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# DOES MUTUAL FUND PERFORMANCE VARY OVER THE BUSINESS CYCLE?

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This paper supersedes an earlier paper with the same title, coauthored by Anthony Lynch and Jessica Wachter, that used the same methodology, but a different mutual fund data set. The earlier paper used the Elton-Gruber-Blake mutual fund database, while this paper uses the CRSP mutual fund database. The authors would like to thank Wayne Ferson, Jeff Busse, participants at the 2005 AFA Meeting, seminar participants at NYU, University of Queensland, Queensland University of Technology, Australian Graduate School of Business, Melbourne Business School, University of Piraeus, and University of Toronto for their comments and suggestions on the earlier paper. All remaining errors in this paper are of course the authors' responsibility. Anthony Lynch wrote parts of the earlier paper while visiting the University of Queensland, and so he would like to thank the people there for their hospitality. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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**ABSTRACT**

We develop a new methodology that allows conditional performance to be a function of information available at the start of the performance period but does not make assumptions about the behavior of the conditional betas. We use econometric techniques developed by Lynch and Wachter (2011) that use all available factor return, instrument, and mutual fund data, and so allow us to produce more precise parameter estimates than those obtained from the usual GMM estimation. We use our SDF-based method to assess the conditional performance of fund styles in the CRSP mutual fund data set, and are careful to condition only on information available to investors, and to control for any cyclical performance by the underlying stocks held by the various fund styles. Moskowitz (2000) suggests that mutual funds may add value by performing well during economic downturns, but we find that not all funds styles produce counter-cyclical performance when using dividend yield or term spread as the instrument: instead, many fund styles exhibit pro-cyclical or non-cyclical performance, especially after controlling for any cyclicality in the performance of the underlying stocks. For many fund styles, conditional performance switches from counter-cyclical to pro- or non- cyclical depending on the instrument or pricing model used. Moreover, we find very little evidence of any business cycle variation in conditional performance for the 4 oldest fund styles (growth and income, growth, maximum capital gains and income) using dividend yield or term spread as the instrument, despite estimating the cyclicality parameter using the GMM method of Lynch and Wachter (2011) that produces more precise parameter estimates than the usual GMM estimation. Our results are important because they call into question the accepted wisdom and Moskowitz's conjecture that the typical mutual fund improves investor utility by producing counter-cyclical abnormal performance.

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# 1 Introduction

Mutual fund performance has long been of interest to financial economists, both because of its implications for market efficiency, and because of its implications for investors. A key issue in evaluating performance is the choice of the benchmark model. Recently, the asset pricing literature has emphasized the distinction between unconditional and conditional asset pricing models.[1] The relative success of conditional models at explaining the cross-section of expected stock returns raises important questions for the mutual fund researcher. How does one evaluate performance when the underlying model is conditional? Might performance itself be conditional? In principle, a conditional model allows both risk loadings and performance over a period to be a function of information available at the start of the period. Several recent papers allow risk loadings to be time-varying, but they either assume that conditional performance is a constant (Farnsworth, Ferson, Jackson, Todd, 2002, for mutual funds), conditional betas are linear in the information variables (Avramov and Wermers, 2006 for mutual funds in a Baysian setting, Christopherson, Ferson and Glassman, 1998, for pension funds, Ferson and Harvey, 1999, and Avramov and Chordia, 2006 for stocks) or both (Ferson and Schadt, 1996, for mutual funds,an important early contribution to the conditional performance literature).[2] Moskowitz (2000) suggests that mutual funds may add value by performing well during economic downturns.

We develop a new methodology that allows conditional performance to be a function of information variables available at the start of the period, but without assumptions on the behavior of the conditional betas.[3] This methodology uses the Euler equation restriction that comes out of a factor model rather than the beta pricing formula itself. It only assumes that the stochastic discount factor (SDF) parameters are linear in the information variables. While the Euler equation does not provide direct information about the nature of time variation in the risk loadings, it can provide direct information about time variation in conditional performance. In contrast, the classic time-series regression methodology can only provide direct information about time-varying performance if strong assumptions are made about time-varying betas.

We are careful to condition only on information available to investors at the start of the period, and to control for any cyclical performance by the underlying stocks held by the various fund styles.

[1] See, for example, Jagannathan and Wang (1996) and Lettau and Ludvigson (2001b).

[2] Lynch and Wachter (2007), which is an earlier version of this paper, allows conditional performance to be time-varying, but uses the Elton, Gruber, Blake (1996) mutual fund database rather than the much more comprehensive CRSP mutual fund database that we use.

[3] Independently, Ferson, Henry and Kisgen (2006) developed a similar methodology, but used it to evaluate the performance of bond funds rather than equity funds which is our focus.

One of our main results is that not all funds styles produce counter-cyclical performance when dividend yield or term spread is used as the instrument: instead, many fund styles exhibit pro-cyclical or non-cyclical performance, especially after controlling for any cyclicality in the performance of the underlying stocks. For many fund styles, conditional performance switches from counter-cyclical to pro- or non-cyclical depending on the instrument or pricing model used. Moreover, we find very little evidence of any business cycle variation in conditional performance for the 4 oldest fund styles (growth and income, growth, maximum capital gains, and income) using dividend yield or term spread as the instrument, despite using the GMM method of Lynch and Wachter (2011) that uses all available factor, instrument, and fund return data to estimate the cyclicality parameter. Our results are important because they call into question the accepted wisdom and Moskowitz's conjecture that the typical mutual fund improves investor utility by producing counter-cyclical abnormal performance.

This important conclusion, that the empirical evidence for countercyclical variation in mutual fund performance is very weak, is well illustrated by the conditional performance results for the equal-weighted portfolio of all mutual funds in our sample each month.[4] We measure the performance of this portfolio's excess-of-riskfree return conditional on either dividend yield or term spread, and relative to either the Fama-French or the Cahart pricing model. The portfolio's conditional performance is only significantly counter-cyclical for one of the four specifications: the one for which performance conditions on dividend yield and is measured relative to the Fama-French model. When we use, for each fund, its return in excess of the return on a matched portfolio (one of the 25 Fama-French size and book-to-market portfolios) to construct a return on the portfolio in excess of a matched portfolio of underlying stocks, we again find that the only specification with significant business-cycle variation in performance is the one that uses dividend yield as the instrument and Fama-French as the pricing model. However, the performance is significantly pro-cyclical, not countercyclical, which is in stark contrast to the case that uses the portfolio's excess-of-riskfree return. This result shows that any evidence of countercyclical variation in mutual fund performance is typically not robust to controlling for business-cycle variation in the conditional alphas of the underlying stocks held by the funds based on their styles.

A set of factors constitutes a conditional beta-pricing model if the conditional expected return on any asset is linear in the return's conditional betas with respect to the factors. It is well known (see Cochrane, 2001) that a set of factors constitutes a conditional beta-pricing model if and only if there

[4]These results are unreported, but available from the authors on request.

exists a linear function of the factors (where the coefficients are in the conditional information set) that can be used as a stochastic discount factor in the conditional Euler equation. Our methodology determines the parameters of this stochastic discount factor by correctly pricing the factor returns. This estimated stochastic discount factor is then used to calculate the conditional performance of a fund by replacing the fund's return in the Euler equation with the fund return in excess of its conditional performance. We allow the parameters of the stochastic discount factor to be linear in the information variables, as in Lettau and Ludvigson (2001b), and we use the same linear specification for conditional fund performance. However, the methodology is sufficiently flexible to allow arbitrary functional forms for both.

We use our Euler equation restrictions to assess the conditional performance of equity funds in the CRSP mutual fund data set. CRSP reports four different fund classification schemes over its data period, so we use cross-tabulations, showing how funds move from an old scheme to a new scheme whenever there is a scheme change, to obtain a single equity fund style classification that is valid at all points in time. We obtain 12 useable equity fund styles with varying start dates that range from 1/62 to 1/95. Conditional performance is estimated for equal-weighted portfolios grouped by fund style. We also consider the effect of total net assets under management (TNA) on fund performance: each year we bifurcate each equity fund category on the basis of TNA.[5] We use two information variables. The first is the 12-month dividend yield on the value-weighted NYSE and the data used to construct this series come from CRSP. The second is the yield spread between 20-year and one-month Treasury securities, obtained from the Ibbotson data service. Both have been found to predict stock returns and move countercyclically with the business cycle, with the term spread capturing higher frequency variation than the dividend yield (see Fama and French, 1989). We have factor return and instrument data back to 1/27, and all data series end 12/07.

We divide the 12 equity fund styles into three groups, reporting results for each group separately. The first group consists of styles for which we have relatively longer data series: growth-income, growth, maximum capital gains, and income. The second group consists of the sector funds: energy/natural resources, financial services, health, technology, and utilities. The third consists of non-sector styles for which we have relatively short series: small cap growth, flexible, and midcap growth.

We estimate the performance parameters using the Euler equation restrictions discussed above. One estimation technique that we employ is regular GMM, which only uses data for the sample

[5]An advantage of using equal-weighted style-TNA portfolios to evaluate mutual fund performance is that the performance estimates are not contaminated by the reverse survivorship bias described by Linnainmaa (2011).

period for which data is available for all moments. For each group of fund styles, the sample period is determined by the latest start date for the fund styles in that group: the start dates for the samples used to estimate regular GMM for the three groups are 1/72 for the first group, 1/91 for the group of sector funds, and 1/95 for the third group. It is also possible to improve the estimation by using available data from other periods for variables that can be used to construct a subset of the moments. Stambaugh (1997) describes an estimation approach that allows the factor returns and information variables to have longer data series than the mutual fund series. A number of recent Bayesian mutual fund papers have taken advantage of the availability of longer data series for the factor returns than the mutual fund returns (see Pastor and Stambaugh, 2002a and 2002b). Lynch and Wachter (2011) have extended these methods to non-linear estimation in a frequentist setting. We use one of their estimation methodologies, the adjusted-moment estimator, to estimate the Euler equation restrictions taking account of factor return and information variable data back to 1927, and all available data for the 12 mutual fund style portfolios. We call this the Full estimation.

For comparison purposes, we also implement the regression-based approach of Ferson and Schadt (1996) which assumes that the conditional betas of the fund style portfolios are linear in the instruments. The regression-based approach is estimated for each group of fund styles using the same sample period for all styles as we use to estimate regular GMM.

We estimate two different factor models using the three estimation techniques: the Fama and French (1993) model whose three factors are the market excess return, the return on a portfolio long high and short low book-to-market stocks, and the return on a portfolio long small stocks and short big stocks; and the four factor model of Carhart (1997) whose factors are the three Fama-French factors plus the return on a portfolio long stocks that performed well the previous year and short stocks that performed poorly. Three versions of each model are estimated. The first is the usual unconditional model. The second is the conditional model with performance not allowed to depend on the information variable, as in Ferson and Schadt (1996). The third is the conditional model with performance that is allowed to vary with the information variable. Implementing this last version for mutual funds is one of the innovations of the paper.

Fund portfolios are constructed by bifurcating each fund style on the basis of net asset value (TNA). When we consider returns in excess of the riskfree rate and use the Full estimation, we find strong evidence of conditional fund performance that varies with the business-cycle instrument: for the first group of fund styles, we can reject the hypotheses that all the bifurcated fund styles have zero business-cycle variation in conditional performance for 3 of the 4 possible combinations of pricing model and instrument; for the second and third groups of fund styles, both of these hypotheses can be rejected for all four possible combinations. In particular, there is evidence that the business cycle variation in performance differs across large-TNA and small-TNA funds within at least one equity fund category for each of the three groups. However, the evidence of counter-cyclical variation in conditional fund performance is quite weak. For the first group, there is some evidence of counter-cyclical variation in performance, but only relative to the Fama-French pricing model and not the Carhart model. For the second and third groups, the conditional performance of several fund styles varies from significantly counter-cyclical to significantly pro-cyclical or insignificant depending on the instrument.

While abnormal conditional performance by the fund manager is one explanation for any business cycle variation in condition performance we report, another explanation is that our pricing model is misspecified in such a way that the underlying stocks exhibit business-cycle variation in their performance that drives the business-cycle variation in fund performance that we report. To control for the conditional performance of the underlying stocks held by a fund style, we match each style-TNA portfolio on the basis of Fama-French (FF) loadings to one of the 25 FF size and book-to-market sorted portfolios, and examine the performance of each style-TNA portfolio's return in excess of the matched portfolio's return. When we examine performance in excess of matched FF portfolio return, we find even weaker evidence of cyclical variation in performance, with the direction of the business cycle variation often changing going from performance in excess of the riskfree rate to performance in excess of matched FF portfolio return. For the first group of fund styles (growth and income, growth, maximum capital gains and income), which have the most data, the hypothesis of zero cyclical variation in conditional performance when using fund return in excess of matched FF portfolio return can only be rejected when measuring conditional performance relative to the FF model. Moreover, conditional performance relative to the FF model is either pro-cyclical or does not move with the business cycle, irrespective of the style-TNA portfolio or the instrument; the only exceptions are the two maximum capital gains portfolios, whose conditional performances are counter-cyclical when using dividend yield as the instrument. Our results strongly suggest that these 4 fund styles, with the possible but unlikely exception of the maximum capital gains style, are unable to produce counter-cyclical performance once the conditional abnormal performance of the underlying stocks is accounted for. Turning to the second and third groups of fund styles, the hypothesis of zero cyclical variation for all portfolios can still be rejected using the Full estimation for all four specifications after adjusting for the conditional performance of the underlying stocks:

depending on the instrument and pricing model, the energy-sector and utilities-sector portfolios exhibit counter-cyclical or non-cyclical performance, while the financial-sector, small-cap growth and flexible portfolios exhibit pro-cyclical or non-cyclical performance. Our results suggest that some of the sector funds can exhibit counter-cyclical performance depending on the pricing model and the instrument, but also suggest that at least one sector fund and some of the newer funds styles can exhibit pro-cyclical performance depending on the pricing model and the instrument.

By enabling us to include factor return and dividend yield data back to 1/27, the Full estimation methodology of Lynch and Wachter (2011) allows us to produce substantially more precise parameter estimates than standard GMM. For the first group of fund styles, the reduction in the asymptotic standard errors for the estimates of performance sensitivity to the information variable is typically around 22%, but never less than 17%, going from the standard GMM estimation to the Full estimation, for returns in excess of the riskless rate. For the coefficients of a given portfolio, this improvement is largely coming from the additional information provided by the factor and instrument data (and the portfolio's own return data if available) from prior to the start of the data period used for the standard GMM estimation. For the second group of fund styles, this reduction in the asymptotic standard errors is typically around 43%, but never less than 25%, while for the third group of fund styles, it's typically around 55%, but never less than 49%. However, for the third, and especially the second, groups of funds, which are the fund styles with the later start dates, a sizeable component of this improvement in precision is coming from information provided by the returns of the other fund-style portfolios prior to the start of the data period used for the standard GMM estimation. The reductions in the standard errors for the estimates of performance sensitivity to the information variable are typically lower when returns are in excess of the matched FF portfolio return rather than the riskfree rate. This result is to be expected since subtracting out the matched FF portfolio return would be expected to reduce the correlations across the fund portfolio moments, and between the factor moments and the the fund portfolio moments.

The performance results for the regression-based approach of Ferson and Schadt (1996) sometimes differ materially from those for the Euler equation-based approach, even when using standard GMM, which uses exactly the same data as the regression-based approach. This is not surprising given that the Euler equation-based approach does not make any of the assumptions about the conditional betas that are made by the regression-based approach. At the same time, the coefficient point estimates are often similar for the regression-based method and the standard GMM Euler-equation estimation. However, the regression-based approach, like the standard GMM approach, provides even weaker evidence than the Full method of counter-cyclical variation in mutual fund performance for the fund styles in the 3 groups.

A number of recent papers have examined how mutual fund performance varies over the business cycle. Kosowski (2006) examines mutual fund performance conditional on the NBER business-cycle variable, or on a two-state latent variable whose probability of being in the "expansion" state moves with the NBER business cycle variable. For each specification, he also allows risk loadings to depend on the state. While he finds that unconditional mutual fund performance relative to the Carhart model is negative, he finds that conditional mutual fund performance is significantly positive when the NBER business cycle variable indicates a recession, and when the latent variable is in its "recession" state. He finds this result holds for all funds, all growth funds, and for four fund styles that closely resemble the four fund styles in our first group of fund styles. Kacperczyk, van Nieuwerburgh, and Veldkamp (2010) develop a model of how fund managers allocate attention over the business cycle which predicts cyclical changes in attention allocation. Consistent with their model, they find that in recessions, mutual funds portfolios covary more with aggregate payoff-relevant information, exhibit more cross-sectional dispersion, and generate higher risk-adjusted returns. Like Kosowski, recession states are identified using the NBER business cycle variable, though they check the robustness of these results to using other proxies for recession: an indicator for negative real consumption growth; the Chicago Fed National Activity Index; and an indicator for the bottom 25% of stock market returns. Finally, Staal (2006) finds that over the 1962 to 2002 period, the average fund's risk-adjusted performance was negatively correlated with the Chicago Fed National Activity Index.

On the surface, our results appear to be inconsistent with these findings. However, all these papers are conditioning on variables each month that are not known to investors at the start of the month, while we are careful to condition only on instruments that are. Notice that the average excess-of-riskfree return on the market is reported to be about -13% per annum during NBER recessions by Kosowski, which is an improbably low number for the expected excess return on the market conditioning only on information available to investors. This distinction is important since performance relative to a pricing model that conditions on information not available to investors cannot be exploited by those investors. Our goal is to determine if there is conditional performance that investors can take advantage of, which is a different goal to that of Kacperczyk, van Nieuwerburgh, and Veldkamp. In addition, these papers do not appear to rule out the possibility that the reported pattern is being driven by counter-cyclical performance by the underlying stock styles held by the funds. In an effort to obtain results that are more directly comparable to Kosowski, we use the NBER recession dummy as the instrument to estimate the cyclicality of conditional fund performance of the 4 fund styles in the first group using our methodology. Somewhat surprisingly, we find little evidence of counter-cyclical performance, irrespective of whether the excess-of-riskless or excess-of-matched returns are used. While the hypothesis that the cyclicality coefficients for the 8 portfolios are all zero is rejected for all but one specification when using the Full estimation, the tests for significance of the individual cyclicality coefficients are always insignificant for all 8 portfolios, irrespective of the estimation method or specification, with only one exception: the large TNA portfolio for one style when using one combination of instrument and pricing model. So while we find evidence that some linear combinations of the cyclicality coefficients are non-zero using the NBER recession dummy as the instrument, our analysis does not produce any evidence that the conditional performance of these 8 fund portfolios is higher during NBER recessions than NBER expansions.

Our paper is also related to Avramov and Wermers (2006), who show that some mutual fund managers are able to produce conditional alphas that vary with information variables and that individuals are able to use a Bayesian framework to identify these fund managers with sufficient accuracy to be able to construct portfolios that earn large positive alphas. However, the question we address is quite different from the one addressed in this paper. We are interested in whether the typical fund manager generates counter-cyclical performance, while this paper is interested in whether particular fund managers are able to produce cyclical performance, either pro- or counter-cyclical, and how accurately investors are able to identify these funds.

So to summarize, Moskowitz (2000) conjectures that mutual funds may add value by performing well during recessions. However, contrary to accepted wisdom and Moskowitz's conjecture, our results indicate that, once care is taken to condition only on information available to investors and to control for cyclical performance by the underlying stocks, the real picture may be more complicated than this, with some fund styles exhibiting counter-cyclical performance and others exhibiting pro- or non-cyclical performance. Moreover, we find very little evidence of any business cycle variation in conditional performance for the 4 oldest fund styles, even though we estimate the cyclicality parameter using Lynch and Wachter's GMM method, which uses all available factor, instrument and fund return data. Finally, since we also can't find any evidence of countercyclical variation in mutual fund performance even when we condition on the NBER business-cycle variable itself, it seems unlikely that mutual fund performnace moves in a countercyclical manner with any predictor of the NBER business-cycle variable that is in the investor's information set at the start of each month.

