The no-arbitrage (moment) conditions in (4a) and (4b) say that there is a positive pricing kernel M_{t+1} that explains the cross-section of asset returns.

Of course, (4a) and (4b) are empty statements as long as the pricing kernel remains unspecified. Assuming the conditional FF pricing model in (2), the pricing kernel becomes

$$M_{t+1} = \frac{1}{1+\rho_t}[1-\lambda_{0t} - \lambda_{mt}EMR_{t+1} - \lambda_{st}SMB_{t+1} - \lambda_{ht}HML_{t+1}] \tag{5}$$

The equivalence of the pricing kernel in (5) to the original pricing model in (2) can be easily verified by substituting (5) into (4b) and using (4a). Note that λ_{ot} is not a price of risk; rather, it is an intercept that is needed to satisfy (4a):

$$\lambda_{ot} = -\lambda_{mt}\, E[\mathrm{EMR}_{t+1}|\Omega_t] - \lambda_{st}\, E[\mathrm{SMB}_{t+1}|\Omega_t] - \lambda_{ht}\, E[\mathrm{HML}_{t+1}|\Omega_t]\ .$$

To test the moment conditions in (4a) and (4b) with the pricing kernel specified by (5), I rely on one auxiliary assumption: the time-varying prices of risks and the intercept in the pricing kernel can be expressed by linear combinations of conditioning information $\boldsymbol{Z}_t$, namely,

$$\lambda_{ot} = \boldsymbol{\phi}_0'\mathbf{Z}_t,\ \lambda_{mt} = \boldsymbol{\phi}_m'\mathbf{Z}_t,\ \lambda_{st} = \boldsymbol{\phi}_s'\mathbf{Z}_t, \text{ and } \lambda_{ht} = \boldsymbol{\phi}_h'\mathbf{Z}_t, \tag{6}$$

where $\boldsymbol{\phi}_0$, $\boldsymbol{\phi}_m$, $\boldsymbol{\phi}_s$ and $\boldsymbol{\phi}_h$, are vectors of constant loadings. It is worth mentioning that, while the prices of risks are specified explicitly in (6), no functional form for the risks themselves is imposed. This implies that covariances are allowed to vary freely through time. The advantage is parsimony, but the disadvantage is that such asset pricing tests cannot tell us anything new (beyond what I find in Section 4) as to how risks are related to the instruments $\boldsymbol{Z}_t$.

With the assumption that the prices of risks are linearly related to a limited set of information variables, I can test whether the moment restrictions in (4a) and (4b) are satisfied. Let u_{t+1} denote the deviation in (4a), i.e.,

$$\begin{aligned} u_{t+1} &= 1 - M_{t+1}(1+\rho_t) \\ &= \boldsymbol{\phi}_0'\mathbf{Z}_t + \boldsymbol{\phi}_m'\mathbf{Z}_t\,\mathrm{EMR}_{t+1} + \boldsymbol{\phi}_s'\mathbf{Z}_t\,\mathrm{SMB}_{t+1} + \boldsymbol{\phi}_h'\mathbf{Z}_t\,\mathrm{HML}_{t+1}\ . \end{aligned} \tag{7}$$

Let $h_{i,t+1}$ denote the scaled pricing error in (4b) for asset i. Taking into account (7) gives

$$\begin{aligned} h_{i,t+1} &= M_{t+1}(1+\rho_t)r_{i,t+1} \\ &= (1-u_{t+1})r_{i,t+1} \\ &= r_{i,t+1} - r_{i,t+1}u_{t+1}. \end{aligned} \tag{8}$$

Taken together, (7) and (8) form an econometric system for testing conditional asset pricing restrictions:

$$E[\boldsymbol{\varepsilon}_{t+1} \,|\mathbf{Z}_t] = E[u_{t+1}, \boldsymbol{h}_{t+1} \,|\mathbf{Z}_t] = \mathbf{0}\ . \tag{9}$$

I use Hansen's (1982) GMM to test and estimate system (9). More precisely, I use Newey and West's (1987a) estimator to account for up-to-lag-3 autocorrelation in pricing errors in forming the weighting matrix $\boldsymbol{W}$ and the iterated GMM advocated by Ferson and Foerster (1994).[8] The *J*-test of the over-identifying restrictions of Hansen (1982) is a χ^2 statistic that provides a metric of goodness-of-fit for the model.

5.2. Conditional pricing tests on various sets of deciles

I use a GMM goodness-of-fit statistic to test whether the way of conditioning model (2) on information using the system in (7) and (8) can be rejected statistically.[9] Table 5 presents the test results on the various decile portfolios, where each set is formed on the basis of a specific definition of past returns as shown in Table 1, Panel A.

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[8] Hansen and Singleton (1982) originally suggest a (still widely used) two-step approach (2-stage GMM). However, Ferson and Foerster (1994) find that an iterated GMM, which repeatedly updates $\boldsymbol{W}$ until the procedure converges according to some prespecified criterion, has better finite sample properties.