Our results are related to several recent papers. Glode (2010) shows how a misspecified pricing kernel can generate negative performance for funds that investors are willing to hold, when those funds are able to generate high returns in end-of-period states in which the correct pricing kernel is high. Chen, Hong, Huang and Kubik (2004) investigate the effect of scale on performance in the active money management industry and find that fund returns, both before and after fees and expenses, decline with lagged fund size, even after accounting for various performance benchmarks. Their results indicate that this association is most pronounced among funds that have to invest in small and illiquid stocks, suggesting that these adverse scale effects are related to liquidity. Finally, Glode, Hollifield, Kacperczyk, and Kogan (2011) examine relative performance across funds, and report that subsequent performance is higher after periods of high market returns, but similar after periods of low market returns, for mutual funds with high rather than low past performance, and for mutual funds with high rather than low past flows.

The paper is organized as follows. Section 2 discusses the theory behind our conditional performance measure. Section 3 discusses the data and Section 4 describes the empirical methodology. Section 5 presents the results and Section 6 concludes.

# 2 Theory

This section discusses the theory behind our conditional performance measure. Section 2.1 describes the benchmark models for asset returns. Performance is always measured relative to a given benchmark model. Section 2.2 defines our measure of conditional abnormal performance and discusses the estimation. Section 2.3 compares our measure to others in the literature.

## 2.1 Benchmark Models

Our paper examines fund performance relative to two benchmark pricing models and this subsection describes the two models. The first is the conditional factor model and the second is the unconditional factor model. Both can have multiple factors.

### 2.1.1 Conditional Factor Model

We start by assuming a conditional beta pricing model of the form

$$E_t[r_{t+1}] = E_t[\mathbf{r}_{\mathbf{1},t+1}]^\top \boldsymbol{\beta}_t, \tag{1}$$

where $\boldsymbol{\beta}_t$ is a column vector equal to

$$\boldsymbol{\beta}_t = \text{Var}_t(\mathbf{r}_{\mathbf{1},t+1})^{-1}\text{Cov}_t(\mathbf{r}_{\mathbf{1},t+1}, r_{t+1}),$$

and $\mathbf{r}_{\mathbf{1},t+1}$ is an $K$x1 column vector of returns on zero-cost benchmark portfolios. In what follows, we will denote excess returns using lower-case $r$; gross returns will be denoted $R$. In the case where $\mathbf{r}_{\mathbf{1},t+1}$ is the return on the market in excess of the riskfree rate, (1) is a conditional CAPM. When $K$ is greater than 1, (1) can be interpreted as an ICAPM, or as a factor model where the factors are returns on zero-cost portfolios.

As is well-known, (1) is equivalent to specifying a conditional stochastic discount factor model in which the stochastic discount factor is linear in $\mathbf{r}$ with coefficients that are elements of the time-$t$ information:

$$M_{t+1} = a_t + \mathbf{c}_t^\top \mathbf{r}_{\mathbf{1},t+1}, \tag{2}$$

while zero-cost portfolios and returns in excess of the riskfree rate satisfy:

$$E_t[r_{t+1}M_{t+1}] = 0. \tag{3}$$

With a stochastic discount factor model, any return $R_{t+1}$ that is correctly priced by the stochastic discount factor,$M_{t+1}$, satisfies:

$$E_t[R_{t+1}M_{t+1}] = 1. \tag{4}$$

Following Cochrane (2001), we make the further assumption that the coefficients are linear functions of an information variable $Z_t$, which summarizes the information available to the investor at time $t$.[6] The linearity assumption has also been recently used in tests of the conditional CAPM (see Lettau and Ludvigson, 2001). With this assumption, the stochastic stochastic discount factor associated with the conditional factor model is given by:

$$M_{t+1} = a + bZ_t + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{1},t+1}. \tag{5}$$

### 2.1.2 Unconditional Factor Model

We also consider an unconditional factor model as the benchmark. An unconditional beta pricing model can be written

$$E[r_{t+1}] = E[\mathbf{r}_{\mathbf{1},t+1}]^\top \boldsymbol{\beta}, \tag{6}$$

[6]The assumption of a single information variable is made for notational convenience. The model easily generalizes to multiple information variables, and even to the case where coefficients are nonlinear functions of $Z_t$.

where $\boldsymbol{\beta}$ is a column vector equal to

$$\boldsymbol{\beta} = \text{Var}(\mathbf{r}_{\mathbf{1},t+1})^{-1}\text{Cov}(\mathbf{r}_{\mathbf{1},t+1}, r_{t+1}).$$

It is easy to show that an unconditional beta pricing model with $\mathbf{r}_{\mathbf{1},t+1}$ as the factors is equivalent to specifying a stochastic discount factor model in which the stochastic discount factor is linear in $\mathbf{r}_{\mathbf{1},t+1}$ with coefficients that are constants:

$$M_{t+1} = a + \mathbf{c}^\top \mathbf{r}_{\mathbf{1},t+1}. \tag{7}$$

With an unconditional stochastic discount factor model, any return $R_{t+1}$ that is correctly priced by the stochastic discount factor,$M_{t+1}$, satisfies:

$$E[R_{t+1}M_{t+1}] = 1 \tag{8}$$

and any correctly priced, zero-cost return $r_{t+1}$ satisfies

$$E[r_{t+1}M_{t+1}] = 0. \tag{9}$$

## 2.2 Performance Measures

For the conditional model, we consider two performance measures, one that allows performance to be a function of the state of the economy at the start of the period, and one that assumes that the abnormal performance is the same each period. For the unconditional model, the only measure we consider assumes that the abnormal performance is the same each period. To identify the stochastic discount factor coefficients associated with the benchmark model, we always assume that the stochastic discount factor correctly prices the factor returns and the riskless asset.

### 2.2.1 Performance Relative to the Conditional Factor Model

Consider the excess return on a fund $r_{i,t+1}$ and suppose that this excess return can be described by

$$E_t[r_{i,t+1}] = \alpha_{it} + E_t[\mathbf{r}_{\mathbf{1},t+1}]^\top \boldsymbol{\beta}_{i,t+1}, \tag{10}$$

where $\alpha_{it}$ represents abnormal performance relative to the conditional factor model described in (1), just as in the static case. This abnormal performance is in the time-$t$ information. Recall that the stochastic discount factor, $M_{t+1} = a_t + \mathbf{c}_t^\top \mathbf{r}_{\mathbf{1},t+1}$, prices any asset return satisfying the conditional beta pricing model described in (1). It is easy to show that the following modification to the conditional stochastic discount factor model holds for $r_{i,t+1}$:

$$E_t\left[(a_t + c_t^\top \mathbf{r}_{\mathbf{1},t+1})(r_{i,t+1} - \alpha_{it})\right] = 0. \tag{11}$$

We consider two specifications for the abnormal performance. In the first, we let $e_i$ and $f_i$ be fund-specific constants such that

$$\alpha_{it} = e_i + f_i Z_t.$$

Under this specification, performance is allowed to be linear in the information variable $Z_t$. Consequently, we refer to this specification as conditional performance relative to the conditional factor model. This specification for the abnormal performance together with the linear specification for the stochastic discount factor in (5) implies that the following moment condition must hold:

$$E_t \left[ (r_{i,t+1} - e_i - f_i Z_t)(a + bZ_t + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{1},t+1}) \right] = 0. \tag{12}$$

In the second specification, we let $e_i$ be a fund-specific constant such that

$$\alpha_{it} = e_i.$$

Since performance is a constant, we refer to this specification as unconditional performance relative to the conditional factor model. Using the linear specification for the stochastic discount factor in (5), we obtain the following moment condition:

$$E_t \left[ (r_{i,t+1} - e_i)(a + bZ_t + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{1},t+1}) \right] = 0. \tag{13}$$

### 2.2.2 Performance Relative to the Unconditional Factor Model

Again consider the excess return on a fund $r_{i,t+1}$, but suppose that this excess return can be described by

$$E[r_{i,t+1}] = \alpha_i + E[\mathbf{r}_{\mathbf{1},t+1}]^\top \boldsymbol{\beta}_i, \tag{14}$$

where $\alpha_i$ represents abnormal performance relative to the unconditional factor model described in (6). It is easy to show that the following modification to the unconditional stochastic discount factor model holds for $r_{i,t+1}$:

$$E \left[ (r_{i,t+1} - \alpha_i)(a + \mathbf{c}^\top \mathbf{r}_{\mathbf{1},t+1}) \right] = 0. \tag{15}$$

## 2.3 Comparison to other measures

An alternative to our method is the regression-based approach of Ferson and Harvey (1999) and Ferson and Schadt (1996). Both papers examine performance relative to the conditional pricing model (1). However, they differ from us in their specification of the conditional moments. Rather than assuming that the stochastic discount factor (5) is linear in the information variables, they assume that the conditional betas are linear.

Ferson and Schadt (1996) estimate a regression equation

$$r_{i,t+1} = \delta_{0,i} + \delta_{m,i} r_{m,t+1} + \delta_{Zm,i} Z_t r_{m,t+1} + \varepsilon_{i,t+1}, \tag{16}$$

where $r_{m,t+1}$ is the excess return on the market, using ordinary least squares.[7] If fund return satisfies (10) with $\alpha_{it} = e_i$, $\beta_t$ linear in $Z_t$, and $r_{m,t+1}$ the only factor, Ferson and Schadt show that $\delta_{0,i}$ equals $e_i$. Thus, $\delta_{0,i}$ can be regarded as a measure of the fund's unconditional performance relative to the conditional factor model in (1).

Ferson and Harvey (1999) extend this approach to estimate conditional abnormal performance. Ferson and Harvey estimate the following unconditional regression:

$$r_{i,t+1} = \delta_{0,i} + \delta_{Z,i} Z_t + \delta_{m,i} r_m + \delta_{Zm,i} Z_t r_{m,t+1} + \varepsilon_{i,t+1}. \tag{17}$$

This specification can measure performance, $\alpha_{it}$, of the form $e_i + f_i Z_t$. In particular, if the fund return satisfies (10) with $\alpha_{it} = e_i + f_i Z_t$, $\beta_t$ linear in $Z_t$, and $r_{m,t+1}$ as the only factor, it is possible to show show that $\delta_{0,i}$ equals $e_i$ and $\delta_{Z,i}$ equals $f_i$.

The disadvantage of this approach is that the interpretations of non-zero $\delta_{0,i}$ and $\delta_{Z,i}$ are sensitive to the assumed linearity of beta as a function of the information variable. For example, suppose that, with $\mathbf{r_1}_{,t+1}$ set equal to $r_{m,t+1}$, (5) represents a stochastic discount factor that prices $r_{i,t+1}$. As we have shown, (1) holds for $r_{i,t+1}$, but $\beta_t$ need not be linear in $Z_t$. Taking unconditional expectations of (4) and using the usual reasoning, it follows that

$$\begin{aligned} E[r_{i,t+1}] &= -\frac{1}{E[M_{t+1}]}\Big(b\mathrm{Cov}(r_{i,t+1}, Z_t) - \mathbf{c}^\top \mathrm{Cov}(r_{i,t+1}, r_{m,t+1}) - \mathbf{d}^\top \mathrm{Cov}(r_{i,t+1}, Z_t r_{m,t+1})\Big) \\ &= \begin{bmatrix} \beta_{i,Z}, & \beta_{i,r_m}, & \beta_{i,Zr_m} \end{bmatrix} \lambda \end{aligned} \tag{18}$$

where $\lambda^\top = \begin{bmatrix} \lambda_Z, & \lambda_{r_m}, & \lambda_{Zr_m} \end{bmatrix}$ is a vector of constants and $\begin{bmatrix} \beta_{i,Z}, & \beta_{i,r_m}, & \beta_{i,Zr_m} \end{bmatrix}$ is a vector of regression slope coefficients from a regression of $r_{i,t+1}$ on $Z_t$, $r_{m,t+1}$, $Z_t r_{m,t+1}$ and a constant. Because (18) must hold for the factor portfolio $r_{m,t+1}$, as well as for the scaled portfolio $Z_t r_{m,t+1}$, it follows that the last two elements of $\lambda$ are the expected returns on these two portfolios; i.e., $\lambda_{r_m} = E[r_{m,t+1}]$ and $\lambda_{Zr_m} = E[Z_t r_{m,t+1}]$. Our model thus implies an unconditional model with 3 factors. Using the definition of regression, it follows that: $\delta_{Z,i} = \beta_{i,z}$, $\delta_{m,i} = \beta_{i,r_m}$ and $\delta_{Zm,i} =$

[7] Ferson and Schadt (1996) also consider multi-factor models, but use a single-factor model to illustrate their methodology.

$\beta_{i,zr_m}$. When conditional betas are not linear, we can expect $\delta_{Z,i}$ to pick up unconditional residual correlation between $r_{i,t+1}$ and $Z_t$. It is therefore possible for $\delta_{Z,i}$ to be nonzero even if skill is not time-varying ($f_i = 0$).

Using the expressions for $\delta_{m,i}$ and $\delta_{Zm,i}$, it follows that $\delta_{0,i}$ and $\delta_{Z,i}$ are related in the following manner:

$$\delta_{0,i} = \delta_{Z,i}(\lambda_Z - E[Z_t]).$$

Consequently, depending on the relative values of $\lambda_Z$ and $E[Z_t]$, $\delta_{0,i}$ need not be zero either. If the betas are not linear, nonzero loadings on $Z_t$ and a nonzero constant term do not necessary imply abnormal performance.

Our approach has several advantages over the regression-based approach. First, it makes clear assumptions about the stochastic discount factor associated with the factor model. Given that $\beta$ is a characteristic of the asset rather than the economy, it may not be possible to write down the stochastic discount factor that would deliver the Ferson and Schadt (1996) specification. Our method is also very flexible. We could allow the coefficients of the stochastic discount factor to be nonlinear functions of $Z_t$ without a significant change to the methodology. While the regression-based approach delivers an estimate of a tightly-parameterized time-varying beta of a mutual fund, our approach delivers an estimate of time-varying performance that is robust to the specification for beta.

We estimate performance using both the SDF and the regression-based approaches. We can therefore determine the extent to which the performance estimates from the regression-based approach arise from the assumption that beta is linear in the information variables.

# 3 Data

The riskfree and factor return data come from Ken French's website. Fama and French (1993) describe the construction of the riskfree rate series, the excess market return, the high minus low book-to-market portfolio return (HML), and the small minus big market capitalization portfolio return (SMB) are constructed. A description of the momentum portfolio return (UMD) can be found on the website. We use two information variables. The first is the 12-month dividend yield on the value-weighted NYSE and the data used to construct this series come from CRSP. The second is a yield spread variable, which up until 12/96 is the yield spread between 20-year and one-month Treasury securities obtained from the Ibbotson data service, and from 1/97 is the the yield spread between 5-year and 3-month discount bonds obtained from the CRSP Fama-Bliss Discount Bond files. We have data on dividend yield, term spread, and the factors from 1/27 to 12/07.

We standardize the term spread to have a mean of zero and a variance of one in each of two sub-samples: 1/27 to 12/96, and 1/97 to 12/07. We do this because our data source for the two sub-samples is different. We standardize the dividend yield to have a mean of zero and a variance of one in each of three sub-samples: 1/27 to 12/54, 1/55 to 12/94, and 1/95 to 12/07. We do this because the dividend yield process likely has structural breaks since Lettau and van Nieuwerburgh (2008) are able to reject the hypothesis of zero breaks in the process. When Lettau and van Nieuwerburgh allow for two breaks, they estimate the breaks to occur at the end of 12/54 and at the end of 12/94.

The mutual fund data is from the CRSP mutual fund database which is free of survivorship bias. For disappearing funds, returns are included through until disappearance so the fund-type returns do not suffer from survivor conditioning.[8] CRSP uses fund style classifications from three sources: Wiesenberger(1961-92), Strategic Insight (1992-99), and Lipper (1999 onwards). Also, Wiesenberger changed its system entirely in 1990, leaving us with four classification schemes. From 1961-1990, CRSP reports Wiesenberger's policy code, and since we are only interested in equity funds, we keep only funds for which the policy code is either reported as 'CS' (common stock) or is missing. From 1990 onwards, there is no counterpart to policy available, so we rely on the fund style classifications to determine whether a fund is an equity fund.

Given the series for a fund (which may have gaps), we need to decide from what date onwards to include the fund in our sample. We apply two filters: a TNA-based filter and a return-based filter. The TNA filter requires that the fund must, at some time before the inclusion date, have had a TNA of at least 2.5 million in December 1976 dollars.[9] Once a fund has satisfied this criterion, we examine subsequent January data for that fund to find the earliest January in which CRSP reports a nonmissing return value, and for which the TNA in the December immediately prior was also nonmissing. This is our return-based filter. We include all returns from that January onwards in our sample. For instance, a fund may have TNA data beginning October 1994, but may not have a

[8]See Brown, Goetzmann, Ibbotson and Ross (1992) and Carpenter and Lynch (1999) for discussions of the effects of survivor conditioning on performance measurement.

[9]According to Elton and Gruber (2011), funds with under $15 million in assets are not required to report TNA on a daily basis, which creates a bias in the CRSP data if these funds are selectively reporting only when their returns are good. For this reason, we redo our analysis using a TNA filter of $15 million for all years. The results are qualitatively similar. According to Evans (2010), incubator funds only report returns from inception if fund performance is good, which creates a bias that is akin to backfill bias. For this reason, we redo our analysis imposing a filter that discards the first 36 months of returns of any new funds added to the database. Again, the results are qualitatively similar.

TNA of 2.5 million in December 1976 dollars (which works out to approximately 6.5 million in 1995 dollars) until November of 1995. If both the return of January 1996 and the TNA of December 1995 are available, the fund is included in our sample from January 1996 onwards.

To assess the extent to which missing returns is an issue given the two filters we use to determine the start of each fund's inclusion in the sample, we calculate the ratio of the number of nonmissing return observations a fund actually has to the number of nonmissing return observations it would have if its return series was complete. Since we form portfolios based on total net assets under management (TNA) as well as style, we also omit from the sample the returns on any fund in a calendar year with no TNA value in the CRSP database at the start of that year. Before omitting fund returns with no TNA, we find that less than 4% of the funds in the sample have any missing returns, and less than 2% have more than 5% of their returns missing. After omitting fund returns with no TNA, we find that less than 5% of the funds in the sample have any missing returns and less than 2% have more than 7% of their returns missing. Where a fund has multiple share groups in the sample in a year, we keep the share class for which the sum of front load, rear load and expense ratio is lowest at the end of the previous year.[10]

To create a single aggregate fund style classification that is valid at all points in time, we need to combine the four fund style classifications reported by CRSP that are described above. We generate cross-tabulations which show how funds move from an old scheme to a new scheme at each point at which the reported classification changes. We also calculate frequency tables that report the number of funds in each style in each month, where the set of possible styles each month depends on the classification scheme in place for that month. Each cross-tabulation calculation includes all funds that are in the sample for the two months that straddle the date that the classification scheme changes, even those funds without returns for both those months. Based on the frequency tables and cross-tabulations, we come up with a list of "usable" styles for each classification scheme. We then use the cross-tabulations to group the "usable styles" into 12 aggregate styles. The twelve aggregate styles are as follows: growth-income (GRI), growth (GRO), income (INC), maximum capital gains (CGM), midcap (MCG), small cap growth (SCG), flexible (FLX), and five sector styles (energy/natural resources, ENR, financial services, FIN, health, HLT, technology TCH, and utilities,UTL).[11] The starting dates of all the fund series are not all the same, and are given in

[10]Where two share classes have equal total fees computed in this way, we choose the share class with the highest TNA at the end of the previous year. If any of the share classes has a missing value for a given fee (expense, front load, or back load) then that fee is not included in the sum. If all three have at least one missing value across the share classes, then we choose the share class with the highest TNA at the end of the previous year.

[11]The mapping from our aggregate styles to the underlying CRSP "usable" styles and the cross-tabulations that

Table 1. All twelve data series end in 12/07. Table 1 also reports the mean, the minimum, and the maximum number of funds in each aggregate style, from the start date for each style through until 12/07.

We then form the equal-weighted portfolios to be used in the estimation. In each month we assign funds to aggregate style categories based on their CRSP styles at the beginning of that month and then, since we want to consider the effect of TNA on fund performance, we bifurcate each style based on TNA at the beginning of the calendar year in which that month falls. Thus, we are careful to form our small and large fund groups for each fund type each year based on information that is publicly available at the start of the year.

# 4 Empirical Methodology

An advantage of our measure of performance is the ease with which it can be estimated. The first subsection describes the moments used in the estimation. These come from the pricing restrictions involving the SDF that were derived in the previous section. The second subsection describes how the usual GMM methodology is used to estimate the parameters, and also how the new methodology of Lynch and Wachter (2007) for unequal data lengths is applied to take advantage of the longer data series for factor returns than for fund portfolio returns, and the longer data series for some fund portfolio returns than other fund portfolio returns.

## 4.1 Moment restrictions used in the SDF-based estimation

The moment restrictions that we use depend on whether we are using the conditional or unconditional factor model as the benchmark model.

### 4.1.1 Conditional factor model as the benchmark

Since $Z_t$ is always a scalar in our specifications, the associated SDF in (5) for a conditional $K$ factor model has $2(K+1)$ parameters to be estimated. The coefficients $a$, $b$, $\mathbf{c}$, and $\mathbf{d}$ can be estimated using the following $2(K+1)$ moment conditions:

$$E[\Big((a+bZ_t)+(\mathbf{c}+\mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{1},t+1}\Big)\begin{bmatrix} R_{f,t+1} \\ \mathbf{r}_{\mathbf{1},t+1}\end{bmatrix}\otimes\begin{bmatrix}1\\ Z_t\end{bmatrix} - \begin{bmatrix}1\\ \mathbf{0}\end{bmatrix}\otimes\begin{bmatrix}1\\ Z_t\end{bmatrix}]=\mathbf{0} \qquad (19)$$

use the individual styles (i.e., as reported by CRSP) and that use the aggregate styles are available from the authors on request.

These must hold if the stochastic discount factor in (5) correctly prices the riskfree return, $R_{f,t+1}$, using (4) and the zero-cost factor portfolio returns, $\mathbf{r}_{\mathbf{1},t+1}$ using (3). Since (5) and (3) are conditional moment restrictions, it is possible to multiply both sides of each by 1 and $Z_t$ and then use the law of iterated expectations to arrive at the unconditional moment restrictions in (19). Since there are $2(K+1)$ moments and parameters, these moments are able to just-identify the SDF parameters.[12]

The moments used to identify the fund-specific performance parameters depend on the abnormal performance specification. However, the basic approach is to take the modified SDF model that prices fund excess returns, (11), and again multiply by variables in the time-$t$ information set before conditioning down. When fund performance is allowed to be linear in $Z_t$ such that $\alpha_{it} = e_i + f_i Z_t$, the following 2 moments conditions can be obtained for excess return $r_i$ by multiplying by 1 and $Z_t$:

$$E[\Big((r_{i,t+1} - e_i - f_i Z_t)\Big((a + bZ_t) + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{1},t+1}\Big)\Big) \otimes \begin{bmatrix} 1 \\ Z_t \end{bmatrix}] \quad = \quad \begin{bmatrix} 0 \\ 0 \end{bmatrix}. \tag{20}$$

Since there are 2 moments and parameters, these moments are able to just-identify the fund-specific performance parameters.

When fund performance is restricted to be a constant such that $\alpha_{it} = e_i$, the following moment condition can be obtained for excess return $r_i$ by multiplying by 1 and conditioning down:

$$E[(r_{i,t+1} - e_i)\Big((a + bZ_t) + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{1},t+1}\Big)] \quad = \quad 0. \tag{21}$$

Since there is 1 moment and parameter, the fund-specific performance parameter is again just-identified. We could have multiplied by $Z_t$ as for the previous specification, but then the parameter would be over-identified. The SDF parameters are estimated using the moment conditions (19) as before.

#### 4.1.2 Unconditional factor model as the benchmark

With an unconditional $K$ factor model, the associated SDF in (7) has $(K+1)$ parameters to be estimated. There is one performance parameter per fund. The $(K+1)$ moments used to identify the $(K+1)$ SDF parameters, follow immediately from the following moment conditions:

$$E[\Big(a + \mathbf{c}^\top \mathbf{r}_{\mathbf{1},t+1}\Big)\begin{bmatrix} R_{f,t+1} \\ \mathbf{r}_{\mathbf{1},t+1} \end{bmatrix} \quad - \quad \begin{bmatrix} 1 \\ \mathbf{0} \end{bmatrix}] = \mathbf{0} \tag{22}$$

[12]The conditional moment restrictions in (5) and (3) can also be multiplied by nonlinear functions of $Z_t$ before conditioning down, which would allow the parameters to be over-identified by the moments.

These must hold if the stochastic discount factor in (7) correctly prices the riskfree return, $R_{f,t+1}$, using (8) and the zero-cost factor portfolio returns, $\mathbf{r}_{\mathbf{1},t+1}$ using (9). The fund-specific performance parameter, $e_i = \alpha_i$ is identified directly by the moment restriction (15). Notice that again the number of moments just equals the number of parameters so that the parameters are just identified.

## 4.2 GMM estimation with unequal length data

We divide the fund styles into three groups, and report results for each group separately. The first group consists of styles for which we have relatively longer data series: GRI, GRO, CGM and INC. The second group consists of the sector funds: ENR, FIN, HLT, TCH and UTL. The third consists of non-sector styles for which we have relatively short series: SCG, FLX and MCG. When using the short and regression-based estimations, we report results for each group using data from the intersection of the sample periods for all the TNA-style portfolios in that group.

We have factor return and instrument data back to 1/27, and multiple start dates for the funds, all after 1/27, which means we have factor return data that goes back much further than fund return data. Moments that identify the SDF parameters do not use fund return data and so we have data on these moments back to 1/27. When using the adjusted-moment estimator, the estimation for a given group uses moments for the fund styles in that group and in any group whose fund styles all have start dates which are the same or earlier than those for the fund styles in that group. So there is a set of fund styles used in the estimation for each fund-style group. The set for the first group of fund styles is just the first group itself, while the set for the second group is the second group plus the first group. The set for the third group is all three groups of fund styles.

For a given set of fund styles, let $n$ be the number of fund-style start dates plus 1 and let the $i$th sample period refer to the $i$th longest period of data for a set of fund styles or factors. So the $n$th sample period always refers to the period from 1/27 to 12/07. For all three sets, the $(n-1)$th sample period always refers to the period from 1/62 to 12/07, the $(n-2)$th sample period always refers to the period from 1/69 to 12/07, and $(n-3)$th sample period always refers to the period from 1/72 to 12/07. For the first set, $n$ is equal to 4. For the last two sets, the $(n-4)$th sample period always refers to the period from 1/91, and for the second set, $n$ is equal to 5. For the last set, the $(n-5)$th sample period always refers to the period from 1/95 to 12/07, and $(n-6)$th sample period always refers to the period from 1/95 to 12/07. For the last set, $n$ is equal to 7. For each set, define the first sample interval to be the short sample period. Define the $i$th interval $\lambda_i$

as follows:

$$\lambda_i = \frac{t_i - t_{i-1}}{t_n} \tag{23}$$

where $t_i$ is the number of observations in the $i$th sample period and $t_0$ is set equal to 0. So $T$ equals $t_n$.

The usual GMM estimation strategy takes the sample period to be that for which data is available for all moments. Here, estimating GMM in the usual way uses only the short sample period data. The problem with this approach is that any information contained in data available before the start of the short period is completely ignored. The factor return data, the instrument data, and the fund return data of funds with earlier start dates than the short sample period start date, all are available before the start of the short period. Lynch and Wachter (2011) have developed asymptotic theory for a variety of GMM estimators that use this additional information. They present two GMM estimators and show that they both have the same asymptotic variance and that this variance is always weakly smaller than that for the usual short sample GMM estimator. The asymptotic theory assumes that data is added to the $n$ intervals in the same ratio as in the available sample. We utilize one of these GMM estimators as a way to utilize useful data available outside the short period.

We describe the two estimation methods that we employ to assess conditional performance relative to the conditional model and then briefly describe how these methods apply to the other performance measures considered. Let $N$ be the number of funds in a given set and divide the funds into $(n-1)$ groups based on their start dates. Let $\mathbf{r}_{i,t+1}$ be the vector of returns on the $N_i$ funds with the $i$th earliest start date and let $\mathbf{r}_{1,t+1}$ be the vector of returns on the $N_1$ factors. To make notation more compact, we define

$$\mathbf{f}_1(\mathbf{r}_{\mathbf{1},t+1}, R_{f,t+1}, Z_t, \theta_1) = \begin{bmatrix} R_{f,t+1} \\ \mathbf{r}_{\mathbf{1},t+1} \end{bmatrix} \Big((a + bZ_t) + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{1},t+1}\Big) \otimes \begin{bmatrix} 1 \\ Z_t \end{bmatrix} - \begin{bmatrix} 1 \\ \mathbf{0} \end{bmatrix} \otimes \begin{bmatrix} 1 \\ Z_t \end{bmatrix} \tag{24}$$

and

$$\mathbf{f}_i(\mathbf{r}_{i,t+1}, \mathbf{r}_{\mathbf{1},t+1}, R_{f,t+1}, Z_t, \theta_1, \theta_i) = (\mathbf{r}_{i,t+1} - \mathbf{e}_i - \mathbf{f}_i Z_t) \otimes \Big((a + bZ_t) + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{1},t+1}\Big) \otimes \begin{bmatrix} 1 \\ Z_t \end{bmatrix}, \tag{25}$$

for $i = 2, 3, \ldots n$, where $\mathbf{e}_i = [e_1 \ldots e_{N_i}]'$, $\mathbf{f}_i = [f_1 \ldots f_{N_i}]$, $\theta_1 = [a\ b\ \mathbf{c}'\ \mathbf{d}']'$ and $\theta_i = [\mathbf{e}_i{}'\ \mathbf{f}_i{}']'$. Note that the $f_1$ moments identify the SDF parameters while the $f_i$ moments identify the parameters for the $i$th fund group of the set.

Define

$$\bar{\lambda}_i \doteq \sum_{k=1}^{i} \lambda_k, \quad i = 1, 2, ..., n, \tag{26}$$

$$\bar{\lambda}_0 \doteq 0, \tag{27}$$

$$\mathbf{g}_{1,\lambda_i T}(\theta) = \frac{1}{\lambda_i T} \sum_{t=(1-\bar{\lambda}_i)T+1}^{(1-\bar{\lambda}_{i-1})T} \mathbf{f}_1(\mathbf{r}_{\mathbf{1},t}, R_{f,t}, Z_{t-1}, \theta_1) \tag{28}$$

$$\mathbf{g}_{1,\bar{\lambda}_i T}(\theta) = \frac{1}{\bar{\lambda}_i T} \sum_{k=1}^{i} (\lambda_k T) \mathbf{g}_{1,\lambda_k T}(\theta) \tag{29}$$

$$\mathbf{g}_{j,\lambda_i T}(\theta) = \frac{1}{\lambda_i T} \sum_{t=(1-\bar{\lambda}_i)T+1}^{(1-\bar{\lambda}_{i-1})T} \mathbf{f}_j(\mathbf{r}_{i,t}, \mathbf{r}_{\mathbf{1},t}, R_{f,t}, Z_{t-1}, \theta_1, \theta_2), \quad j = 2, ..., n \tag{30}$$

$$\mathbf{g}_{j,\bar{\lambda}_i T}(\theta) = \frac{1}{\bar{\lambda}_j T} \sum_{k=1}^{i} (\lambda_k T) \mathbf{g}_{j,\lambda_k T}(\theta), \quad j = 2, ..., n, \tag{31}$$

$$\tag{32}$$

where $\theta = [\theta_1 \ \theta_2]$.

The canonical GMM estimator takes the following form:

$$\hat{\theta}_T = \text{argmin}_\theta \ \mathbf{h}_T^\top \mathbf{W}_T \mathbf{h}_T. \tag{33}$$

The usual GMM estimator only uses data from the period with data for all the sample moments. This estimator is referred to as the Short estimator and sets

$$\mathbf{h}_T^{\mathcal{S}}(\theta) = \left[\mathbf{g}_{1,\lambda_1 T}(\theta)^\top \ ... \ \mathbf{g}_{n,\lambda_1 T}(\theta)^\top\right]^\top. \tag{34}$$

These sample moments correspond to the population moments on the left hand sides of (19) and (20) which explains why asymptotically they are equal to zero under the null, as required by the GMM methodology. For each of the three groups, the Short estimates of the performance coefficients for all the TNA-style portfolios in that group and all the hypothesis tests for that group are performed using data from the intersection of the sample periods for all the TNA-style portfolios in that group.[13]

Before we define the estimator that uses more data than the short sample period, we define the asymptotic covariance matrix **S** for sample moments of the Short estimator by defining the $(i, j)^{\text{th}}$

[13]The Short estimation results are qualitatively unchanged if the $e$ and $f$ coefficients for a fund-style portfolio are estimated using all available data for that portfolio, and if each hypothesis test is performed using data from the intersection of the sample periods for the fund-style portfolios involved in the test.

element of $\mathbf{S}$, which might be a matrix or a vector depending on the dimensions of $\mathbf{f}_i$ and $\mathbf{f}_j$:

$$\mathbf{S}_{ij} = \sum_{k=-\infty}^{\infty} E\left[\mathbf{f}_i(\mathbf{r}_0,\theta)\mathbf{f}_j(\mathbf{r}_{-k},\theta)^\top\right], \tag{35}$$

where

$$\begin{aligned}\mathbf{f}_1(\mathbf{r}_{t+1},\theta) &= \mathbf{f}_1(\mathbf{r}_{\mathbf{1},t+1},R_{f,t+1},Z_t,\theta_1)\\ \mathbf{f}_i(\mathbf{r}_{t+1},\theta) &= \mathbf{f}_i(\mathbf{r}_{i,t+1},\mathbf{r}_{\mathbf{1},t+1},R_{f,t+1},Z_t,\theta_1,\theta_2), \quad i=2,3,...,n.\end{aligned}$$

We assume $\hat{\mathbf{S}}_{ij}(\tilde{\theta})$ is a consistent estimator of $\mathbf{S}_{ij}$ whenever the parameter estimate $\tilde{\theta}$ is a consistent estimator of the true parameter vector $\theta_0$.

The estimator that uses more data than the short sample period is labeled the adjusted moment estimator by Lynch and Wachter [2007] and sets

$$\mathbf{h}_T^{\mathcal{A}}(\theta) = \begin{bmatrix} \mathbf{g}_{1,\bar{\lambda}_n T}(\theta) \\ \mathbf{g}_{2,\bar{\lambda}_{n-1}T}(\theta) - \frac{\lambda_n}{\bar{\lambda}_n}\hat{\mathbf{B}}_{2,1\to1}[\bar{\mathbf{g}}_{1,\bar{\lambda}_{n-1}T}(\theta) - \bar{\mathbf{g}}_{1,\lambda_n T}(\theta)] \\ \mathbf{g}_{3,\bar{\lambda}_{n-2}T}(\theta) - \frac{\lambda_{n-1}}{\bar{\lambda}_{n-1}}\hat{\mathbf{B}}_{3,1\to2}[\bar{\mathbf{g}}_{2,\bar{\lambda}_{n-2}T}(\theta) - \bar{\mathbf{g}}_{2,\lambda_{n-1}T}(\theta)] - \frac{\lambda_n}{\bar{\lambda}_n}\hat{\mathbf{B}}_{3,1\to1}[\mathbf{g}_{1,\bar{\lambda}_{n-1}T}(\theta) - \bar{\mathbf{g}}_{1,\lambda_n T}(\theta)] \\ . \\ . \\ \mathbf{g}_{j,\bar{\lambda}_{n-j+1}(\theta)} - \sum_{i=1}^{j-1}\frac{\lambda_{n-j+i+1}}{\bar{\lambda}_{n-j+i+1}}\hat{\mathbf{B}}_{j,1\to j-i}[\bar{\mathbf{g}}_{j-i,\bar{\lambda}_{n-j+i}}(\theta) - \bar{\mathbf{g}}_{j-i,\lambda_{n-j+i+1}}(\theta)] \\ . \\ . \\ \mathbf{g}_{n,\bar{\lambda}_1}(\theta) - \sum_{i=1}^{n-1}\frac{\lambda_{i+1}}{\bar{\lambda}_{i+1}}\hat{\mathbf{B}}_{n,1\to n-i}[\bar{\mathbf{g}}_{n-i,\bar{\lambda}_i}(\theta) - \bar{\mathbf{g}}_{n-i,\lambda_{i+1}}(\theta)] \end{bmatrix} \tag{36}$$

where

$$\bar{\mathbf{g}}_{i,.}(\theta) \doteq \begin{bmatrix} \mathbf{g}_{1,.}(\theta) \\ \mathbf{g}_{2,.}(\theta) \\ \mathbf{g}_{3,.}(\theta) \\ . \\ . \\ . \\ \mathbf{g}_{i,.}(\theta) \end{bmatrix}, \quad i=1,2,...,n, \tag{37}$$

$$\hat{\mathbf{B}}_{i,j\to k} = \hat{\mathbf{S}}_{i,j\to k}(\tilde{\theta})\left(\hat{\mathbf{S}}_{j\to k,j\to k}(\tilde{\theta})\right)^{-1}, \quad j\le k, \tag{38}$$

$$\hat{\mathbf{S}}_{i,j\to k}(\tilde{\theta}) = \begin{bmatrix} \hat{\mathbf{S}}_{ij}(\tilde{\theta}) & ... & \hat{\mathbf{S}}_{ik}(\tilde{\theta}) \end{bmatrix}, \quad j\le k \tag{39}$$

and

$$\hat{\mathbf{S}}_{j\to k,j\to k}(\tilde{\theta}) = \begin{bmatrix} \hat{\mathbf{S}}_{jj}(\tilde{\theta}) & ... & \hat{\mathbf{S}}_{jk}(\tilde{\theta}) \\ ... & ... & ... \\ \hat{\mathbf{S}}_{kj}(\tilde{\theta}) & ... & \hat{\mathbf{S}}_{kk}(\tilde{\theta}) \end{bmatrix}, \quad j \leq k \tag{40}$$

for some prespecified $\tilde{\theta}$ that is a consistent estimate of $\theta_0$, the true parameter vector. Note that $\hat{\mathbf{B}}_{i,j\to k}$ is a consistent estimate of $\mathbf{B}_{i,j\to k}$, the matrix of regression coefficients from regressing the $\mathbf{f}_i$ functions for the funds with the $i$th earliest start date on the $\mathbf{f}_j$, ..., and $\mathbf{f}_k$ functions for funds with the $j$th through $k$th earliest start dates.