[9] Each pricing test uses K = 11 moment conditions (ten decile portfolios and one pricing kernel) and l = 6 instruments (including a constant). The number of parameters P is equal to 24 (three factors plus an intercept, each having loadings on six instruments). Therefore, the degrees of freedom of the χ^2 statistic for the *J*-test are equal to 42 ($= K \times l - P = 11 \times 6 - 24$).

Panel A of Table 5 describes the results for ranking Past2-12, which exhibits short-term return continuation. Recall that the unconditional version of the FF three-factor pricing model fails to accommodate this phenomenon. In contrast, the conditional tests do not reject the hypothesis of multifactor explanation of return continuation: the *J*-test for goodness-of-fit produces a χ^2 statistic of 38.29 with a *p*-value of 0.63. Thus, the null hypothesis of zero deviations in the no-arbitrage (moment) conditions cannot be rejected. I also compute three heteroskedasticity-consistent Wald-test statistics, one for each of the hypotheses that a particular price of risk is zero. As prices of risks are assumed to be linearly related to the instruments including a constant, the null hypothesis in each Wald test is that the loadings for these six instrumental variables are jointly zero.[10] The resulting χ^2 statistics for prices per unit of covariance risk to, respectively, the market, SMB, and HML are 27.74, 40.34, and 31.34, all of which have *p*-values equal to 0.00. In summary, test results in Table 5, Panel A show that each of the conditional FF three factors seems priced and provide no evidence that a momentum factor is needed next to these factors.

Panel B in Table 5 summarizes the tests for ranking Past13-60, the one that produces long-term return reversal. Consistent with the unconditional test results in FF (1996), the results here confirm that long-term return reversal is also compatible with the conditional model with a strategy space enlarged by the conditioning information. The χ^2 statistic for goodness-of-fit, 28.08, has a *p*-value of 0.95. In the Wald tests of the hypothesis that the price of risk is zero, the

[10] Results from the LR test (not reported) are consistent with those from the Wald test. The LR test, i.e., the D-test described by Newey and West (1987b), is used in Harvey's approach later in this paper.

χ^2 statistics are 36.01, 65.64, and 59.05 respectively, and each of the *p*-values is again equal to 0.00. In other words, the hypothesis that each of the three factors is not priced is rejected.[11]

Note that the estimation reported in Table 5 is calculated separately for each set of decile portfolios, because Hansen's GMM needs a manageably small system. Thus, in the above tests the estimated prices of risks depend on which set of portfolios is used for estimation. For example, the coefficient on *EMR*(-1) for ϕ_m is significantly positive (0.018; *t*-value=2.28) in Panel A of Table 5, while it is significantly negative (-0.013; *t*-value=-2.36) in Panel B. Thus, from the above tests it is by no means obvious yet that there actually exists one set of prices of risks that can simultaneously price both continuation portfolios (as in Panel A) and reversal portfolios (Panel B). This issue is addressed in the next two subsections.

To test whether one set of prices of risks can price, simultaneously, portfolios that exhibit both reversal and momentum, in the remainder of this section I focus on the pooled set of ten portfolios, where five portfolios exhibit continuation and the other five reversal. To this data set I will apply the Dumas-Solnik tests. However, I also adopt an alternative test method, originated by Harvey (1989), to check robustness. Section 5.3 describes the alternative test, while Section 5.4 presents the test results.

5.3. Econometric test using Harvey's approach

To test a conditional CAPM, Harvey (1989) proposes a method that allows for time-varying covariances between excess returns and the market excess return. Harvey's method can be easily extended for the conditional multifactor model in (2) as follows:

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[11] I have obtained similar results with test portfolios based on longer ranking periods, namely, Past2-24, Past2-36, Past2-48, and Past2-60, respectively.

$$\boldsymbol{\mu}_t = E_t[(\boldsymbol{r}_{t+1} - \boldsymbol{\mu}_t)(\boldsymbol{f}_{t+1} - \boldsymbol{\delta}_t)']\boldsymbol{\lambda}_t, \tag{10}$$

where $\boldsymbol{r}_{t+1}$ is the vector of excess returns on test portfolios; $E_t[.]$ is the expectation conditioned on the information available at time t; $\boldsymbol{\mu}_t = E_t[\boldsymbol{r}_{t+1}]$, the vector of conditional expected excess returns; $\boldsymbol{f}_{t+1}$ is a vector of FF three factors; $\boldsymbol{\delta}_t = E_t[\boldsymbol{f}_{t+1}]$, the vector of conditional mean of the FF three factors; and $\boldsymbol{\lambda}_t$ is the vector of prices of risks. The model is further parameterized by assuming $\boldsymbol{\mu}_t = C\boldsymbol{Z}_t$ and $\boldsymbol{\delta}_t = D\boldsymbol{Z}_t$, where D and C are matrices of coefficients to be estimated. Harvey assumes that $\boldsymbol{\lambda}_t$ is constant and estimates (10) by examining the moment conditions:

$$E_t[\boldsymbol{r}_{t+1} - C\boldsymbol{Z}_t] = 0, \tag{11a}$$

$$E_t[\boldsymbol{f}_{t+1} - D\boldsymbol{Z}_t] = 0, \tag{11b}$$

$$E_t[\boldsymbol{r}_{t+1} - (\boldsymbol{r}_{t+1} - C\boldsymbol{Z}_t)(\boldsymbol{f}_{t+1} - D\boldsymbol{Z}_t)']\,\boldsymbol{\lambda}_t = 0. \tag{11c}$$