Given $\mathbf{S}$, the covariance matrix of the unadjusted moments, we can obtain an analytical expression for $\mathbf{S}^{\mathcal{A}}$, the covariance matrix of the adjusted moments. There is a simple expression for the the $(k,j)^{\text{th}}$ block of the $\mathbf{S}^{\mathcal{A}}$ matrix: for any $j \leq k \leq n$,

$$S^{\mathcal{A}}_{k,j} = \frac{S_{k,j}}{\bar{\lambda}_{n-j+1}} - \sum_{i=1}^{j-1} \frac{\lambda_{n-j+i+1}}{\bar{\lambda}_{n-j+i+1}\bar{\lambda}_{n-j+i}} S_{k,1\to j-i} S^{-1}_{1\to j-i,1\to j-i} S_{1\to j-i,j}.$$

Notice that there are two differences between this estimator,which we refer to as the Full estimator, because it uses all available data for the estimation, and the usual Short GMM estimator. First, the sample moments that estimate the stochastic discount factor parameters use the entire sample period for which we have factor and instrument data going back to 1/27 instead of just the short sample period for which there is data for all the sample moments. Second, the sample moments used to estimate the fund performance parameters for each set of fund types with the same data start dates take the analogous short sample moments and modify them to incorporate information from the sample SDF moments and the sample moments for the fund types with earlier data start dates.

To use the adjusted-moment method, we need consistent estimates of $\mathbf{B}_{i,1\to k}$ where $k \leq i$ which requires consistent estimates of $\mathbf{S}_{1\to i,1\to i}$. To estimate $\mathbf{S}_{1\to i,1\to i}$ consistently, we need a consistent estimate of the parameter vector that determines the sample moments with the the first $i$ start dates, $\tilde{\theta}_{1\to i}$. To obtain the estimate $\tilde{\theta}_j$ for funds with the $j$th earliest data start date (so $j = 2, 3, \cdots, n$ for a given set of funds), we run separate adjusted-moment estimations for each fund, that is, estimations in which we adjust each fund's moments only with respect to the factor moments. To do this for each fund, we first need an estimate of the covariance matrices of each fund's moments and the factor moments. We calculate this covariance matrix using the fund-by-fund short estimates just talked about and the intersection of the data series of each fund with the factor series. Each such separate adjusted-moment estimation yields estimates of the parameters of the fund under consideration, but also yields estimates of the SDF parameters $\tilde{\theta}_1$.[14] This is how we construct $\tilde{\theta}_{1\to i}$ for a given $i$.

Given this parameter vector, we can now construct the adjusted moments for each fund. Using $\tilde{\theta}_{1\to i}$, we calculate an estimate of $\mathbf{S}_{1\to i,1\to i}$ for the funds with the $i$th earliest data start date, $\hat{\mathbf{S}}_{1\to i,1\to i}(\tilde{\theta})$, which is then used to construct $\hat{\mathbf{B}}_{i,1\to k}$, the estimate of $\mathbf{B}_{i,1\to k}$. We use as much data as possible in this estimation: that is, we use the intersection of each fund's data series with the data series of all funds which have a longer data series and with the factor series.[15] We estimate covariances and variances of the moments consistently using Newey-West with 6 lags and centered moments. The advantage of this estimator is that the estimate of $\mathbf{S}_{1\to i,1\to i}$ is the same no matter how many funds with later start dates than the $i$th earliest start date are included in the estimation. In other words, adding funds with a shorter data length does not affect the estimate of the covariances for the moments of those funds with longer data and of the factors.

With appropriate regularity conditions, Lynch and Wachter (2007) show that this estimator is consistent. They also show that the Full method achieves asymptotic efficiency gains relative to the usual Short method. Hansen [1982] shows that the asymptotically efficient GMM estimator for a given set of moment conditions is obtained by using a weighting matrix that converges to the inverse of covariance matrix for the sample moments. The GMM objective function is exactly identified so the adjusted moment estimator based on these $\mathbf{S}_{1\to i,1\to i}$ estimates, $\hat{\theta}_{1\to i}$ does not depend on the GMM weighting matrix.

The covariance matrix of the Full estimates is obtained as follows:

$$V[\sqrt{T}\hat{\theta}] = D'^{-1}S^{\mathcal{A}}D^{-1}$$

where $D$ the matrix of derivatives of the moments with respect to the parameters. We obtain a consistent estimator of $V[\sqrt{T}\theta]$ by using $\hat{D}'^{-1}\hat{S}^{\mathcal{A}}\hat{D}^{-1}$ where $\hat{S}^{\mathcal{A}}$ is a consistent estimator of the covariance matrix of the adjusted moments and $\hat{D}$ a consistent estimator of the matrix of derivatives of the moments with respect to the parameters. The $\hat{S}^{\mathcal{A}}$ matrix is calculated from the covariance matrix of the unadjusted moments, $S$, which we again estimate using Newey-West with six lags and centered moments. Rather than obtain a single estimate of $\hat{D}$ and $\hat{S}$ using the intersection of all data series, we instead estimate, for each hypothesis test we perform, different

[14]Note that the estimates of the SDF parameters are always the same, however, because these estimates depend only on the factor and instrument data back to 1/27, which do not change.

[15]This is an improvement on using a single variance covariance matrix, which would have to be estimated with the intersection of the data series of all funds and the factors.

$\hat{D}$ and $\hat{S}$ matrices, using the longest data series possible for the funds involved in that hypothesis test. So the significance tests for the coefficients for a fund with the $i$th earliest data start date are based on $\hat{\mathbf{S}}_{1\to i,1\to i}$ calculated using all data from the $i$th earliest data start date onwards. So each $\hat{\mathbf{S}}_{1\to i,1\to i}$ matrix is calculated in the same way as the estimate of $\hat{\mathbf{S}}_{1\to i,1\to i}$ is obtained to calculate the estimate of $\mathbf{B}_{i,1\to k}$, except that that $\theta_{1\to i}$ is set equal to the Full estimator, $\hat{\theta}_{1\to i}$, rather than $\tilde{\theta}_{1\to i}$. This procedure has the advantage that the p-values of the hypothesis tests of the parameters of funds with earlier start-dates are invariant to the addition of new funds with shorter series. For the Short estimation, standard errors are calculated using Newey-West evaluated at the parameter estimates reported for the Full estimation.[16] Doing so allows the efficiency gains from using the Full estimators instead of the Short estimator to be quantified more easily.

The Full method achieves asymptotic efficiency gains relative to the usual Short method. The maximum possible gain is 1 less the square root of the ratio of the length of the short sample to the length of the longest sample, which is the factor and instrument data. This maximum efficiency gain is achieved for the SDF parameters since the SDF moments are able to identify these parameters and there is data for these moments back to 1927. For the fund specific performance parameters, which only appear in the fund-specific moments, the magnitude of the gain increases as the correlation between the SDF and the fund-specific moments increases.

The above discussion focuses on how to implement the two estimation methods when estimating conditional performance relative to a conditional model. It is straight forward to adapt these implementations to estimate unconditional performance relative to a conditional model and unconditional performance relative to an unconditional model. To estimate the former, the definition for $\mathbf{f}_1$ remains the same, but the definition for $\mathbf{f}_i, i = 2, 3, ..., n$ becomes:

$$\mathbf{f}_i(\mathbf{r}_{i,t+1}, \mathbf{r}_{\mathbf{1},t+1}, R_{f,t+1}, Z_t, \theta_1, \theta_2) = (\mathbf{r}_{i,t+1} - \mathbf{e}) \otimes \left((a + bZ_t) + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{1},t+1}\right). \tag{41}$$

With this definition of $\mathbf{f}_i$, the associated sample moments $\mathbf{g}_{i,\lambda_1 T}$ in the Short estimation correspond to the population moments on the left hand side of (21). Notice that the Short and Full estimations remain just-identified. To estimate unconditional performance relative to the unconditional model, the definitions for $\mathbf{f}_1$ and $\mathbf{f}_i, i = 2, 3, ..., n$ become

$$\mathbf{f}_1(\mathbf{r}_{\mathbf{1},t+1}, R_{f,t+1}, \theta_1) = \begin{bmatrix} R_{f,t+1} \\ \mathbf{r}_{\mathbf{1},t+1} \end{bmatrix} \left(a + \mathbf{c}^\top \mathbf{r}_{\mathbf{1},t+1}\right) - \begin{bmatrix} 1 \\ \mathbf{0} \end{bmatrix} \tag{42}$$

[16]The results are qualitatively similar if, for the Short estimation, standard errors are calculated using Newey-West evaluated at the parameter estimates reported for the Short estimation itself.

and

$$\mathbf{f}_i(\mathbf{r}_{i,t+1}, \mathbf{r}_{\mathbf{1},t+1}, R_{f,t+1}, \theta_1, \theta_2) = (\mathbf{r}_{i,t+1} - \mathbf{e} - \mathbf{f}Z_t) \otimes \left(a + \mathbf{c}^\top \mathbf{r}_{\mathbf{1},t+1}\right). \tag{43}$$

With these definitions, the associated sample moments $\mathbf{g}_{1,\lambda_1 T}$ and $\mathbf{g}_{i,\lambda_1 T}$ in the Short estimation correspond respectively to the population moments on left hand sides of (22) and (15) with $e_i = \alpha_i$. Again, the Short and Full estimations remain just-identified.

### 4.3 Regression-based estimation

The regression-based (Reg) estimation approach of Ferson and Harvey (1999), Ferson and Schadt (1996) and Fama and French (1993) is also used to estimate performance parameter estimates. While efficiency gains could also be achieved for the regression-based estimation by using the adjusted moment method, we only report results using the standard GMM method.[17] For each of the three groups, the Reg estimates of the performance coefficients for all the TNA-style portfolios in that group and all the hypothesis tests for that group are performed using data from the intersection of the sample periods for all the TNA-style portfolios in that group.[18] Standard errors are again calculated using Newey-West with 6 lags. All three performance measures are estimated using the regression-based methodology: conditional performance relative to the conditional model; unconditional performance relative to the conditional model; and unconditional performance relative to the unconditional model.

### 4.4 Performance in excess of a matched portfolio

One concern is that any abnormal performance we detect for the fund portfolios is not due to the skill of the fund managers but due to the abnormal performance of the underlying stocks held by the funds. To control for this possibility, we match each fund portfolio to one of the 25 FF size and book-to-market portfolios, using the mean-squared deviation between the factor loadings of the fund portfolio and the FF portfolio as a matching criterion. We then repeat the estimation using the return on the fund portfolio in excess of the return on its matched FF portfolio, instead of the return in excess of the risk-free rate.

[17]When using the Reg method, efficiency gains are possible for the TNA-style portfolios with later start dates because their moments are likely correlated with the moments for the TNA-style portfolios with earlier start dates; however, there are no efficiency gains when all fund styles have the same start date, with only the factors and instruments having earlier start dates.

[18]The Reg estimation results are qualitatively unchanged if the $e$ and $f$ coefficients for a fund-style portfolio are estimated using all available data for that portfolio, and if each hypothesis test is performed using data from the intersection of the sample periods for the fund-style portfolios involved in the test.

Consider, for concreteness, unconditional performance relative to an unconditional factor model. Let $\delta_i$ be the coefficient vector for the factors in a regression of fund portfolio $i$ on the factors. Let $\delta_p$ be the coefficient vector for the factors in a regression of any given FF portfolio, $p$, on the factors. Then we choose as the matching portfolio the portfolio $p$ that minimizes:

$$(\delta_i - \delta_p)'(\delta_i - \delta_p). \tag{44}$$

Mutual funds may hold part of their assets in cash, or may be levered up. We adjust our matching procedure to take care of this. Let $a$ be the reciprocal of the weight of the portfolio that is invested in cash. Let $\delta_s$ be the vector of factor loadings on the stock component of the fund's portfolio. Then,

$$a\delta_i = \delta_s.$$

We do not observe $a$, but instead, for each pair of fund and FF portfolios, we choose $a$ to be that value that minimizes the squared deviation between the factor loadings on the fund portfolio and the FF portfolio; that is, we choose $a$ to minimize:

$$(a\delta_i - \delta_p)'(a\delta_i - \delta_p). \tag{45}$$

The solution is

$$a = \delta_i'\delta_p/(\delta_i'\delta_i).$$

Having chosen $a$ in this manner for all fund-FF portfolio pairs, we then choose, as the matched portfolio, the FF portfolio $p$ that minimizes the expression in (45) above.

We run the matching procedure for each of the five models we consider: unconditional performance with an unconditional factor model, unconditional performance with a conditional factor model (two instruments) and conditional performance with a conditional factor model (two instruments).

We test two forms of the matching criterion function: mean squared deviation and mean absolute deviation. In the conditional models, we also make sure our results are robust to whether or not we include the coefficient on the interaction term between the factor and the instrument in the matching criterion. The interaction term allows the conditional loadings to be linear in the information variable which means that matching on this term ensures that the conditional loadings for the matching FF portfolio move with the information variable in a similar fashion to those for the fund-style portfolio being matched. For each of these four cases, we obtain similar results. This is principally due to the fact that the procedure produces similar matches for any one fund, regardless of what criterion is used. We report results using the mean squared deviation, and including the loadings on the interaction terms.

# 5 Results

This section reports performance results when funds are grouped on the basis of the equity fund style classifications reported by CRSP and when each fund category is bifurcated on the basis of net asset value. CRSP reports fund style classifications from 3 sources: Wiesenberger(1961-92), Strategic Insight (1992-99), and Lipper (1999 onwards). Also, Wiesenberger changed its system entirely in 1990, leaving us with four classification schemes. Performance is assessed relative to two different factor models: the Fama and French (1993) model (FF model) whose three factors are the market excess return, the return on a portfolio long high and short low book-to-market stocks, and the return on a portfolio long big stocks and short big stocks; and the four factor model of Carhart (1997) (C model) whose factors are the three FF factors plus the return on a portfolio long stocks that performed well the previous year and short stocks that performed poorly.

The conditional performance of a fund's underlying stocks could vary over the business cycle, which would cause the conditional performance of the fund to vary over the business cycle, even if the manager did not possess any stock-picking ability. This section also examines whether such mispricing of the underlying stocks held by the funds can explain the conditional fund performance that we document, by considering, for each TNA-style portfolio, performance in excess of a matched FF 25 portfolio, where the matching is performed based on FF-model loadings. All the conditional models are estimated using two different instruments: dividend yield and term spread. So there are 8 specifications for each portfolio when estimating performance relative to conditional models, since all possible combinations of two excess-return definitions, two pricing models, and two instruments are estimated. Similarly, there are 4 specifications for each portfolio when estimating performance relative to unconditional models.

Throughout, unless stated otherwise, we normalize both instruments to be mean zero and unit standard deviation, as described in section 3. Doing so makes $e_i$ and $f_i$ easier to interpret. In particular, an $e$ value of zero implies that the unconditional mean abnormal performance is zero. Further, $f$ measures the shift in conditional abnormal performance that results from a one standard error shift in the instrument's value. For the hypothesis tests, significance is determined using a 5% cutoff, while for the coefficient estimates, significance is determined using a 5% one-tail cutoff.

## 5.1 Conditional performance: Growth and Income (GRI), Growth (GRO), Maximum Capital Gains (CGM), and Income (INC)

Table 2 reports conditional fund performance relative to a conditional factor model with dividend yield as the instrument for the following fund styles: growth and income (GRI), growth (GRO), maximum capital gains (CGM), and income (INC). $Sm$ ($Lg$) refers to the portfolio of funds with beginning of year TNA below (above) the median for the specified fund style. Performance results are reported relative to the FF pricing model in the first 8 columns and relative to the Carhart pricing model in the last 8 columns. For each pricing model, performance results are reported for return in excess of the riskfree rate (excess-of-riskfree return) in the first 4 columns, and in excess of return on a portfolio matched on the basis of FF loadings (excess-of-matched return) in the last 4 columns. The matched portfolio is always one of the FF 25 portfolios formed on the basis of market capitalization and book-to-market. Panels A and B report the abnormal performance parameters $e$ and $f$ respectively for the TNA-style portfolios, where $e$ measures mean conditional performance and $f$ measures the extent to which the conditional performance varies with the information variable. When parameters $e$ and $f$ are identified by moment conditions (19) and (20), they are estimated for each TNA-style portfolios using the adjusted moment (Full) method that uses all available data, and using the standard (Short) GMM method that only uses data from the intersection of the sample periods for the 4 fund styles. Standard errors for both are calculated using the adjusted-moment coefficients. For each TNA-style portfolio, parameters $e$ and $f$ are also estimated for the regression-based (Reg) approach of Ferson and Harvey (1996) using data from the intersection of the sample periods for the 4 fund styles. Newey-West standard errors for the parameter estimates of all 3 are in italics. For each style-TNA portfolio, the % Reduction column (% Red) contains the percent reduction in the coefficient standard error from (in the first row) using the Full method rather than the Short method and (in the second row) from using the Full method rather than a portfolio-by-portfolio adjusted moment method, which uses only the factor moments and the moments for that TNA-style portfolio, constructed using all available data for the factors, the instruments and the returns on that portfolio. Panel C reports the p-values for Wald tests of joint significance based on the Newey-West covariances. Table 3 reports conditional fund performance relative to a conditional factor model with term spread as the instrument, and is formatted exactly the same as Table 2.

Relying on the Full estimation for excess-of-riskfree returns, we can reject the hypothesis that all $f$ coefficients are equal to zero using either instrument for the FF model, but only using term spread for the C model. Both the hypothesis that all $f$ coefficients are the same for all these TNA-style portfolios, and the hypothesis that the $f$ coefficients are the same for the low and high TNA portfolios for all 4 fund styles, can also be rejected for the same three out of four specifications. The $f$ coefficient for the INC-$Lg$ portfolio is significantly larger than both the $f$ coefficient for the INC-$Sm$ portfolio and zero in the same three cases. For the FF model, the $f$ coefficients are significantly greater than zero for both the small- and large-fund GRI portfolios using dividend yield as the instrument but only for the GRI-$Sm$ portfolio using term spread. Lastly, for the FF model using dividend yield as the instrument, the $f$ coefficient for the GRO-$Sm$ portfolio is significantly greater than 0, and the $f$ coefficient for the INC-$Sm$ portfolio is significantly less than 0.

Turning to Full estimation results for excess-of-matched returns, the general hypothesis tests of all $f$ coefficients being equal to zero, all $f$ coefficients being equal, and the $f$ coefficients for the low and high TNA portfolios being equal for all fund styles all remain significant whenever the FF model is used, but are never significant using the C model. This suggests that the significant conditional performance of these fund styles relative to the FF model might be robust to correcting for conditional abnormal performance by the underlying stocks. However, the patterns of significance when using the FF model are not the same for excess-of-matched return as for excess-of-riskfree return. The lower $f$ coefficient of the small-fund INC portfolio relative to the large-fund INC portfolio is robust when using dividend yield but not term spread. Using dividend yield as the instrument, the significant $f$ coefficients on the GRI portfolios disappear, while the $f$ coefficients on both GRO portfolios become significantly negative and the $f$ coefficients on both CGM portfolios become significantly positive. Using term spread as the instrument for the GRI portfolios, the $f$ coefficient becomes significantly negative on the large-fund portfolio and insignificant on the small-fund portfolio, while the difference between the two coefficients, small fund minus large fund, becomes significantly positive. Finally, the 2 hypothesis tests that the average $f$ coefficient is equal to zero for the 4 small-TNA portfolios, and for the 4 large-TNA portfolios, are both insignificant for all 8 specifications, irrespective of the pricing model, the instrument, and whether returns are in excess of the riskfree rate, or matched portfolio returns.

These results provide only weak evidence of variation in conditional performance for these 4 fund styles over the business cycle. Across the 8 portfolios for these 4 styles, conditional performance relative to the C model only varies over the business cycle for the INC-$Lg$ portfolio, and even then only when term spread is used as the instrument and returns are in excess of the riskless rate. Hence, the evidence for variation in conditional performance over the business cycle for these 4 fund styles relative to the C model is very weak. The evidence is stronger for the FF model, but the patterns of variation observed depend on the instrument used and whether returns are in excess of the riskfree rate or a matched portfolio. There is some evidence of counter-cyclical variation in conditional performance relative to the FF model for returns in excess of the riskfree rate: both GRI portfolios, the low-TNA GRO portfolio, and the high-TNA INC portfolio all have counter-cyclical performance for at least one of the instruments, while only the INC-$Sm$ portfolio with term spread as the instrument produces pro-cyclical performance. Measuring return in excess of matched FF-portfolio return causes the performance of all but the two CGM portfolios to either be pro-cyclical or not move with the business cycle, with the CGM portfolios exhibiting counter-cyclical performance only when dividend yield is being used as the instrument. Our results suggest that these 4 fund styles, with the possible exception of the CGM style, do not produce counter-cyclical performance once the conditional abnormal performance of the underlying stocks is accounted for. There is also evidence that when returns are measured in excess of matched FF-portfolio returns, fund TNA affects how performance relative to the FF model moves over the business cycle for the INC, GRI, and CGM styles, though only using one or other of the instruments, never both: increasing TNA makes INC performance less cyclical and GRI and CGM performance more cyclical.

Comparing the performance results from using the Full method (which uses all available factor, instrument, and fund portfolio return data) rather than the Short method (which only uses factor, instrument, and fund portfolio data from 1/72, the latest start date of the 4 styles in this group), we see substantial improvements in the precision of the point estimates of $e$ and $f$. The reduction in the standard errors for the estimates of performance sensitivity to the information variable (the $f$ estimates) from using the Full method rather than the Short method is on average around 28%, but never less than 20%, irrespective of pricing model or instrument, when using excess-of-riskfree returns. Since the fund styles in this first group have the earliest start dates, with 2 of the 4 styles having the earliest start date of any fund style, and the other 2 both starting no more than 10 years after this date, the improvement for a given portfolio is largely coming from the additional information provided by the factor and instrument data from the period between 1/27 and 1/72, and any return data for the portfolio available before 1/72. For a given style-TNA portfolio, only a small fraction of the improvement is coming from the additional information provided by the return data available for the other portfolios prior to 1/72. Consistent with this argument, the second row entries of the "% Red" column report reductions that are on average around 1%, but never higher than 3%, in the magnitude of the standard errors for the $f$ coefficients going from an adjusted moment estimation, one that estimates performance for a given TNA-style portfolio using all available factor and instrument data from 1/27, and all available return data for only that TNA-style portfolio, to the Full estimation (that also uses the return data for all the fund styles with earlier start dates); by construction, these reductions are 0 for the two styles with the earliest start dates, GRI and GRO. The reductions in the standard errors for the estimates of $e$ and $f$ are typically lower when returns are in excess of matched FF-portfolio returns and not the riskfree rate: for the $f$ estimates, the reduction is on average around 15%, and never higher than 21%. This result is to be expected since subtracting out the matched FF-portfolio return would be expected to reduce the correlations across the fund portfolio moments and between the factor moments and the the fund portfolio moments.

Moreover, using the Short method, we can only reject two of the 24 general hypothesis tests of all $f$ coefficients being equal to zero, all $f$ coefficients being equal, and the $f$ coefficients for the low and high TNA portfolios being equal for all the fund styles: the two tests are all $f$ coefficients equal for the case using dividend yield, the FF model and excess-of-matched returns and all $f$ coefficients equal to zero for the case using term spread, the FF model and excess-of-riskfree returns. Consequently, our ability to reject joint hypotheses is severely curtailed by using the Short method rather than the Full method, which further confirms the greater precision of the estimates using the Full method instead of the Short method.

Turning to the Reg estimation results, only one of these 24 hypothesis tests, all $f$ coefficients equal to zero for the case using dividend yield, the FF model and excess-of-riskfree returns, is rejected by the Reg method. This hypothesis is also rejected by the Full method. For this case, the two methods generate the same pattern of significant coefficients, except that the Reg method produces a significant $f$ coefficient for one portfolio whose $f$ coefficient using the Full method is the same sign but insignificant. In sum, the Reg results are much weaker than the Full results, but are quite similar when both produce significant coefficients. The reduced significance is likely due to the Reg method using less data than the Full method.

Turning our attention to the $e$ coefficient estimates and focusing on the results for the Full estimation, the hypothesis test of all $e$ coefficients equal to zero can be easily rejected, irrespective of pricing model, instrument or whether excess-of-riskfree or excess-of-matched returns are used. However, only 11 out of 64 $e$ coefficients (across 8 portfolios and 8 specifications) are significantly different from zero and 7 of those 11 are for the 2 CGM portfolios. The 2 GRO portfolios never have a significant $e$ coefficient while for the GRI portfolios, only the large-GRI portfolio using excess-of-matched returns together with the FF model and term spread has a significant $e$ coefficient, and that coefficient is negative. And when using the excess-of-matched returns of the 2 INC portfolios, both the small INC portfolio using term spread and the large INC portfolio using dividend yield have a significant $e$ coefficient relative to the C model, and those coefficients are positive. In contrast, when using the excess-of-matched returns of the 2 CGM portfolios, only the large-cap CGM portfolio using dividend yield and the FF model and the small-cap CGM portfolio using term spread and the FF model have $e$ coefficients that aren't significantly negative. We also test equality of the $e$ coefficients across the 8 TNA-style portfolios and are always able to reject this hypothesis. While the hypothesis of average $e$ equal to zero is never rejected, the average $e$ coefficient is negative for 6 of the 8 specifications, with the average only being positive for the specification using excess-of-riskfree returns together with dividend yield and the FF model and the specification using excess-of-matched returns together with term spread and the C model. For the other two estimation methods, Short and Reg, the average $e$ coefficient is always negative, though the the hypothesis test of the average $e$ coefficient being equal to zero is only rejected by the Reg estimation when using excess-of-riskfree returns.

### 5.2 Unconditional and average conditional performance: Growth and Income (GRI), Growth (GRO), Maximum Capital Gains (CGM), and Income (INC)

Table 4 reports unconditional fund performance relative to an unconditional factor model for the following fund styles: growth and income (GRI), growth (GRO), maximum capital gains (CGM), and income (INC). The format of the table is similar to Table 2 except there are 2 panels rather than 3; the columns are the same. Panel A reports the abnormal performance parameter $e$ for the TNA-style portfolios, where $e$ measures unconditional performance. When parameter $e$ is identified by moment conditions (22) and (15), it is estimated for each TNA-style portfolio using the adjusted moment (Full) method that uses all available data, and using the standard GMM (Short) method that only uses data from the intersection of the sample periods for the 4 fund styles. Standard errors for both are calculated using the adjusted-moment coefficients. For each TNA-style portfolio, parameter $e$ is also estimated for the regression-based (Reg) approach of Fama and French (1993) using data from the intersection of the sample periods for the 4 fund styles. Newey-West standard errors for the parameter estimates of all 3 are in italics. The % Reduction column (% Red) is the same as in Table 2. Panel B reports the p-values for Wald tests of joint significance based on the Newey-West covariances.

Focusing on the results for the Full estimation, the hypothesis test of all $e$ coefficients equal to zero can be easily rejected, irrespective of pricing model or whether excess-of-riskfree or excess-of-matched returns are used. However, only 4 out of 32 $e$ coefficients (across 8 portfolios and 4 specifications) are significantly different from zero, and those are the negative coefficients obtained for the 2 CGM portfolios when using excess-of-matched returns and either pricing model. We also test equality of the $e$ coefficients across the 8 TNA-style portfolios and are always able to reject this hypothesis. While the hypothesis of average $e$ equal to zero is never rejected, the average $e$ coefficient is always negative, except for the specification using dividend yield, the FF model and excess-of-riskfree returns. For the other two estimation methods, Short and Reg, the average $e$ coefficient is always negative, though the the hypothesis test of the average $e$ coefficient being equal to zero is only rejected by the Reg estimation for both specifications that use excess-of-riskfree returns.

Table 5 reports unconditional fund performance relative to a conditional factor model with dividend yield as the instrument for the same 4 fund styles. The format of the table is similar to Table 2 except there are 2 panels rather than 3; the columns are the same. Panel A reports the abnormal performance parameter $e$ for the TNA-style portfolios, where $e$ measures unconditional performance. When parameter $e$ is identified by moment conditions (19) and (21), it is estimated for each TNA-style portfolio using the adjusted moment (Full) method that uses all available data, and using the standard GMM method (Short) that only uses data from the intersection of the sample periods for the 4 fund styles. Standard errors for both are calculated using the adjusted-moment coefficients. For each TNA-style portfolio, parameter $e$ is also estimated for the regression-based (Reg) approach of Ferson and Harvey (1996) using data from the intersection of the sample periods for the 4 fund styles and setting $f = 0$ in the regression. Newey-West standard errors for the parameter estimates of all 3 are in italics. The % Reduction column (% Red) is the same as in Table 2. Panel B reports the p-values for Wald tests of joint significance based on the Newey-West covariances. Table 6 reports unconditional fund performance relative to a conditional factor model with term spread as the instrument for the same 4 fund styles, and is formatted exactly the same as Table 5.

Focusing on the results for the Full estimation, the hypothesis test of all $e$ coefficients equal to zero can be easily rejected, irrespective of pricing model, instrument or whether excess-of-riskfree or excess-of-matched returns are used. Turning to the individual $e$ coefficients for the portfolios, we first focus on the specifications that use excess-of-riskless returns. Only five of the 32 $e$ coefficients (8 portfolios and 4 specifications) are significant: both GRI portfolios have significantly negative coefficients using dividend yield and the FF model, and 3 of the 8 $e$ coefficients for the INC portfolios are significant, one negative and one positive for the INC-$Lg$ portfolio, and one positive for the INC-$Lg$ portfolio. Turning to the specifications that use excess-of-matched returns, we find that, for the 2 GRI portfolios, only the large-GRI portfolio using the FF model and term spread has a significant $e$ coefficient and that significant coefficient is negative. The 2 GRO portfolios only have significant $e$ coefficients when using the FF model and dividend yield, and both significant coefficients are positive, while the 2 CGM portfolios always have significantly negative $e$ coefficients using excess-of-matched returns. Using the Carhart model, each INC portfolio has only one significant $e$ coefficient, the large-INC portfolio when using dividend yield, and the small-INC portfolio when using term spread, with both coefficients positive; the large-INC portfolio using term spread is the only $e$ coefficient that is significant using the FF model, and this coefficient is negative.

We also test equality of the $e$ coefficients across the 8 TNA-style portfolios and are always able to reject this hypothesis across all 8 specifications, irrespective of pricing model, instrument or whether excess-of-riskfree or excess-of-matched returns are used. While the hypothesis of average $e$ equal to zero is only rejected when using excess-of-matched returns together with the FF model and term spread, the average $e$ coefficient is always negative across all 8 specifications. For the other two estimation methods, Short and Reg, the average $e$ coefficient is always negative, though across the two estimation methods, the hypothesis test of the average $e$ coefficient being equal to zero is only rejected by the Reg estimation in three of the 4 specifications that use excess-of-riskfree returns.

To summarize, there is strong evidence that not all the portfolios have zero unconditional performance relative to any of the unconditional or conditional factor models we examine:when using excess-of-matched returns, both CGM portfolios always have significantly negative unconditional performance irrespective of the factor model being used. However, somewhat surprisingly, there is very little evidence that the average unconditional performance across the 8 portfolios is different from 0 relative to any of the unconditional or conditional factor models we examine, though the point estimates for the average unconditional performance are almost always negative, irrespective of whether the unconditional performance is relative to a conditional or an unconditional factor model. There is some evidence from the Reg method that the average unconditional performance is negative when using excess-of-riskless returns, but this negative unconditional performance disappears once we control for the unconditional performance of the matched FF portfolios.

It is interesting to compare the unconditional performance of the TNA-style portfolios relative to conditional models with their unconditional performance relative to unconditional models. Such a comparison is similar to the comparison performed in Ferson and Schadt (1996) using the regression-based methodology. They find that unconditional performance for mutual funds is typically higher when measured relative to the conditional rather than the unconditional version of a particular factor model. Their explanation for this finding relies on the negative covariances between conditional fund betas and conditional risk premia that they find in their sample. The intuition is that for a given mean conditional beta, this negative correlation causes the product of conditional beta and the risk premia to be lower on average, which, for given performance relative to the conditional factor model, makes unconditional expected fund return lower. Since a fund's mean conditional beta is likely close to its unconditional beta, a zero value for this correlation translates into near-identical performance for the conditional and unconditional versions of the model. Taking performance relative to the conditional factor model as given, performance relative to the unconditional factor model becomes lower as this correlation becomes more negative.

Perhaps somewhat surprisingly, comparing Tables 5 and 6 to Table 4, we see that the signs of the differences between the $e$ coefficients for conditional and unconditional models vary across the TNA-style portfolios and across the specifications. The implication is that the signs of the covariances between conditional fund betas and conditional risk premia vary across the TNA-style portfolios and across the specifications.

## 5.3 Conditional performance: Sector funds

Tables 7 and 8 report conditional fund performance relative to a conditional factor model with dividend yield and term spread respectively as the instrument for the following fund styles: energy (ENR), financial (FIN), health (HLT), technology (TCH), and utilities (UTL). Both these tables are formatted exactly the same as Table 2. Relying on the Full estimation, we can always reject the hypotheses that all $f$ coefficients are equal to zero, that all $f$ coefficients are the same, and that the $f$ coefficients are the same for the low and high TNA portfolios for all fund styles, irrespective of the instrument, the pricing model, or the particular excess returns being used. In contrast, using the Short method, not one of these hypotheses is rejected for the 5 sector-fund styles across the 8 specifications reported, while using the Reg method, only one of these hypotheses is rejected, and only for one of the 8 specifications reported.

This finding highlights the improvement in the precision of the $e$ and $f$ estimates obtained from using the Full method (which uses all available factor, instrument, and fund portfolio return data) rather than the Short method (which only uses factor, instrument, and fund portfolio data from 1/91, the start date of the 5 sector styles in this group). The reductions in the standard errors for the estimates of performance sensitivity to the information variable (the $f$ estimates) from using the Full method rather than the Short method are larger in magnitude than for the first group of fund styles, on average around 43% but never less than 25%, irrespective of pricing model or instrument, when using excess-of-riskfree returns. Part of the improvement in precision of the estimates here is coming from the additional information provided by the factor and instrument data from the period between 1/27 and 1/91. However, since the sector-fund styles have a much later start date than the start dates for the 4 fund styles in the first group, an important part of the improvement in precision could also be coming from information provided by the return data available before 1/91 for the TNA-style portfolios in the first group. It turns out this second channel makes a non-trivial contribution to the improvements in precision going from Short to Full, because the second row entries of the "% Red" column report reductions that are on average around 12%, and sometimes as high as 22%, in the magnitude of the standard errors for the $f$ coefficients going from an adjusted moment estimation, one that estimates performance for a given TNA-style portfolio using all available factor and instrument data from 1/27, and return data from 1/91 for only that TNA-style portfolio, to the Full estimation (that also uses the return data for all the fund styles with earlier start dates). As would be expected, the reductions in the standard errors for the estimates of $e$ and $f$ are typically smaller when returns are in excess of a matched FF-portfolio's return and not the riskfree rate, though not for every $e$ and $f$ coefficient: for the $f$ estimates, the reductions are on average 34% and never more than 47%, irrespective of pricing model or instrument. Based on the second row entries of the "% Red" column, information provided by the moments for the TNA-style portfolios in the first group, constructed using data prior to 1/91, are again making a non-trivial contribution to the improvements in precision going from Short to Full when returns are in excess of matched FF-portfolio returns.

Focusing first on the performance results for the excess-of-riskfree returns, the average $f$ coefficents for the small-fund and the large-fund portfolios are both significantly positive using term spread irrespective of the pricing model, but are both significantly negative with the former significantly less negative than the latter using dividend yield and the FF model. However, the behavior of average $f$ is not the whole story because there is considerable variation in the signs and magnitudes of the $f$ coefficients across the sector-style portfolios. Using the FF model, the ENR portfolios both have $f$ coefficients that are significantly positive irrespective of the instrument, while using the C model, the small-fund ENR portfolio has a $f$ coefficient that is significantly positive using dividend yield but significantly negative using term spread. When using dividend yield for the UTL portfolios, both portfolios using the FF model and the small-fund portfolio using the C model have $f$ coefficients that are significantly negative. However, when using term spread, both UTL portfolios have significantly positive $f$ coefficients irrespective of the pricing model. The FIN portfolios only have significant $f$ coefficients when using the FF model and dividend yield: both have significantly negative $f$ coefficients in this case. The $f$ coefficients for both HLT portfolios are significantly negative when dividend yield is used, irrespective of the pricing model, but are significantly positive for both when term spread and the C model is used. When the FF model is used, both TCH portfolios have significantly negative $f$ coefficients with dividend yield as the instrument, while the large-fund TCH portfolio has a significant positive $f$ coefficient when term spread is the instrument.

Let the difference between the small-fund and the large-fund $f$ coefficients for a sector-style be the small-fund $f$ less the large-fund $f$ for that sector-style. We find that the direction of any significant difference between the small-fund and the large-fund $f$ coefficients for a given sector-style is always the same irrespective of the pricing model used (holding the instrument fixed), but switches sign for 2 of the 5 sector-styles depending on the instrument. For the ENR sector-style, the difference is significantly positive using dividend yield, but significantly negative using term spread, while the converse is true for the UTL sector-style. The difference is only significant for 2 of the 4 specifications for the FIN sector-style (both positive), the HLT sector-style (both positive), and the TCH sector-style (both negative). While the hypothesis of the small-fund portfolio's $f$ coefficient equalling the large-fund's coefficient for all 5 sector-styles can be rejected for all 4 specifications using excess-of-riskless returns, the average $f$ coefficient is only significantly larger for the small-fund than the large-fund portfolios when dividend yield is used, irrespective of the pricing model, though only the ENR style has a small-fund portfolio with a significantly larger $f$ coefficient than the large-fund portfolios for both pricing models when using dividend yield.

Turning to the performance results for excess-of-matched returns, there is considerable variation in the signs and magnitudes of the $f$ coefficients across the sector-styles. The $f$ coefficients for the ENR portfolios exhibit the same patterns as exhibited for excess-of-riskfree returns for all cases except the low-TNA portfolio when the term spread is used. The small-fund ENR portfolio has a significantly positive $f$ coefficient for both specifications that use dividend yield, while the large-fund ENR portfolio has a significantly positive $f$ coefficient when using the FF model irrespective of the instrument. The $f$ coefficients for both FIN portfolios are significantly negative for excess-of-matched returns when using term spread irrespective of the pricing model, while the only $f$ coefficient that is significant when using dividend yield is the negative one obtained for the FIN-$Lg$ portfolio when the FF model is used. The average $f$ coefficient for the FIN portfolios is always significantly lower than for the average of the other sector-style portfolios, except when using dividend yield and the C model; the same is true for excess-of-riskfree returns, except when using dividend yield and either model. None of the $f$ coefficients for the HLT portfolios are significant when dividend yield is used, while only 2 of the 4 are significant and positive when term spread is used, namely, for the HLT-$Sm$ portfolio when using the FF model, and for the HLT-$Lg$ portfolio when using the C model. The TCH portfolios only have significant $f$ coefficients using the C model and term spread: the coefficients are negative for both portfolios. The average $f$ coefficient for the TCH portfolios is significantly lower than the average coefficient for the remaining portfolios for this specification and the one using the FF model and dividend yield. When excess-of-matched rather than excess-of-riskfree returns are used, the $f$ coefficients for three of the UTL portfolio go from negative to positive or insignificant using dividend yield and the FF model, while the $f$ coefficients for both UTL portfolios remain positive using term spread and the C model. As reported for the excess-of-riskless returns, both the large- and small-fund UTL portfolios have significantly positive $f$ coefficients for the specification using the C model and term spread, while the only other significant $f$ coefficient on a UTL portfolio is the positive one on the UTL-$Sm$ portfolio for the specification using dividend yield and the FF model.