With no significant loss of generality, He, Kan, Ng, and Zhang (1996) drop the term $C\boldsymbol{Z}_t$, to obtain a more parsimonious empirical framework. They also allow prices of risks to vary through time by specifying $\boldsymbol{\lambda}_t = A\boldsymbol{Z}_t$, where

$$A = (\phi_m, \phi_s, \phi_h)', \tag{12}$$

and the ϕ's are defined the same way as their counterparts in (6). The model is tested parsimoniously by examining the moment conditions:

$$E_t[\boldsymbol{f}_{t+1} - D\boldsymbol{Z}_t] = 0, \tag{13a}$$

$$E_t[\boldsymbol{r}_{t+1} - \boldsymbol{r}_{t+1}(\boldsymbol{f}_{t+1} - D\boldsymbol{Z}_t)'A\boldsymbol{Z}_t] = 0. \tag{13b}$$

I test (13a) and (13b) using, again, Hansen's GMM (see e.g., He, Ng, and Wu, 1997).

5.4. Conditional pricing tests on pooled portfolios of momentum and reversal

If the conditional FF three factor model is true, the same set of prices of risks should explain both return momentum and reversal. To have a sharper test, I pool two sets of quintile portfolios, one set being sorted to exhibit return momentum and the other being formed to show reversal. Table 6 reports the results of the tests on this mixed sample.

Panel A in Table 6 describes results from Dumas-Solnik's approach, while Panel B summarizes the findings using Harvey's (1989) approach. The *J*-test for goodness-of-fit produces χ^2 statistics of 49.38 (Panel A) and 46.93 (Panel B), with upper-tail *p*-values of 0.20 and 0.28, respectively. Thus, the null hypothesis of zero deviations in the moment conditions in either (9) or (13) is not rejected.

To test whether the three FF factors are priced and whether prices of risks are time-varying, I compute the heteroskedasticity-consistent Wald-test statistics in Dumas-Solnik's approach and the LR test statistics in Harvey's approach.[12] As the prices of risks are assumed to be linearly related to the instruments, the null hypothesis in each Wald test in Table 6, Panel A, is that the loadings for these six instrumental variables are jointly zero. The resulting χ^2 statistics for prices of the exposures to, respectively, the market, SMB, and HML are 59.22, 58.20, and 43.95, all of which have *p*-values equal to 0.00. Similarly, in Panel B, for each of the FF three factors the LR tests reject the exclusion of the loadings for all six instrumental variables. The resulting χ^2 statistics for prices of exposures to, respectively, the market, SMB, and HML are 44.90, 39.75, and 64.24, all of which have *p*-values equal to 0.00. The results confirm that the FF three factors are priced.

[12] The LR test is called for here because Harvey's moment conditions consist of non-linear functions.

The Wald tests and LR tests also indicate that each of the FF three prices of risks is time-varying. In Table 6, Panel A, the Wald tests for each of the three prices of risks reject the exclusion of the loadings for all five time-varying instruments. The χ^2 statistics are 39.12, 54.25, and 32.93 respectively (*p*-values are all equal to 0.00). This holds equally true in Panel B, where the counterpart χ^2 statistics are 61.05, 36.82, and 35.17 respectively (*p*-values are all equal to 0.00). The consistent test results from two different test methods demonstrate that not only FF's three factors are priced, but also that the prices of these factor risks vary through time in response to market-wide information.

The close parallel between the two alternative methods regarding the conclusions also survives a close examination of the parameter estimation. Noticeably, all the significant coefficients in Table 6, Panel A, have the same sign as their counterparts in Panel B. As a matter of fact, the correlation coefficient between each price of risk in Panel A and its counterpart in Panel B is above 0.95.

6. Conclusion

This paper shows that conditioning market-wide information plays an important role in asset pricing, in particular, to capture return momentum. When I explicitly model the exposures to FF's three factors using a conditional regression, where the exposures are assumed to be linear in the instruments, I find that the risk exposures, particularly to SMB and HML, for the best winners and the worst losers tend to be time varying. Moreover, in contrast to their similar unconditional risk patterns between return momentum and reversal, these two opposite kinds of portfolios do have different conditional risk characteristics. Results show that, like the SMB risks, the HML risks for the short-term winners and losers are significantly *negatively* cross-correlated while the HML risks for long-term winners and losers are significantly *positively* cross-correlated. This evidence supports the view that incorporating conditioning information into an asset-pricing model is a crucial step to capture both momentum and reversal return patterns.