Continuing to focus on the excess-of-matched return results, the average $f$ coefficient for the small-fund portfolios is significantly larger than that for the large-fund portfolio when using dividend yield and either model. We can see which sector styles are driving these results by seeing which sector styles have a small-fund portfolio with a significantly larger $f$ coefficient than its large-fund portfolio when using dividend yield: this is true for the ENR and FIN styles irrespective of the model, and for the HLT and UTL styles only when using the FF model. When using term spread, the same result is obtained for the UTL style in both specifications, and for the HLT style using the FF model, while the only other significant difference between the small-fund and large-fund $f$ coefficients is the lower small-fund coefficient for the ENR style using the FF model.

These results show that, when using dividend yield as an instrument, the average conditional performance of the sector-style portfolios, particularly the small-fund portfolios, after adjusting for the conditional performance of the underlying stocks, is countercyclical. However, the same result does not hold when using term spread as the instrument. The results are quite sensitive to adjusting for the conditional performance of the underlying stocks, with the average performance of the large- and small-fund portfolios typically going from pro-cyclical to counter-cyclical after the adjustment when using dividend yield, but often becoming more pro-cyclical after the adjustment when using term spread. There is substantial variation in the sign of the significant $f$ coefficients across the various styles: after adjusting for the conditional performance of the underlying stocks, any significant cyclicality in performance that we find is always counter-cyclical for the ENR and UTL portfolios and always pro-cyclical for the FIN portfolios. For many specifications and styles, the $f$ coefficient using excess-of-matched returns for the small-fund portfolio is significantly more counter-cyclical than that for the large-fund portfolio, while the converse is only true for one style in one specification.

Focusing on the $e$ coefficients for the Full estimation, the hypothesis tests of all $e$ coefficients equal to zero, and all $e$ coefficients equal to each other, can both be easily rejected, irrespective of pricing model, instrument or whether excess-of-riskfree or excess-of-matched returns are used. The following patterns of $e$ coefficients are obtained when excess-of-matched return is used. First, the $e$ coefficients are significantly positive for both ENR portfolios when using the C model and dividend yield, and insignificant otherwise. Both FIN portfolios have significant negative $e$ coefficients irrespective of pricing model when using dividend yield, while FIN-$Sm$ has a significantly positive $e$ coefficient when using the FF model and term spread. Both HLT and both UTL portfolios almost always have significantly positive $e$ coefficients irrespective of the pricing model or instrument, with the exceptions being the UTL-$Lg$ portfolio when using the FF model and term spread and the two HLT portfolios when using the C model and dividend yield. The TCH portfolios only have 4 significant $e$ coefficients out of 16 coefficients across the 8 specifications reported, two significantly positive for the TCH-$Lg$ portfolio, and one significantly positive and another significantly negative for the TCH-$Sm$ portfolio. The average $e$ coefficient is positive for all 8 specifications, and the hypothesis that the average $e$ coefficient is equal to zero is always rejected, except when using excess-of-riskfree returns together with the C model and either instrument. For the other two estimation methods, Short and Reg, the average $e$ coefficient is also always positive, though the the hypothesis test of the average $e$ being equal to zero is only rejected by the Reg estimation when using excess-of-matched returns together with dividend yield and the FF model.

### 5.4 Conditional performance: Small-cap Growth (SCG), Flexible (FLX), and Mid-cap Growth (MCG)

Tables 9 and 10 report conditional fund performance relative to a conditional factor model with dividend yield and term spread respectively as the instrument for the following three fund styles: small-cap growth (SCG), flexible (FLX), and mid-cap growth (MCG). Both these tables are formatted exactly the same as Table 2. Relying on the Full estimation for either excess-of-riskfree or excess-of-matched returns, we can always reject the hypotheses that all $f$ coefficients are equal to zero, that all $f$ coefficients are the same, and that the $f$ coefficients are the same for the low and high TNA portfolios for all fund styles, irrespective of the instrument, the pricing model or the particular excess returns being used. Turning to the Short method, 11 of these 24 hypotheses (3 hypotheses across 8 specifications) are rejected, while only 5 of them, all using term spread as the instrument, are not rejected using the Reg method.

This finding suggests some improvement in the precision of the $e$ and $f$ estimates obtained from using the Full method (which uses all available factor, instrument, and fund portfolio return data) rather than the Short method (which only uses factor, instrument, and fund portfolio data from 1/95, the latest start date of the 3 styles in this group) for these 3 fund styles. However, the reductions in the standard errors for the estimates of performance sensitivity to the information variable (the $f$ estimates) from using the Full method rather than the Short method are larger in magnitude than for the first and second groups of fund styles, on average around 58%, but never less than 55%, when using excess-of-riskfree returns, irrespective of pricing model or instrument. Somewhat surprisingly, most of the improvement in precision of the estimates here for a given portfolio is coming from the additional information provided by the factor and instrument data from the period between 1/27 and 1/95 and any return data available before 1/95 for the given portfolio. Only a very small component of the improvement in precision is coming from the additional information provided by the portfolio return data available before 1/95 for the other styles, including those styles in the first two groups. The second row entries of the "% Red" column report reductions in the magnitude of the standard errors for the $f$ coefficients that average only 7% going from the adjusted moment estimation, one that estimates performance for a given TNA-style portfolio using all the factor and instrument data from 1/27, and all available return data for only that TNA-style portfolio, to the Full estimation (that uses all available factor, instrument and fund data that is useful), which is small relative to the average reduction going from the Short to the Full method. Again, as would be expected, the reductions in the standard errors for the estimates of $e$ and $f$ are typically smaller when returns are in excess of matched FF-portfolio returns and not the riskfree rate, though not for every $e$ and $f$ coefficient, and by less than for the second group of styles: for the $f$ estimates, the reductions are on average 51% and never more than 59% irrespective of pricing model or instrument. Based on an average second row entry in the "% Red" column of around 17%, information provided by the moments for the TNA-style portfolios in the first two groups are making a larger contribution to the improvements in precision going from Short to Full when using excess-of-matched returns rather than excess of riskfree returns.

We again focus on the results for the Full estimation when assessing the conditional performance of these 3 mutual fund styles. Starting with the performance results for the excess-of-riskfree returns, the average $f$ for the both the small-fund and the large-fund portfolios are both significantly positive using term spread, irrespective of the pricing model. Using the term spread, both portfolios for all three styles have $f$ coefficients that are significantly positive irrespective of the pricing model, while using dividend yield and the FF model, both MCG portfolios and the large-fund SCG portfolio have $f$ coefficients that are significantly negative. The small-fund SCG portfolio has a significantly higher $f$ coefficient than the large-fund SCG portfolio for all specifications. The small-fund MCG portfolio has a significantly lower $f$ coefficient than the large-fund MCG portfolio for the 2 specifications that use dividend yield as the instrument, while the small-fund FLX portfolio has a significantly lower $f$ coefficient than the large-fund FLX portfolio for the 2 specifications that use the FF model.

We turn now to the performance results for excess-of-matched returns. For both specifications that use dividend yield, the average $f$ coefficient is significantly negative for the small-fund portfolios, significantly positive for large-fund portfolios, and significantly higher for the large-fund portfolios than the small-fund portfolios. The same is true for the specification that uses the FF model and term spread, except that the average $f$ coefficient for the large-fund portfolios, while significantly larger than for the average small-fund portfolio $f$ coefficient, is still significantly less than zero, just like the average small-fund portfolio $f$ coefficient. For the specification that uses the C model and term spread, the average $f$ coefficient for the large-fund portfolios is significantly negative, just like the other specification that uses term spread, and significantly lower for the large-fund portfolios than the small-fund portfolios, which is not the case for any of the other three specifications.

When using dividend yield, the $f$ coefficient for the large-MCG portfolio is significantly positive irrespective of the pricing model, which explains why the average $f$ coefficient is positive and significant for both these specifications. The average $f$ coefficient is negative and significant for both specifications that use term spread as the instrument, with the 3 large-fund portfolios all having significantly negative average $f$ coefficients using the FF model, and the large-MCG portfolio being the only large-fund portfolio with a significantly negative $f$ coefficient using the C model. For the small-fund portfolios, the significantly negative average $f$ coefficient when dividend yield is the instrument is being driven by the significantly negative $f$ coefficient for the small-MCG portfolio, irrespective of pricing model, while the significantly negative average $f$ coefficient when using term spread and the FF model is being driven by the significantly negative $f$ coefficients for all three small-TNA portfolios.

For the FLX style, the small-fund portfolio always has a significantly smaller $f$ coefficient than the large fund portfolio, except when using the C model and term spread. For the MCG style, except when using term spread and the C model, the small-MCG portfolio always has a significantly smaller $f$ coefficient than the large-MCG portfolio, while for the SCG style, except when using dividend and the C model, the small-SCG portfolio always has a significantly larger $f$ coefficient than the large-SCG portfolio

Finally, the Reg method produces only 2 significant $f$ coefficients estimates where the corresponding Full estimates are insignificant or significant with the opposite sign, and both these Reg method estimates are negative, which means pro-cyclical performance. Further, the Short method produces only 2 significant $f$ coefficient estimates where the corresponding Full estimates are insignificant or significant with the opposite sign, and again, all three of these Short method estimates are negative.

The results suggest that conditional performance becomes less counter-cyclical for these 3 styles after adjusting for the cyclicality of the conditional performance of the underlying stocks. The large-MCG portfolio still exhibits counter-cyclical performance using dividend yield as the instrument, but otherwise, any business-cycle variation in performance is procyclical, irrespective of the instrument or pricing model. After adjusting for the conditional performance of the underlying stocks, significant pro-cyclical performance is exhibited by both the low and high TNA portfolios for all three styles using term spread and the FF model, by the large-MCG portfolio using term spread and the C model, and by the small-MCG portfolio for all specifications but the one using term spread and the C model. The small-fund portfolio is more cyclical than the large-fund portfolio for the FLX and MCG styles, while the converse is true for the SCG style.

Continuing to focus on the results for the Full estimation, the hypothesis test of all $e$ coefficients equal to zero can be easily rejected, irrespective of pricing model, instrument or whether excess-of-riskfree or excess-of-matched returns are used. When using excess-of-matched returns, the 2 FLX portfolios only have significant $e$ coefficients using dividend yield and the C model, and those coefficients are both negative. The large-SCG portfolio only has two significant $e$ coefficients, both negative, one using excess-of-riskfree returns and the other using excess-of-matched returns, while the small-SCG portfolio always has a significantly negative $e$ coefficient when using excess-of-matched returns and the term spread as the instrument. When using the excess-of-matched returns, the $e$ coefficient is always significantly negative for the large-MCG portfolio, but is only significant for the small-MCG portfolio in the specification with the C model and dividend yield that produces a negative coefficient. In contrast, when using excess-of-riskfree returns, the $e$ coefficient is only significant for the small-MCG portfolio when using term spread and the FF model, and this significant coefficient is positive. We also test equality of the $e$ coefficients across the 6 TNA-style portfolios and are always able to reject this hypothesis. The hypothesis of average $e$ equal to zero is only rejected when using excess-of-matched returns and dividend yield, and the average $e$ coefficient is negative for 5 of the 8 specifications, including both of the specifications that use excess-of-matched returns and dividend yield. For the other two estimation methods, Short and Reg, the average $e$ coefficient is always negative, except for one Short estimation, and the hypothesis test of the average $e$ coefficient being equal to zero is only rejected for one Reg estimation with a negative average $e$ coefficient.

### 5.5 Conditional performance using NBER business cycle variable: GRI(Growth and Income), GRO(Growth), CGM(Maximum Capital Gains), and INC(Income)

Tables 2 and 3 contains conditional performance results for the 4 styles for which we have the most data (growth and income, GRI, growth, GRO, maximum capital gains, CGM, and income, INC) using dividend yield and term spread as the instruments. Both these variables have been found to move countercyclically with the business cycle, yet we find very little evidence in support of the conjecture first advanced by Moskowitz (2000) that conditional fund performance is countercyclical, even before we adjust fund returns for any cyclical variation in the conditional performance of the typical stocks held by the various fund styles. Papers that explore Moskowitz's conjecture including Moskowitz himself use measures of the state of the economy that are not known at the start of the period like the NBER business-cycle dummy. The NBER recession start and end dates are not announced until months after those dates occur, and so it is unlikely that the NBER business-cycle dummy is in the information set of investors at the start of each month. The instruments that we use, dividend yield and term spread, are both publicly available at the start of each month, which is one reason why we chose them. To examine whether conditional performance for these 4 mutual fund styles varies depending on the value taken by the NBER business-cycle dummy, we repeated the analysis reported in Tables 2 and 3 using the NBER business-cycle dummy as the instrument.

The results are presented in Table 11, which is formatted exactly the same as Table 2. We find no evidence of counter-cyclical performance by these 4 fund styles using the NBER business-cycle variaable as the indicator, irrespective of whether the excess-of-riskless or excess-of match returns are used, or whether the Full, Short, or Reg method is used. When using the Short method, the hypotheses that all $f$ coefficients are equal to zero is only rejected for one of the 4 specifications, the one using the C model and excess-of-matched returns. The same is true when using the Reg model. When using the Full method, the hypotheses that all $f$ coefficients are equal to zero is rejected for all but the specification using the C model and excess-of-riskfree returns. However, the tests for significance of the individual $f$ coefficients are always insignificant for all 8 coefficients, irrespective of method or specification, with one exception: the $f$ coefficient for the CGM-$Lg$ portfolio is significantly negative when using the C model and excess-of-matched returns. The same is true when we test for the significance of the average $f$ coefficients grouped by style (4 styles) and by TNA (low TNA portfolios across styles and high TNA portfolios across styles).

Using the Short method, the average $f$ coefficient across the 8 style-TNA portfolios is positive for three of the four specifications, though the maximum recession-in-excess-of-expansion performance, attained by the specification that uses the C model and excess-of-matched returns is only around 0.5% p.a., ; when only considering the specifications that use excess-of-riskfree returns, the maximum recession-in-excess-of-expansion performance is less than 0.28% p.a. While the $f$ coefficient estimates obtained for the Reg method are always the same as those obtained for the Small method, the average $f$ coefficient is always negative for the Full method. So while there is some evidence that there exists linear combinations of the $f$ coefficients that are non-zero, our analysis does not produce any evidence that conditional performance of these fund portfolios is higher during NBER recessions than NBER expansions.[19]

[19]Kosowski (2006) reports results that indicate that the conditional performance of equity mutual funds is higher in NBER recessions than NBER expansions and show that the magnitude is both statistically and economically significant. However, we are not able to produce the same results when we attempt to implement his methodology. An Appendix A available from the authors upon request summarizes how we implement the Kosowski methodology, and what we find when we do so.

## 6 Conclusions

We develop a new methodology that allows conditional performance to be a function of information variables available at the start of the period, but without making assumptions about the behavior of the conditional betas. This methodology uses the Euler equation restriction that comes out of the factor model rather than the beta pricing formula itself. It assumes that the stochastic discount factor (SDF) parameters are linear in the information variables. The Euler equation restrictions that we develop can be estimated using standard GMM, which does not use all available data when the mutual fund data starts at different times for different funds and later than the factor and instrument data. We also use econometric techniques developed by Lynch and Wachter (2007) to estimate the Euler equation restrictions taking account of all available factor return, instrument, and mutual fund data. These techniques allow us to produce more precise parameter estimates than those obtained from the usual GMM estimation. We use our SDF-based method to assess the conditional performance of funds in the CRSP mutual fund data set. We are careful to condition only on information available to investors at the start of the period, and to control for any cyclical performance by the underlying stocks held by the various fund styles.

Using dividend yield and term spread to track the business cycle, we find that conditional mutual fund performance relative to conditional versions of the Fama-French and Carhart pricing models moves with the business cycle. However, we find that not all funds styles produce counter-cyclical performance: instead, many fund styles exhibit pro-cyclical or non-cyclical performance, especially after controlling for any cyclicality in the performance of the underlying stocks. For many fund styles, conditional performance often differs across large-TNA and small-TNA funds, and switches from counter-cyclical to pro- or non-cyclical depending on the instrument or pricing model used. Moreover, we find very little evidence of any business cycle variation in conditional performance for the 4 oldest fund styles, even though we estimate the cyclicality parameter using Lynch and Wachter's GMM method, which uses all available factor, instrument and fund return data.

Moskowitz (2000) conjectures that mutual funds may add value by performing well during recessions. However, contrary to accepted wisdom and Moskowitz's conjecture, our results suggest that, once care is taken to conditional only on information available to investors and to control for cyclical performance by the underlying stocks, the real picture may be more complicated than this, with some fund styles exhibiting counter-cyclical performance, and others exhibiting pro- or non-cyclical performance.

Our results raise the question of why mutual fund performance varies over the business cycle. In particular, what are the economic mechanisms that cause managerial skill to vary over the business cycle? Why does this variation exhibit different patterns for different fund styles? We leave these questions to future research.

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Table 1: Descriptive statistics for the CRSP mutual fund data.

This table reports the mean, minimum and maximum number of funds per month over the length of the available data series for the 12 mutual fund styles in our sample. Starting dates for each style's return series are also reported in the last column. All style return series end 12/07. The mutual fund data used in this paper is from the CRSP mutual fund database, and is free of survivorship bias. A TNA-based filter and a return-based filter are used to determine the start date for each fund in our sample. CRSP uses fund style classifications from three sources: Wiesenberger(1961-92), Strategic Insight (1992-99), and Lipper (1999 onwards). Also, Wiesenberger changed its system entirely in 1990, leaving us with four classification schemes. From 1961-1990, we keep only funds for which Wiesenberger's policy code is either reported as 'CS' (common stock) or is missing. After 1990, we rely solely on the fund style classification to determine whether a fund is an equity fund. A single aggregate fund style classification that is valid at all points in time is obtained by combining together the four fund style classifications used by CRSP using cross-tabulations, which show how funds move from an old scheme to a new scheme at each point at which the classifications used by CRSP changes, and frequency tables, which report the number of funds in each style in each month. The frequency tables and cross-tabulations identify 12 aggregate styles: growth-income (GRI), growth (GRO), income (INC), maximum capital gains (CGM), midcap growth (MCG), small cap growth (SCG), flexible (FLX), and five sector styles (energy/natural resources, ENR, financial services, FIN, health, HLT, technology TCH, and utilities, UTL). Further details of the sample construction are contained in section 3.

| | Average | Min | Max | Start-date |
|---|---|---|---|---|
| GRI | 182.31 | 52 | 483 | 1/62 |
| GRO | 309.70 | 49 | 975 | 1/62 |
| CGM | 111.02 | 62 | 208 | 1/69 |
| INC | 69.83 | 5 | 265 | 1/72 |
| ENR | 29.43 | 14 | 45 | 1/91 |
| FIN | 25.69 | 7 | 43 | 1/91 |
| HLT | 31.60 | 9 | 69 | 1/91 |
| TCH | 59.08 | 15 | 137 | 1/91 |
| UTL | 32.65 | 15 | 46 | 1/91 |
| SCG | 319.27 | 46 | 540 | 1/91 |
| FLX | 116.84 | 41 | 262 | 1/93 |
| MCG | 198.15 | 51 | 344 | 1/95 |

Table 2: Conditional fund performance relative to a conditional factor model with dividend yield as the instrument.