The conditional linear-exposure FF regression model seems, however, to remain misspecified. Conversely, when the linearity assumption is relaxed and cross-sectional restrictions are imposed, the conditional cross-sectional asset pricing tests, which allow more reliable conclusions with regard to the specification of the model, tell a different story. The results from two well-established test methods, which can be viewed as alternative conditional analogues to the static GRS multivariate test, indicate that conditioning information does help the FF model to capture the cross-sectional patterns of return continuation as well as return reversal.

The work of this paper is closely related to Ferson and Harvey (1999). Although they reject the FF three-factor model in their two-pass pricing tests, using an additional pricing factor that is based purely on conditioning information, yet their pricing factor alone cannot explain the cross section of asset returns. Thus, they have not found a better alternative to the less-than-perfect FF model. However, more importantly, they show that their conditioning-information-based pricing factor can significantly explain the cross-sectional patterns in the pricing errors missed by the FF model. This paper, building on Ferson and Harvey's work, demonstrates that incorporating conditioning information into asset pricing can capture return momentum and reversal without sacrificing the insights of existing unconditional models.

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Table 1:

Average Post-Formation Excess Returns of Decile and Quintile Portfolios Formed Monthly Based on Past Returns

At the beginning of each month t+1, decile portfolios (Panel A) or quintile portfolios (Panel B) are formed on the continuously compounded returns between $t+1-x$ and $t+1-y$ of all NYSE and AMEX U.S. common stocks. For example, the label Past2-12 (i.e., from t-11 to t-1 in general) (Panel A) or Past2-12q (Panel B) means that the stocks are allocated to the decile portfolios or quintile portfolios for July 1963 based on their continuously compounded returns for July 1962 through May 1963. Decile 1 (Panel A) or quintile 1 (Panel B) contains the stocks with the lowest continuously compounded past returns (the worst past losers). The portfolios are rebalanced monthly, and equal-weight simple returns in excess of the holding period return on the one-month T-bill are calculated for July 1963 through December 1995. The averages of these excess returns (in percent) and the t-values of the average are presented in the table for the sample period (390 months).

Panel A

Portfolio	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
				Excess Return of Decile Porfolios						
Past2-12	**-0.02**	**0.46**	**0.54**	**0.68**	**0.74**	**0.79**	**0.91**	**1.04**	**1.26**	**1.46**
Past13-60	**1.41**	**0.95**	**0.77**	**0.71**	**0.81**	**0.75**	**0.72**	**0.67**	**0.56**	**0.35**
				***t*-value of Mean Excess Return**						
Past2-12	**-0.05**	**1.39**	**1.77**	**2.37**	**2.69**	**2.93**	**3.35**	**3.78**	**4.21**	**4.23**
Past13-60	**3.11**	**2.90**	**2.65**	**2.59**	**3.12**	**2.96**	**2.85**	**2.59**	**2.03**	**1.11**

Panel B

	Excess Return of Quintile Portfolios					***t*-value of Mean Excess Return**				
Portfolio	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
Past2-12q	**0.20**	**0.62**	**0.81**	**1.01**	**1.38**	**0.52**	**2.09**	**2.97**	**3.68**	**4.32**
Past13-60q	**1.14**	**0.70**	**0.77**	**0.64**	**0.47**	**2.99**	**2.48**	**3.01**	**2.54**	**1.60**

Table 2:

Summary Statistics for Instrumental Variables

EMR(-1) is the lagged (*NYSE*, *AMEX*, and *Nasdaq*) value-weighted market excess return (i.e., *MR-RF* lagged by one month, from Eugene Fama). *TB*1 denotes the one-month U.S. T-bill rate (Fama file in *CRSP*). *TB*31 stands for the yield spread between the lagged three- and one-month U.S. T-bills (Fama file). *JUNK* represents the yield spread between Corporate Baa- and Aaa-bonds (*Federal Reserve Bulletin*). *DIV*(-1) is defined as the one-month lagged spread between a dividend yield and the one-month T-bill holding period return, where the dividend yield is defined as the 12-month backward moving average of dividends divided by the current end-of-period index price, and the dividend yield is computed from the monthly S&P stock returns with and without dividends (*Ibbotson Associates*). The table contains the mean and standard deviations of monthly excess returns or yields (in percent) on the five instrumental variables, the pair-wise correlations and individual autocorrelation of these instrumental variables for July 1963 through December 1995 (390 months).