This table reports performance results for the following fund styles: Growth and Income (GRI), Growth (GRO), Maximum Capital Gains (CGM), Income (INC). The mutual fund data is from CRSP's mutual fund database, and is free of survivorship bias. Return data is available from 1/62 to 12/07 for GRI and GRO, from 1/69 to 12/07 for CGM and from 1/72 to 12/07 for INC. Factor and instrument data are available from 1/27 to 12/07. *Sm* (*Lg*) refers to the portfolio of funds with beginning of year TNA below (above) the median for the specified fund style. Performance results are reported relative to the Fama-French pricing model in the first 8 columns and relative to the Carhart pricing model in the last 8 columns. For each pricing model, performance results are reported for return in excess of the riskfree rate in the first 4 columns, and in excess of return on a portfolio matched on the basis of Fama-French loadings in the last 4 columns. Panels A and B report the abnormal performance parameters $e$ and $f$ respectively for the fund-style portfolios, where $e$ measures mean conditional performance and $f$ measures the extent to which the conditional performance varies with the information variable. When parameters $e$ and $f$ are identified by moment conditions (21) and (22), they are estimated for each fund-style portfolio using the adjusted moment (Full) method that uses all available data, and using the standard GMM method (Short) that only uses data from 1/72 to 12/07. Standard errors for both are calculated using the adjusted-moment coefficients. For each fund-style portfolio, parameters $e$ and $f$ are also estimated for the regression-based (Reg) approach of Ferson and Harvey (1996) using data from 1/72 to 12/07. Newey-West standard errors for the parameter estimates of all 3 are in italics. In the % Reduction column (% Red), we report the percent reduction in the coefficient standard error from (in the first row) using the Full method rather than the Short method and (in the second row) from using the Full method rather than the portfolio-by-portfolio adjusted moment method, which, for each portfolio, uses only the factor moments and the moments for that TNA-style portfolio, constructed using all available data for the factors, the instruments and the returns on that portfolio. Panel C reports the p-values for Wald tests of joint significance based on the Newey-West covariances. The Wald tests for the Short and Reg methods only use data from 1/72 to 12/07. Further details of the methodologies employed are in section 4.

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel A: Abnormal performance: $e$ parameters (% per month) | | | | | | | | | | | | | | | | |
| GRI-*Sm* | -0.074 | -0.128 | 30.1 | -0.123 | -0.058 | -0.158 | 12.5 | -0.160 | -0.048 | -0.085 | 29.7 | -0.080 | -0.086 | -0.132 | 14.0 | -0.134 |
| | *0.064* | *0.092* | 0.0 | *0.031* | *0.060* | *0.069* | 0.0 | *0.069* | *0.064* | *0.091* | 0.0 | *0.031* | *0.063* | *0.073* | 0.0 | *0.071* |
| GRI-*Lg* | -0.039 | -0.087 | 31.4 | -0.084 | -0.022 | -0.118 | 13.1 | -0.121 | -0.039 | -0.060 | 31.4 | -0.056 | -0.077 | -0.107 | 14.3 | -0.110 |
| | *0.063* | *0.092* | 0.0 | *0.025* | *0.057* | *0.066* | 0.0 | *0.066* | *0.062* | *0.090* | 0.0 | *0.023* | *0.058* | *0.068* | 0.0 | *0.066* |
| GRO-*Sm* | 0.068 | -0.065 | 26.2 | -0.060 | 0.135 | 0.098 | 14.5 | 0.101 | 0.005 | -0.071 | 27.0 | -0.065 | 0.073 | 0.029 | 13.1 | 0.032 |
| | *0.078* | *0.106* | 0.0 | *0.039* | *0.090* | *0.105* | 0.0 | *0.087* | *0.080* | *0.109* | 0.0 | *0.041* | *0.079* | *0.091* | 0.0 | *0.077* |
| GRO-*Lg* | 0.014 | -0.060 | 28.7 | -0.057 | 0.081 | 0.102 | 15.8 | 0.104 | -0.042 | -0.071 | 29.1 | -0.068 | 0.026 | 0.029 | 14.3 | 0.030 |
| | *0.069* | *0.097* | 0.0 | *0.035* | *0.084* | *0.100* | 0.0 | *0.089* | *0.072* | *0.101* | 0.0 | *0.038* | *0.073* | *0.086* | 0.0 | *0.079* |
| CGM-*Sm* | 0.104 | -0.145 | 22.5 | -0.142 | -0.227 | -0.301 | 10.1 | -0.291 | -0.102 | -0.230 | 24.3 | -0.225 | -0.304 | -0.398 | 12.6 | -0.386 |
| | *0.091* | *0.118* | 1.7 | *0.081* | *0.103* | *0.115* | 1.0 | *0.107* | *0.112* | *0.148* | 2.2 | *0.083* | *0.105* | *0.120* | 1.4 | *0.106* |
| CGM-*Lg* | 0.157 | 0.027 | 25.0 | 0.027 | -0.127 | -0.130 | 10.2 | -0.122 | -0.037 | -0.067 | 26.9 | -0.068 | -0.214 | -0.235 | 11.5 | -0.228 |
| | *0.086* | *0.115* | 1.3 | *0.073* | *0.083* | *0.092* | 0.9 | *0.082* | *0.101* | *0.139* | 1.5 | *0.066* | *0.081* | *0.091* | 1.3 | *0.075* |
| INC-*Sm* | -0.090 | -0.094 | 26.9 | -0.100 | -0.038 | -0.044 | 9.7 | -0.051 | -0.037 | -0.037 | 26.5 | -0.043 | 0.034 | 0.037 | 12.2 | 0.025 |
| | *0.066* | *0.090* | 1.4 | *0.042* | *0.082* | *0.091* | 1.7 | *0.083* | *0.063* | *0.086* | 1.3 | *0.041* | *0.090* | *0.102* | 1.7 | *0.086* |
| INC-*Lg* | 0.018 | -0.019 | 24.0 | -0.014 | 0.065 | 0.031 | 6.2 | 0.035 | 0.087 | 0.032 | 21.8 | 0.031 | 0.154 | 0.106 | 8.7 | 0.099 |
| | *0.075* | *0.099* | 0.9 | *0.055* | *0.082* | *0.088* | 3.5 | *0.089* | *0.074* | *0.095* | 1.4 | *0.056* | *0.086* | *0.094* | 2.6 | *0.088* |
| Average $e$ | 0.020 | -0.071 | | -0.069 | -0.024 | -0.065 | | -0.063 | -0.027 | -0.074 | | -0.072 | -0.049 | -0.084 | | -0.084 |

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel B: Abnormal performance: $f$ parameters (% per month) | | | | | | | | | | | | | | | | |
| GRI-*Sm* | 0.136 | 0.123 | 30.4 | 0.104 | -0.050 | -0.023 | 15.8 | -0.017 | 0.062 | 0.091 | 29.9 | 0.071 | -0.060 | 0.001 | 16.5 | 0.013 |
| | *0.069* | *0.099* | 0.0 | *0.035* | *0.056* | *0.066* | 0.0 | *0.062* | *0.067* | *0.095* | 0.0 | *0.036* | *0.058* | *0.069* | 0.0 | *0.064* |
| GRI-*Lg* | 0.140 | 0.107 | 31.8 | 0.094 | -0.046 | -0.040 | 15.8 | -0.027 | 0.052 | 0.072 | 31.6 | 0.053 | -0.070 | -0.018 | 16.5 | -0.005 |
| | *0.070* | *0.102* | 0.0 | *0.027* | *0.056* | *0.066* | 0.0 | *0.063* | *0.066* | *0.097* | 0.0 | *0.025* | *0.055* | *0.066* | 0.0 | *0.061* |
| GRO-*Sm* | 0.135 | 0.141 | 27.7 | 0.117 | -0.187 | 0.062 | 19.1 | 0.045 | 0.041 | 0.103 | 27.7 | 0.079 | -0.036 | 0.035 | 17.6 | 0.020 |
| | *0.074* | *0.102* | 0.0 | *0.041* | *0.096* | *0.119* | 0.0 | *0.089* | *0.071* | *0.098* | 0.0 | *0.044* | *0.088* | *0.107* | 0.0 | *0.077* |
| GRO-*Lg* | 0.088 | 0.094 | 29.1 | 0.079 | -0.234 | 0.015 | 20.1 | 0.007 | 0.030 | 0.064 | 28.4 | 0.048 | -0.047 | -0.004 | 18.4 | -0.010 |
| | *0.068* | *0.096* | 0.0 | *0.037* | *0.093* | *0.116* | 0.0 | *0.091* | *0.066* | *0.092* | 0.0 | *0.039* | *0.084* | *0.103* | 0.0 | *0.076* |
| CGM-*Sm* | 0.127 | 0.110 | 26.5 | 0.097 | 0.287 | 0.208 | 9.5 | 0.162 | -0.046 | 0.047 | 26.0 | 0.025 | 0.030 | 0.130 | 14.2 | 0.075 |
| | *0.083* | *0.114* | 1.5 | *0.074* | *0.087* | *0.096* | 0.9 | *0.088* | *0.098* | *0.133* | 2.0 | *0.081* | *0.088* | *0.102* | 1.5 | *0.094* |
| CGM-*Lg* | 0.047 | 0.068 | 27.2 | 0.066 | 0.179 | 0.166 | 9.6 | 0.131 | 0.008 | 0.034 | 27.1 | 0.035 | 0.073 | 0.116 | 11.3 | 0.085 |
| | *0.077* | *0.106* | 1.1 | *0.069* | *0.073* | *0.081* | 0.6 | *0.074* | *0.087* | *0.119* | 1.6 | *0.064* | *0.074* | *0.083* | 1.1 | *0.068* |
| INC-*Sm* | 0.016 | 0.032 | 29.8 | 0.056 | -0.180 | -0.035 | 13.2 | -0.006 | 0.076 | 0.045 | 28.3 | 0.071 | -0.024 | 0.029 | 14.2 | 0.085 |
| | *0.079* | *0.112* | 0.9 | *0.043* | *0.081* | *0.093* | 3.6 | *0.077* | *0.067* | *0.094* | 1.0 | *0.042* | *0.085* | *0.099* | 3.2 | *0.088* |
| INC-*Lg* | 0.197 | 0.136 | 25.2 | 0.113 | 0.003 | 0.068 | 10.8 | 0.051 | 0.173 | 0.157 | 22.8 | 0.160 | 0.078 | 0.141 | 13.8 | 0.174 |
| | *0.071* | *0.095* | 1.1 | *0.054* | *0.072* | *0.081* | 3.0 | *0.089* | *0.072* | *0.094* | 1.6 | *0.058* | *0.082* | *0.095* | 1.9 | *0.093* |
| Panel C: Null hypotheses and test p-values | | | | | | | | | | | | | | | | |
| All $e = 0$ | 0.000 | 0.031 | | 0.001 | 0.000 | 0.006 | | 0.005 | 0.029 | 0.154 | | 0.056 | 0.000 | 0.000 | | 0.001 |
| All $e$ same | 0.000 | 0.018 | | 0.016 | 0.000 | 0.015 | | 0.012 | 0.017 | 0.108 | | 0.077 | 0.000 | 0.005 | | 0.003 |
| Avg $e = 0$ | 0.772 | 0.468 | | 0.024 | 0.623 | 0.269 | | 0.215 | 0.721 | 0.493 | | 0.028 | 0.289 | 0.128 | | 0.072 |
| All $f = 0$ | 0.001 | 0.107 | | 0.029 | 0.000 | 0.061 | | 0.082 | 0.294 | 0.422 | | 0.107 | 0.491 | 0.539 | | 0.265 |
| All $f$ same | 0.003 | 0.195 | | 0.392 | 0.000 | 0.045 | | 0.057 | 0.637 | 0.500 | | 0.447 | 0.387 | 0.494 | | 0.237 |
| Av $f = 0$ | 0.044 | 0.250 | | 0.001 | 0.377 | 0.626 | | 0.723 | 0.386 | 0.390 | | 0.029 | 0.243 | 0.902 | | 0.946 |
| Av $f_{\text{GRI}} =$ Av $f_{\text{rest}}$ | 0.043 | 0.275 | | 0.006 | 0.402 | 0.223 | | 0.373 | 0.421 | 0.456 | | 0.071 | 0.157 | 0.495 | | 0.651 |
| Av $f = 0$ | 0.112 | 0.231 | | 0.010 | 0.025 | 0.741 | | 0.768 | 0.595 | 0.372 | | 0.116 | 0.627 | 0.882 | | 0.948 |
| Av $f_{\text{GRO}} =$ Av $f_{\text{rest}}$ | 0.148 | 0.219 | | 0.034 | 0.010 | 0.899 | | 0.948 | 0.816 | 0.497 | | 0.250 | 0.595 | 0.898 | | 0.725 |
| Av $f = 0$ | 0.257 | 0.405 | | 0.227 | 0.002 | 0.027 | | 0.059 | 0.830 | 0.741 | | 0.653 | 0.500 | 0.164 | | 0.291 |
| Av $f_{\text{CGM}} =$ Av $f_{\text{rest}}$ | 0.529 | 0.569 | | 0.505 | 0.000 | 0.025 | | 0.065 | 0.500 | 0.981 | | 0.935 | 0.413 | 0.219 | | 0.447 |
| Av $f = 0$ | 0.119 | 0.390 | | 0.015 | 0.209 | 0.835 | | 0.765 | 0.047 | 0.246 | | 0.003 | 0.724 | 0.348 | | 0.128 |
| Av $f_{\text{INC}} =$ Av $f_{\text{rest}}$ | 0.210 | 0.542 | | 0.218 | 0.183 | 0.871 | | 0.988 | 0.011 | 0.218 | | 0.015 | 0.623 | 0.409 | | 0.148 |
| Av $f_{Sm} = 0$ | 0.149 | 0.328 | | 0.012 | 0.517 | 0.389 | | 0.346 | 0.662 | 0.510 | | 0.140 | 0.650 | 0.423 | | 0.318 |
| Av $f_{Lg} = 0$ | 0.081 | 0.305 | | 0.007 | 0.612 | 0.379 | | 0.450 | 0.354 | 0.427 | | 0.022 | 0.852 | 0.305 | | 0.176 |
| Av $f_{Sm}$ =Av $f_{Lg}$ | 0.513 | 0.988 | | 0.839 | 0.720 | 0.988 | | 0.839 | 0.134 | 0.677 | | 0.610 | 0.155 | 0.677 | | 0.610 |
| All $f_{Sm} = f_{Lg}$ | 0.002 | 0.137 | | 0.152 | 0.001 | 0.136 | | 0.152 | 0.411 | 0.365 | | 0.218 | 0.445 | 0.365 | | 0.218 |
| $f_{\text{GRI-Sm}} = f_{\text{GRI-Lg}}$ | 0.838 | 0.498 | | 0.664 | 0.838 | 0.498 | | 0.664 | 0.624 | 0.430 | | 0.451 | 0.624 | 0.430 | | 0.451 |
| $f_{\text{GRO-Sm}} = f_{\text{GRO-Lg}}$ | 0.053 | 0.102 | | 0.025 | 0.053 | 0.102 | | 0.025 | 0.667 | 0.215 | | 0.101 | 0.667 | 0.215 | | 0.101 |
| $f_{\text{CGM-Sm}} = f_{\text{CGM-Lg}}$ | 0.105 | 0.448 | | 0.536 | 0.029 | 0.457 | | 0.536 | 0.315 | 0.818 | | 0.867 | 0.423 | 0.818 | | 0.867 |
| $f_{\text{INC-Sm}} = f_{\text{INC-Lg}}$ | 0.004 | 0.151 | | 0.408 | 0.003 | 0.151 | | 0.408 | 0.119 | 0.108 | | 0.157 | 0.103 | 0.109 | | 0.157 |

Table 3: Conditional fund performance relative to a conditional factor model with term spread as the instrument.

This table reports performance results for the following fund styles: Growth and Income (GRI), Growth (GRO), Maximum Capital Gains (CGM), Income (INC). The mutual fund data is from CRSP's mutual fund database, and is free of survivorship bias. Return data is available from 1/62 to 12/07 for GRI and GRO, from 1/69 to 12/07 for CGM and from 1/72 to 12/07 for INC. Factor and instrument data are available from 1/27 to 12/07. *Sm* (*Lg*) refers to the portfolio of funds with beginning of year TNA below (above) the median for the specified fund style. Performance results are reported relative to the Fama-French pricing model in the first 8 columns and relative to the Carhart pricing model in the last 8 columns. For each pricing model, performance results are reported for return in excess of the riskfree rate in the first 4 columns, and in excess of return on a portfolio matched on the basis of Fama-French loadings in the last 4 columns. Panels A and B report the abnormal performance parameters $e$ and $f$ respectively for the fund-style portfolios, where $e$ measures mean conditional performance and $f$ measures the extent to which the conditional performance varies with the information variable. When parameters $e$ and $f$ are identified by moment conditions (21) and (22), they are estimated for each fund-style portfolio using the adjusted moment (Full) method that uses all available data, and using the standard GMM method (Short) that only uses data from 1/72 to 12/07. Standard errors for both are calculated using the adjusted-moment coefficients. For each fund-style portfolio, parameters $e$ and $f$ are also estimated for the regression-based (Reg) approach of Ferson and Harvey (1996) using data from 1/72 to 12/07. Newey-West standard errors for the parameter estimates of all 3 are in italics. In the % Reduction column (% Red), we report the percent reduction in the coefficient standard error from (in the first row) using the Full method rather than the Short method and (in the second row) from using the Full method rather than the portfolio-by-portfolio adjusted moment method, which, for each portfolio, uses only the factor moments and the moments for that TNA-style portfolio, constructed using all available data for the factors, the instruments and the returns on that portfolio. Panel C reports the p-values for Wald tests of joint significance based on the Newey-West covariances. The Wald tests for the Short and Reg methods only use data from 1/72 to 12/07. Further details of the methodologies employed are in section 4.