Panel A: Instruments

	Mean	Std.Div.	Pairwise Correlations				
***EMR*(-1)**	**0.48**	**4.34**	**1.00**				
TB1	**0.51**	**0.22**	**-0.12**	**1.00**			
TB31	**0.04**	**0.04**	**-0.01**	**0.14**	**1.00**		
JUNK	**1.06**	**0.47**	**0.14**	**0.54**	**0.32**	**1.00**	
***DIV*(-1)**	**-0.21**	**0.17**	**0.10**	**-0.89**	**-0.21**	**-0.48**	**1.00**

Panel B: Autocorrelations

	ρ_1	ρ_2	ρ_3	ρ_6	ρ_9	ρ_{12}	ρ_{24}	ρ_{36}
***EMR*(-1)**	**0.05**	**-0.04**	**0.00**	**-0.06**	**-0.02**	**0.02**	**-0.01**	**-0.03**
TB1	**0.95**	**0.91**	**0.87**	**0.81**	**0.76**	**0.69**	**0.40**	**0.21**
TB31	**0.36**	**0.24**	**0.12**	**0.21**	**0.17**	**0.40**	**0.23**	**0.05**
JUNK	**0.97**	**0.92**	**0.89**	**0.81**	**0.73**	**0.64**	**0.40**	**0.19**
***DIV*(-1)**	**0.91**	**0.84**	**0.80**	**0.70**	**0.63**	**0.53**	**0.22**	**0.02**

Table 3:

Conditional Regression Estimation of Risk Exposures for Winners and Losers

The table presents the estimation results for four extreme winners and losers from Past2-12 and Past13-60 defined in Table 1, namely, the worst short-term losers (SL), the best short-term winners (SW), the worst long-term losers (LL), and the best long-term winners (LW), using the following conditional regression:

$$r_{i,t+1} = \alpha + \mathbf{Z}_t\boldsymbol{\beta}_m \text{ EMR}_{t+1} + \mathbf{Z}_t\boldsymbol{\beta}_s \text{ SMB}_{t+1} + \mathbf{Z}_t\boldsymbol{\beta}_h \text{ HML}_{t+1} + \eta_{i,t+1}$$

where $r_{i,t+1}$ is the excess return (total return) on portfolio (arbitraging portfolio) i (i = SL, SW, LL, LW) and is regressed on the FF three factors: EMR_{t+1}, $\text{SMB}_{t+1,}$ and $\text{HML}_{t+1.}$ The regression slopes are linear in instruments $\mathbf{Z}_t$ (a row vector) that include a constant term, *EMR*(-1), *TB*1, *TB*31, *JUNK* and *DIV*(-1) (see definitions in Table 2). α is the regression intercept while $\boldsymbol{\beta}_{m,}$ $\boldsymbol{\beta}_{s,}$ and $\boldsymbol{\beta}_h$ are vectors of constant weights on $\mathbf{Z}_t$. That a risk loading (slope) is not linearly related to the last five time-varying instruments in $\mathbf{Z}_t$ (excluding the constant term) is tested using the Wald test under the hypothesis that the last five coefficients of individual vectors of $\boldsymbol{\beta}_m$, $\boldsymbol{\beta}_s$, or $\boldsymbol{\beta}_h$ are jointly zero. The χ^2 statistic has the degrees of freedom equal to five. The *p*-value is the probability that a χ^2 variate exceeds the sample value of the statistic. Estimates and *t*-values of α, $\boldsymbol{\beta}_{m,}$ $\boldsymbol{\beta}_{s,}$ and $\boldsymbol{\beta}_h$, the χ^2 statistics with their *p*-values, adjusted R^2s and the Durbin-Watson statistics are reported. The sample size is 390 months (7/1963–12/1995).

	SL	SW	LL	LW	SL	SW	LL	LW
		α				$t(\alpha)$		
	-1.42	0.54	-0.33	-0.27	-7.13	4.15	-1.49	-3.21
		β_m				$t(\beta_m)$		
CONST	0.93	1.05	0.69	1.20	4.41	7.51	2.54	11.48
EMR(-1)	0.00	-0.01	0.00	0.00	0.25	-0.98	0.23	0.41
TB1	-0.53	0.49	0.09	0.06	-0.88	1.18	0.13	0.23
TB31	1.41	0.10	1.55	0.23	0.74	0.10	0.75	0.42
JUNK	0.26	-0.04	0.43	-0.10	1.65	-0.32	2.74	-1.29
DIV(-1)	-0.53	0.80	0.92	0.05	-0.72	1.70	1.16	0.16
		$\chi^2(5)$				*p*-value		
Wald test	9.84	6.33	15.23	4.16	0.08	0.28	0.01	0.53
		β_s				$t(\beta_s)$		
CONST	2.42	1.21	2.40	0.66	5.81	5.01	3.26	4.91
EMR(-1)	0.04	0.03	0.07	0.01	1.31	1.94	1.31	1.33
TB1	-3.63	1.24	-2.77	0.36	-3.01	1.46	-1.58	0.89
TB31	-5.35	0.93	-4.29	-0.02	-1.67	0.52	-1.32	-0.02
JUNK	0.41	-0.42	0.27	-0.10	1.34	-2.36	0.96	-0.82
DIV(-1)	-4.02	1.89	-2.88	0.12	-2.85	2.17	-1.50	0.25
		$\chi^2(5)$				*p*-value		
Wald test	30.87	33.74	34.61	5.29	0.00	0.00	0.00	0.38
		β_h				$t(\beta_h)$		
CONST	0.69	0.28	1.54	-0.04	2.27	1.43	3.25	-0.32
EMR(-1)	0.03	-0.02	0.04	0.00	1.08	-1.19	0.89	0.43
TB1	-0.60	-0.02	-2.25	0.27	-0.64	-0.02	-2.06	0.69
TB31	5.35	-3.01	1.91	1.72	2.35	-1.81	0.91	1.96
JUNK	-0.15	0.20	0.25	-0.19	-0.47	0.80	0.89	-1.47
DIV(-1)	-0.40	1.16	-0.85	0.70	-0.35	1.41	-0.61	1.43
		$\chi^2(5)$				*p*-value		
Wald test	11.34	25.42	23.56	14.06	0.05	0.00	0.00	0.02
Adj-R^2	0.79	0.88	0.78	0.94				
DW	1.97	1.96	1.81	1.69				

Table 4:

Time Path Patterns of the Conditional Risk Exposures for Winners and Losers

The table reports the time-series statistics of conditional risk exposures for four extreme winners and losers from Past2-12 and Past13-60 defined in Table 1, namely the worst short-term losers (SL), the best short-term winners (SW), the worst long-term losers (LL), and the best long-term winners (LW). The conditional risk loadings, $\mathbf{Z}_t\boldsymbol{\beta}_m$, $\mathbf{Z}_t\boldsymbol{\beta}_s$, $\mathbf{Z}_t\boldsymbol{\beta}_h$ represent the market risk, the SMB risk and the HML risk, respectively. The conditional risks are linear in the instrumental variables $\mathbf{Z}_t$ (a row vector) that include a constant term, *EMR*(-1), *TB*1, *TB*31, *JUNK* and *DIV*(-1) (see definitions in Table 2), where the corresponding constant weights $\boldsymbol{\beta}_m$, $\boldsymbol{\beta}_s$, and $\boldsymbol{\beta}_h$ are estimated from the conditional regression. Panel A presents some summary statistics of the conditional risks. Panel B exhibits autocorrelations of conditional risks. Panel C shows the cross-correlations of each of the three risk exposures between SL, SW, LL, and LW. The sample size is 390 months (7/1963–12/1995).

	Market Risk				**SMB Risk**				**HML Risk**			
	SL	**SW**	**LL**	**LW**	**SL**	**SW**	**LL**	**LW**	**SL**	**SW**	**LL**	**LW**
Panel A: Conditional Risks												
Mean	**1.11**	**1.09**	**1.06**	**1.12**	**1.67**	**1.04**	**1.74**	**0.71**	**0.55**	**0.11**	**0.94**	**-0.19**
St.Dev	**0.15**	**0.08**	**0.21**	**0.04**	**0.41**	**0.27**	**0.44**	**0.07**	**0.26**	**0.23**	**0.39**	**0.13**
Median	**1.08**	**1.10**	**1.04**	**1.13**	**1.70**	**1.07**	**1.76**	**0.71**	**0.53**	**0.17**	**1.00**	**-0.18**
q1	**1.01**	**1.05**	**0.90**	**1.10**	**1.44**	**0.90**	**1.48**	**0.67**	**0.41**	**-0.01**	**0.72**	**-0.26**
q3	**1.19**	**1.14**	**1.17**	**1.15**	**1.92**	**1.22**	**2.03**	**0.75**	**0.65**	**0.27**	**1.19**	**-0.10**
Min	**0.76**	**0.69**	**0.64**	**0.99**	**0.27**	**-0.05**	**0.32**	**0.35**	**-0.31**	**-0.91**	**-0.71**	**-0.74**
Max	**1.82**	**1.35**	**1.96**	**1.19**	**3.26**	**1.80**	**3.08**	**0.98**	**1.80**	**0.53**	**2.08**	**0.19**
Panel B: Autocorrelation												
ρ_1	**0.70**	**0.36**	**0.85**	**0.87**	**0.40**	**0.59**	**0.28**	**0.24**	**0.25**	**0.61**	**0.62**	**0.75**
ρ_2	**0.63**	**0.21**	**0.74**	**0.82**	**0.18**	**0.54**	**0.10**	**0.25**	**0.12**	**0.56**	**0.49**	**0.62**
ρ_3	**0.58**	**0.26**	**0.67**	**0.79**	**0.20**	**0.52**	**0.14**	**0.24**	**0.02**	**0.53**	**0.45**	**0.56**
ρ_6	**0.57**	**0.22**	**0.47**	**0.73**	**0.14**	**0.55**	**0.06**	**0.25**	**0.11**	**0.46**	**0.38**	**0.55**
ρ_{12}	**0.49**	**0.24**	**0.17**	**0.59**	**0.15**	**0.46**	**0.10**	**0.16**	**0.35**	**0.46**	**0.30**	**0.53**
ρ_{24}	**0.25**	**0.11**	**0.03**	**0.28**	**0.06**	**0.21**	**0.03**	**-0.05**	**0.23**	**0.11**	**0.12**	**0.31**
ρ_{36}	**0.08**	**-0.04**	**-0.04**	**0.06**	**-0.05**	**0.01**	**-0.05**	**-0.14**	**0.10**	**-0.05**	**0.06**	**0.06**
Panel C: Cross-correlation of Risks between Portfolios												
SL	**1.00**				**1.00**				**1.00**			
SW	**-0.61**	**1.00**			**-0.22**	**1.00**			**-0.47**	**1.00**		
LL	**0.74**	**-0.05**	**1.00**		**0.93**	**0.10**	**1.00**		**0.69**	**0.17**	**1.00**	
LW	**-0.70**	**0.28**	**-0.62**	**1.00**	**0.05**	**0.42**	**0.30**	**1.00**	**0.54**	**0.25**	**0.46**	**1.00**

Table 5:

Conditional Cross-sectional Pricing Tests on Deciles Formed on Past Returns

The table presents the GMM tests on the following orthogonality conditions using each of the decile portfolios formed on various past returns defined in Table 1, Panel A:

$$E[\, u_{t+1} \otimes \mathbf{Z}_t \,] = \mathbf{0},$$

$$E[(\mathbf{r}_{t+1} - \mathbf{r}_{t+1}\, u_{t+1}\,) \otimes \mathbf{Z}_t] = \mathbf{0},$$

where $u_{t+1} = \boldsymbol{\phi}_0'\mathbf{Z}_t + \boldsymbol{\phi}_m'\mathbf{Z}_t\,\mathrm{EMR}_{t+1} + \boldsymbol{\phi}_s'\mathbf{Z}_t\,\mathrm{SMB}_{t+1} + \boldsymbol{\phi}_h'\mathbf{Z}_t\,\mathrm{HML}_{t+1}$, with the $\boldsymbol{\phi}$'s being vectors of constant weights on the instruments $\mathbf{Z}_t$ that include a constant term. $\mathbf{r}_{t+1}$ is the excess returns on decile portfolios. The *J*-test is the test on over-identifying restrictions for goodness-of-fit, and is distributed χ^2 with the degrees of freedom equal to the number of orthogonality conditions [(10 assets and one pricing kernel) times six instruments = 66] minus the number of parameters [(three pricing factors and one conditional intercept in the pricing kernel) times six instruments = 24], i.e., 42. That a pricing factor is not priced is tested using the heteroskedasticity-consistent Wald test under the null hypothesis that the six weights in a $\boldsymbol{\phi}$ vector are jointly zero. The *p*-value is the probability that a χ^2 variate exceeds the sample value of the statistic. Panel A and Panel B report the estimates and *t*-values of $\boldsymbol{\phi}_{0}$, $\boldsymbol{\phi}_m$, $\boldsymbol{\phi}_s$ and $\boldsymbol{\phi}_h$ from the pricing test on decile portfolios (Past2-12) and (Past13-60) respectively. The sample size is 390 months (7/1963 – 12/1995).

Panel A: Estimation with Short-Term Return Continuation Deciles (Past2-12)								
Instrument	ϕ_0	ϕ_m	ϕ_s	ϕ_h	***t*-value**			
CONST	**0.151**	**0.228**	**-0.048**	**-0.666**	**0.63**	**2.10**	**-0.27**	**-2.91**
***EMR* (-1)**	**0.020**	**0.018**	**0.035**	**0.059**	**0.89**	**2.28**	**3.90**	**3.49**
***TB* 1**	**-0.780**	**-0.276**	**0.907**	**4.014**	**-0.98**	**-0.80**	**1.49**	**4.27**
***TB* 31**	**2.515**	**-3.349**	**2.012**	**-2.539**	**1.33**	**-3.26**	**1.47**	**-1.72**
JUNK	**-0.153**	**0.018**	**-0.210**	**-0.766**	**-0.80**	**0.24**	**-2.01**	**-3.41**
***DIV* (-1)**	**-0.613**	**-0.605**	**2.131**	**3.028**	**-0.71**	**-1.41**	**3.20**	**2.82**
Wald Test					***J*-Test**			
$\chi^2(6)$		**27.74**	**40.34**	**31.34**	$\chi^2(42)$	**38.29**		
***p*-value**		**0.00**	**0.00**	**0.00**	***p*-value**	**0.63**		
Panel B: Estimation with Long-Term Return Reversal Deciles (Past13-60)								
Instrument	ϕ_0	ϕ_m	ϕ_s	ϕ_h	***t*-value**			
CONST	**0.342**	**0.139**	**-0.486**	**0.148**	**1.56**	**1.36**	**-3.60**	**0.79**
***EMR* (-1)**	**-0.028**	**-0.013**	**0.047**	**-0.003**	**-1.41**	**-2.36**	**6.07**	**-0.29**
***TB* 1**	**-0.890**	**-0.587**	**1.669**	**-0.120**	**-1.19**	**-1.97**	**3.52**	**-0.24**
***TB* 31**	**-12.549**	**-0.857**	**10.480**	**5.940**	**-5.14**	**-1.16**	**5.88**	**5.36**
JUNK	**-0.185**	**0.155**	**-0.294**	**-0.147**	**-1.17**	**2.65**	**-2.84**	**-1.60**
***DIV* (-1)**	**-1.701**	**-0.503**	**1.799**	**-0.266**	**-2.12**	**-1.44**	**3.24**	**-0.46**
Wald Test					***J*-Test**			
$\chi^2(6)$		**36.01**	**65.64**	**59.05**	$\chi^2(42)$	**28.08**		
***p*-value**		**0.00**	**0.00**	**0.00**	***p*-value**	**0.95**		

Table 6:

Conditional Cross-sectional Pricing Tests on Pooled Two Sets of Quintile Portfolios That Represent Return Momentum and Reversal Patterns Respectively

The table presents the GMM tests using both Dumas-Solnik's approach (Panel A) and Harvey's approach (Panel B) on pooled two sets of quintile portfolios described in Table 1 (Panel B). The empirical framework in Dumas-Solnik's approach is shown in Table 5. Harvey's approach examines the following orthogonality conditions:

$$E[(\boldsymbol{f}_{t+1} - D\mathbf{Z}_t) \otimes \mathbf{Z}_t] = \mathbf{0},$$

$$E[\boldsymbol{r}_{t+1} - \boldsymbol{r}_{t+1}(\boldsymbol{f}_{t+1} - D\mathbf{Z}_t)'A\mathbf{Z}_t) \otimes \mathbf{Z}_t] = \mathbf{0}$$

where $\boldsymbol{r}_{t+1}$ are the excess returns on the pooled two quintile portfolios, D and A are coefficient matrices, $A = (\boldsymbol{\phi}_m, \boldsymbol{\phi}_s, \boldsymbol{\phi}_h)'$ (see definitions of similar notations in Table 5). The *J*-test is the test on over-identifying restrictions for goodness-of-fit, and is distributed χ^2 with the degrees of freedom equal to the number of orthogonality conditions [(10 test assets and three factors) times six instruments = 78] minus the number of parameters [(three factors and three reward to risk ratios) times six instruments = 36], i.e., 42. The Wald test (Panel A) and the LR test (Panel B) are used to test the exclusion of the six weights (including the constant) or five weights in a $\boldsymbol{\phi}$ ector are jointly zero. The sample size is 390 months (7/1963 – 12/1995).

Panel A: Dumas-Solnik's Approach								
Instrument	$\boldsymbol{\phi_0}$	$\boldsymbol{\phi_m}$	$\boldsymbol{\phi_s}$	$\boldsymbol{\phi_h}$	***t*-value**			
CONST	**-0.247**	**0.143**	**0.119**	**0.587**	**-1.69**	**1.84**	**0.93**	**3.84**
***EMR* (-1)**	**-0.011**	**-0.026**	**0.033**	**-0.047**	**-0.70**	**-5.29**	**5.14**	**-5.26**
***TB* 1**	**0.256**	**-0.552**	**0.344**	**-1.071**	**0.53**	**-2.55**	**0.95**	**-2.44**
***TB* 31**	**-3.563**	**0.138**	**4.442**	**0.158**	**-2.01**	**0.23**	**4.22**	**0.18**
JUNK	**-0.132**	**0.084**	**-0.235**	**-0.061**	**-0.99**	**1.83**	**-3.14**	**-0.71**
***DIV* (-1)**	**-0.552**	**-0.512**	**0.946**	**-0.737**	**-0.95**	**-1.93**	**2.22**	**-1.40**
Wald Test								
$\chi^2(6)$		**59.22**	**58.20**	**43.95**				
***p*-value**		**0.00**	**0.00**	**0.00**		***J*-Test**		
$\chi^2(5)$		**39.12**	**54.25**	**32.93**		$\chi^2(42)$	**49.38**	
***p*-value**		**0.00**	**0.00**	**0.00**		***p*-value**	**0.20**	

Panel B: Harvey's Approach						
Instrument	$\boldsymbol{\phi_m}$	$\boldsymbol{\phi_s}$	$\boldsymbol{\phi_h}$	***t*-value**		
CONST	**0.324**	**-0.091**	**0.510**	**2.98**	**-0.60**	**3.14**
***EMR* (-1)**	**-0.036**	**0.051**	**-0.055**	**-5.20**	**5.53**	**-5.21**
***TB* 1**	**-1.136**	**0.847**	**-1.061**	**-3.42**	**1.86**	**-1.96**
***TB* 31**	**0.664**	**7.750**	**-0.557**	**0.89**	**6.71**	**-0.50**
JUNK	**0.097**	**-0.290**	**-0.018**	**1.88**	**-3.33**	**-0.21**
***DIV* (-1)**	**-0.912**	**1.344**	**-0.796**	**-2.37**	**2.65**	**-1.17**
LR Test						
$\chi^2(6)$	**44.90**	**39.75**	**64.24**			
***p*-value**	**0.00**	**0.00**	**0.00**	***J*-Test**		
$\chi^2(5)$	**61.05**	**36.82**	**35.17**	$\chi^2(42)$	**46.93**	
***p*-value**	**0.00**	**0.00**	**0.00**	***p*-value**	**0.28**	