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel A: Abnormal performance: $e$ parameters (% per month) | | | | | | | | | | | | | | | | |
| GRI-*Sm* | -0.067 | -0.114 | 30.9 | -0.116 | -0.089 | 0.039 | 15.7 | 0.045 | -0.036 | -0.071 | 30.0 | -0.075 | 0.036 | 0.016 | 15.2 | 0.025 |
| | *0.070* | *0.101* | 0.0 | *0.034* | *0.077* | *0.091* | 0.0 | *0.087* | *0.069* | *0.098* | 0.0 | *0.031* | *0.071* | *0.084* | 0.0 | *0.079* |
| GRI-*Lg* | -0.070 | -0.069 | 32.0 | -0.072 | -0.166 | -0.132 | 15.9 | -0.130 | -0.034 | -0.038 | 31.6 | -0.044 | -0.012 | -0.117 | 14.2 | -0.109 |
| | *0.071* | *0.105* | 0.0 | *0.031* | *0.063* | *0.075* | 0.0 | *0.069* | *0.068* | *0.099* | 0.0 | *0.029* | *0.059* | *0.069* | 0.0 | *0.068* |
| GRO-*Sm* | -0.024 | -0.058 | 27.2 | -0.060 | -0.046 | 0.094 | 15.9 | 0.101 | 0.025 | -0.057 | 27.5 | -0.059 | 0.097 | 0.029 | 14.8 | 0.042 |
| | *0.082* | *0.112* | 0.0 | *0.038* | *0.094* | *0.112* | 0.0 | *0.097* | *0.082* | *0.112* | 0.0 | *0.039* | *0.082* | *0.097* | 0.0 | *0.084* |
| GRO-*Lg* | -0.054 | -0.072 | 29.3 | -0.073 | -0.077 | 0.081 | 16.2 | 0.088 | -0.042 | -0.079 | 29.3 | -0.083 | 0.030 | 0.008 | 15.4 | 0.018 |
| | *0.074* | *0.104* | 0.0 | *0.035* | *0.088* | *0.105* | 0.0 | *0.096* | *0.075* | *0.106* | 0.0 | *0.036* | *0.077* | *0.091* | 0.0 | *0.084* |
| CGM-*Sm* | 0.133 | -0.094 | 22.7 | -0.105 | -0.156 | -0.195 | 9.8 | -0.212 | -0.076 | -0.186 | 24.1 | -0.200 | -0.247 | -0.292 | 12.2 | -0.305 |
| | *0.092* | *0.118* | 2.1 | *0.080* | *0.105* | *0.116* | 2.1 | *0.117* | *0.106* | *0.139* | 2.3 | *0.080* | *0.099* | *0.113* | 2.0 | *0.107* |
| CGM-*Lg* | 0.106 | 0.015 | 24.6 | 0.011 | -0.187 | -0.085 | 10.3 | -0.096 | -0.016 | -0.070 | 26.4 | -0.075 | -0.182 | -0.176 | 11.6 | -0.180 |
| | *0.086* | *0.113* | 1.8 | *0.064* | *0.084* | *0.094* | 2.1 | *0.080* | *0.096* | *0.131* | 1.8 | *0.061* | *0.082* | *0.092* | 2.0 | *0.071* |
| INC-*Sm* | -0.006 | -0.073 | 27.3 | -0.068 | 0.028 | 0.080 | 17.0 | 0.093 | 0.038 | -0.025 | 27.4 | -0.025 | 0.242 | 0.050 | 17.1 | 0.049 |
| | *0.066* | *0.091* | 1.4 | *0.041* | *0.091* | *0.109* | 8.0 | *0.099* | *0.069* | *0.095* | 1.4 | *0.043* | *0.113* | *0.136* | 1.6 | *0.106* |
| INC-*Lg* | -0.184 | -0.063 | 25.8 | -0.064 | -0.138 | -0.007 | 9.2 | -0.009 | -0.038 | -0.013 | 22.5 | -0.014 | 0.093 | 0.062 | 12.4 | 0.061 |
| | *0.080* | *0.108* | 1.1 | *0.055* | *0.093* | *0.102* | 3.9 | *0.102* | *0.078* | *0.100* | 1.7 | *0.057* | *0.097* | *0.110* | 3.0 | *0.097* |
| Average $e$ | -0.021 | -0.066 | | -0.069 | -0.104 | -0.016 | | -0.015 | -0.023 | -0.067 | | -0.072 | 0.007 | -0.053 | | -0.050 |

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel B: Abnormal performance: $f$ parameters (% per month) | | | | | | | | | | | | | | | | |
| GRI-*Sm* | 0.086 | 0.015 | 30.6 | 0.004 | 0.068 | 0.038 | 15.8 | 0.062 | 0.031 | 0.018 | 29.3 | 0.000 | 0.043 | 0.024 | 15.2 | 0.066 |
| | *0.047* | *0.068* | 0.0 | *0.026* | *0.064* | *0.076* | 0.0 | *0.069* | *0.046* | *0.065* | 0.0 | *0.026* | *0.062* | *0.073* | 0.0 | *0.068* |
| GRI-*Lg* | 0.066 | 0.010 | 31.5 | -0.005 | -0.114 | -0.021 | 14.6 | -0.010 | 0.035 | 0.014 | 30.9 | -0.008 | -0.081 | -0.047 | 15.0 | -0.014 |
| | *0.048* | *0.070* | 0.0 | *0.025* | *0.064* | *0.075* | 0.0 | *0.065* | *0.044* | *0.064* | 0.0 | *0.025* | *0.061* | *0.072* | 0.0 | *0.066* |
| GRO-*Sm* | 0.064 | 0.035 | 26.8 | 0.028 | 0.046 | 0.059 | 14.6 | 0.087 | 0.062 | 0.033 | 28.0 | 0.026 | 0.074 | 0.039 | 13.8 | 0.093 |
| | *0.058* | *0.079* | 0.0 | *0.030* | *0.077* | *0.090* | 0.0 | *0.074* | *0.058* | *0.081* | 0.0 | *0.029* | *0.070* | *0.082* | 0.0 | *0.071* |
| GRO-*Lg* | 0.047 | 0.006 | 29.3 | 0.002 | 0.029 | 0.029 | 14.5 | 0.061 | 0.058 | 0.021 | 29.6 | 0.003 | 0.070 | 0.026 | 14.3 | 0.070 |
| | *0.056* | *0.079* | 0.0 | *0.032* | *0.072* | *0.085* | 0.0 | *0.075* | *0.057* | *0.081* | 0.0 | *0.031* | *0.067* | *0.078* | 0.0 | *0.074* |
| CGM-*Sm* | 0.092 | 0.020 | 23.6 | -0.027 | -0.026 | -0.010 | 10.9 | -0.083 | 0.101 | 0.046 | 25.1 | -0.013 | 0.049 | -0.015 | 12.2 | -0.072 |
| | *0.080* | *0.104* | 1.5 | *0.069* | *0.078* | *0.087* | 1.7 | *0.089* | *0.087* | *0.116* | 1.7 | *0.063* | *0.074* | *0.085* | 2.3 | *0.083* |
| CGM-*Lg* | 0.093 | 0.075 | 27.8 | 0.055 | -0.003 | 0.045 | 10.3 | -0.001 | 0.075 | 0.083 | 28.8 | 0.063 | 0.027 | 0.022 | 14.3 | 0.004 |
| | *0.077* | *0.106* | 1.4 | *0.047* | *0.065* | *0.072* | 2.2 | *0.064* | *0.085* | *0.119* | 1.5 | *0.043* | *0.065* | *0.076* | 3.0 | *0.055* |
| INC-*Sm* | -0.068 | -0.062 | 23.5 | -0.041 | -0.029 | -0.039 | 20.9 | 0.018 | -0.046 | -0.039 | 25.8 | -0.041 | 0.083 | -0.059 | 19.8 | -0.062 |
| | *0.040* | *0.053* | 1.5 | *0.038* | *0.078* | *0.098* | 6.5 | *0.079* | *0.046* | *0.062* | 1.9 | *0.035* | *0.102* | *0.127* | 2.8 | *0.086* |
| INC-*Lg* | 0.165 | 0.063 | 23.7 | 0.056 | 0.092 | 0.048 | 9.1 | 0.037 | 0.107 | 0.054 | 20.6 | 0.048 | 0.160 | 0.034 | 17.2 | 0.027 |
| | *0.064* | *0.084* | 1.6 | *0.044* | *0.082* | *0.090* | 5.5 | *0.078* | *0.061* | *0.077* | 2.2 | *0.043* | *0.091* | *0.110* | 3.4 | *0.081* |
| Panel C: Null hypotheses and test p-values | | | | | | | | | | | | | | | | |
| All $e = 0$ | 0.001 | 0.101 | | 0.006 | 0.000 | 0.002 | | 0.004 | 0.000 | 0.115 | | 0.039 | 0.000 | 0.006 | | 0.011 |
| All $e$ same | 0.001 | 0.068 | | 0.061 | 0.026 | 0.083 | | 0.078 | 0.000 | 0.079 | | 0.061 | 0.000 | 0.055 | | 0.080 |
| Avg $e = 0$ | 0.760 | 0.505 | | 0.018 | 0.069 | 0.820 | | 0.813 | 0.754 | 0.516 | | 0.019 | 0.893 | 0.401 | | 0.355 |
| All $f = 0$ | 0.000 | 0.020 | | 0.169 | 0.000 | 0.283 | | 0.540 | 0.031 | 0.147 | | 0.117 | 0.094 | 0.874 | | 0.480 |
| All $f$ same | 0.000 | 0.070 | | 0.139 | 0.000 | 0.261 | | 0.433 | 0.034 | 0.206 | | 0.085 | 0.059 | 0.810 | | 0.376 |
| Av $f = 0$ | 0.106 | 0.858 | | 0.982 | 0.669 | 0.895 | | 0.644 | 0.451 | 0.795 | | 0.855 | 0.707 | 0.849 | | 0.638 |
| Av $f_{\text{GRI}} =$ Av $f_{\text{rest}}$ | 0.130 | 0.956 | | 0.771 | 0.400 | 0.983 | | 0.678 | 0.812 | 0.961 | | 0.575 | 0.146 | 0.731 | | 0.622 |
| Av $f = 0$ | 0.322 | 0.791 | | 0.626 | 0.609 | 0.613 | | 0.321 | 0.291 | 0.735 | | 0.616 | 0.288 | 0.676 | | 0.257 |
| Av $f_{\text{GRO}} =$ Av $f_{\text{rest}}$ | 0.579 | 0.849 | | 0.626 | 0.438 | 0.496 | | 0.227 | 0.453 | 0.845 | | 0.622 | 0.313 | 0.554 | | 0.166 |
| Av $f = 0$ | 0.221 | 0.643 | | 0.789 | 0.833 | 0.820 | | 0.563 | 0.288 | 0.573 | | 0.598 | 0.563 | 0.966 | | 0.598 |
| Av $f_{\text{CGM}} =$ Av $f_{\text{rest}}$ | 0.278 | 0.602 | | 0.825 | 0.720 | 0.889 | | 0.413 | 0.317 | 0.554 | | 0.596 | 0.830 | 0.980 | | 0.476 |
| Av $f = 0$ | 0.282 | 0.998 | | 0.799 | 0.639 | 0.954 | | 0.677 | 0.508 | 0.904 | | 0.902 | 0.188 | 0.913 | | 0.828 |
| Av $f_{\text{INC}} =$ Av $f_{\text{rest}}$ | 0.577 | 0.746 | | 0.916 | 0.557 | 0.931 | | 0.721 | 0.884 | 0.829 | | 0.959 | 0.204 | 0.880 | | 0.705 |
| Av $f_{Sm} = 0$ | 0.419 | 0.979 | | 0.749 | 0.786 | 0.861 | | 0.717 | 0.557 | 0.870 | | 0.810 | 0.234 | 0.967 | | 0.898 |
| Av $f_{Lg} = 0$ | 0.132 | 0.670 | | 0.253 | 0.983 | 0.643 | | 0.666 | 0.299 | 0.657 | | 0.240 | 0.350 | 0.875 | | 0.655 |
| Av $f_{Sm} =$Av $f_{Lg}$ | 0.027 | 0.174 | | 0.151 | 0.692 | 0.749 | | 0.981 | 0.163 | 0.296 | | 0.161 | 0.454 | 0.694 | | 0.546 |
| All $f_{Sm} = f_{Lg}$ | 0.000 | 0.141 | | 0.169 | 0.001 | 0.134 | | 0.207 | 0.031 | 0.440 | | 0.188 | 0.238 | 0.580 | | 0.204 |
| $f_{\text{GRI-Sm}} = f_{\text{GRI-Lg}}$ | 0.232 | 0.806 | | 0.664 | 0.009 | 0.472 | | 0.323 | 0.801 | 0.847 | | 0.646 | 0.077 | 0.388 | | 0.280 |
| $f_{\text{GRO-Sm}} = f_{\text{GRO-Lg}}$ | 0.467 | 0.278 | | 0.107 | 0.467 | 0.278 | | 0.107 | 0.873 | 0.640 | | 0.140 | 0.873 | 0.640 | | 0.140 |
| $f_{\text{CGM-Sm}} = f_{\text{CGM-Lg}}$ | 0.996 | 0.231 | | 0.130 | 0.574 | 0.236 | | 0.130 | 0.557 | 0.457 | | 0.150 | 0.625 | 0.457 | | 0.150 |
| $f_{\text{INC-Sm}} = f_{\text{INC-Lg}}$ | 0.000 | 0.053 | | 0.088 | 0.162 | 0.384 | | 0.820 | 0.008 | 0.156 | | 0.100 | 0.179 | 0.152 | | 0.100 |

Table 4: Unconditional fund performance relative to an unconditional factor model.

This table reports performance results for the following fund styles: Growth and Income (GRI), Growth (GRO), Maximum Capital Gains (CGM), Income (INC). The mutual fund data is from CRSP's mutual fund database, and is free of survivorship bias. Return data is available from 1/62 to 12/07 for GRI and GRO, from 1/69 to 12/07 for CGM and from 1/72 to 12/07 for INC. Factor and instrument data are available from 1/27 to 12/07. $Sm$ ($Lg$) refers to the portfolio of funds with beginning of year TNA below (above) the median for the specified fund style. Performance results are reported relative to the Fama-French pricing model in the first 8 columns and relative to the Carhart pricing model in the last 8 columns. For each pricing model, performance results are reported for return in excess of the riskfree rate in the first 4 columns, and in excess of return on a portfolio matched on the basis of Fama-French loadings in the last 4 columns. Panel A reports the abnormal performance parameter $e$ for the fund-style portfolios, where $e$ measures unconditional performance. When parameter $e$ is identified by moment conditions (24) and (17), it is estimated for each fund-style portfolio using the adjusted moment (Full) method that uses all available data, and using the standard GMM method (Short) that only uses data from 1/72 to 12/07. Standard errors for both are calculated using the adjusted-moment coefficients. For each fund-style portfolio, parameter $e$ is also estimated for the regression-based (Reg) approach of Fama and French (1993) using data from 1/72 to 12/07. Newey-West standard errors for the parameter estimates of all 3 are in italics. In the % Reduction column (% Red), we report the percent reduction in the coefficient standard error from (in the first row) using the Full method rather than the Short method and (in the second row) from using the Full method rather than the portfolio-by-portfolio adjusted moment method, which, for each portfolio, uses only the factor moments and the moments for that TNA-style portfolio, constructed using all available data for the factors, the instruments and the returns on that portfolio. Panel B reports the p-values for Wald tests of joint significance based on the Newey-West covariances. The Wald tests for the Short and Reg methods only use data from 1/72 to 12/07. Further details of the methodologies employed are in section 4.

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel A: Abnormal performance: $e$ parameters (% per month) | | | | | | | | | | | | | | | | |
| GRI-$Sm$ | -0.071 | -0.114 | 30.6 | -0.114 | -0.094 | 0.026 | 15.2 | 0.026 | -0.062 | -0.073 | 30.1 | -0.073 | -0.003 | 0.015 | 15.0 | 0.015 |
| | *0.071* | *0.103* | 0.0 | *0.033* | *0.079* | *0.094* | 0.0 | *0.084* | *0.071* | *0.102* | 0.0 | *0.031* | *0.071* | *0.083* | 0.0 | *0.076* |
| GRI-$Lg$ | -0.052 | -0.066 | 31.7 | -0.066 | -0.096 | -0.125 | 11.9 | -0.125 | -0.045 | -0.041 | 31.5 | -0.041 | -0.079 | -0.109 | 12.4 | -0.109 |
| | *0.072* | *0.106* | 0.0 | *0.029* | *0.061* | *0.069* | 0.0 | *0.068* | *0.071* | *0.103* | 0.0 | *0.027* | *0.058* | *0.066* | 0.0 | *0.066* |
| GRO-$Sm$ | 0.048 | -0.051 | 27.1 | -0.051 | 0.025 | 0.089 | 13.7 | 0.089 | -0.022 | -0.056 | 27.3 | -0.056 | 0.037 | 0.033 | 14.5 | 0.033 |
| | *0.083* | *0.114* | 0.0 | *0.038* | *0.098* | *0.113* | 0.0 | *0.096* | *0.084* | *0.115* | 0.0 | *0.039* | *0.083* | *0.097* | 0.0 | *0.081* |
| GRO-$Lg$ | -0.013 | -0.053 | 29.3 | -0.053 | -0.036 | 0.087 | 14.6 | 0.087 | -0.065 | -0.065 | 29.2 | -0.065 | -0.006 | 0.023 | 15.6 | 0.023 |
| | *0.075* | *0.106* | 0.0 | *0.034* | *0.092* | *0.108* | 0.0 | *0.096* | *0.076* | *0.107* | 0.0 | *0.035* | *0.079* | *0.094* | 0.0 | *0.081* |
| CGM-$Sm$ | 0.108 | -0.107 | 23.4 | -0.107 | -0.191 | -0.215 | 8.9 | -0.215 | -0.129 | -0.190 | 23.5 | -0.190 | -0.289 | -0.307 | 10.4 | -0.307 |
| | *0.094* | *0.123* | 1.4 | *0.075* | *0.103* | *0.113* | 1.3 | *0.109* | *0.107* | *0.140* | 2.0 | *0.079* | *0.100* | *0.112* | 1.3 | *0.102* |
| CGM-$Lg$ | 0.111 | 0.014 | 25.7 | 0.014 | -0.181 | -0.093 | 8.8 | -0.093 | -0.087 | -0.079 | 26.5 | -0.079 | -0.245 | -0.195 | 9.3 | -0.195 |
| | *0.089* | *0.120* | 1.3 | *0.064* | *0.082* | *0.090* | 1.4 | *0.078* | *0.096* | *0.131* | 1.5 | *0.059* | *0.077* | *0.085* | 1.1 | *0.069* |
| INC-$Sm$ | -0.023 | -0.088 | 27.2 | -0.088 | 0.034 | -0.017 | 16.6 | -0.017 | -0.013 | -0.031 | 26.8 | -0.031 | -0.002 | -0.031 | 14.5 | -0.031 |
| | *0.069* | *0.095* | 1.1 | *0.044* | *0.094* | *0.112* | 1.4 | *0.084* | *0.067* | *0.091* | 1.2 | *0.042* | *0.096* | *0.112* | 1.3 | *0.085* |
| INC-$Lg$ | -0.103 | -0.031 | 24.4 | -0.031 | -0.064 | 0.019 | 6.4 | 0.019 | 0.026 | 0.013 | 21.2 | 0.013 | 0.071 | 0.089 | 8.5 | 0.089 |
| | *0.079* | *0.104* | 0.5 | *0.060* | *0.086* | *0.092* | 3.4 | *0.094* | *0.078* | *0.098* | 0.9 | *0.061* | *0.088* | *0.096* | 1.7 | *0.093* |
| Average $e$ | 0.001 | -0.062 | | -0.062 | -0.076 | -0.029 | | -0.029 | -0.050 | -0.065 | | -0.065 | -0.064 | -0.060 | | -0.060 |
| Panel B: Null hypotheses and test p-values | | | | | | | | | | | | | | | | |
| All $e = 0$ | 0.000 | 0.111 | | 0.028 | 0.000 | 0.013 | | 0.009 | 0.042 | 0.254 | | 0.159 | 0.000 | 0.014 | | 0.012 |
| All $e$ same | 0.000 | 0.077 | | 0.113 | 0.000 | 0.154 | | 0.134 | 0.025 | 0.188 | | 0.156 | 0.003 | 0.150 | | 0.086 |
| Avg $e = 0$ | 0.993 | 0.551 | | 0.035 | 0.173 | 0.665 | | 0.603 | 0.492 | 0.534 | | 0.037 | 0.169 | 0.288 | | 0.205 |

Table 5: Unconditional fund performance relative to a conditional factor model with dividend yield as the instrument.

This table reports performance results for the following fund styles: Growth and Income (GRI), Growth (GRO), Maximum Capital Gains (CGM), Income (INC). The mutual fund data is from CRSP's mutual fund database, and is free of survivorship bias. Return data is available from 1/62 to 12/07 for GRI and GRO, from 1/69 to 12/07 for CGM and from 1/72 to 12/07 for INC. Factor and instrument data are available from 1/27 to 12/07. *Sm* (*Lg*) refers to the portfolio of funds with beginning of year TNA below (above) the median for the specified fund style. Performance results are reported relative to the Fama-French pricing model in the first 8 columns and relative to the Carhart pricing model in the last 8 columns. For each pricing model, performance results are reported for return in excess of the riskfree rate in the first 4 columns, and in excess of return on a portfolio matched on the basis of Fama-French loadings in the last 4 columns. Panel A reports the abnormal performance parameter $e$ for the fund-style portfolios, where $e$ measures unconditional performance. When parameter $e$ is identified by moment conditions (21) and (23), it is estimated for each fund-style portfolio using the adjusted moment (Full) method that uses all available data, and using the standard GMM method (Short) that only uses data from 1/72 to 12/07. Standard errors for both are calculated using the adjusted-moment coefficients. For each fund-style portfolio, parameter $e$ is also estimated for the regression-based (Reg) approach of Ferson and Harvey (1996) using data from 1/72 to 12/07 and setting $f = 0$ in the regression. Newey-West standard errors for the parameter estimates of all 3 are in italics. In the % Reduction column (% Red), we report the percent reduction in the coefficient standard error from (in the first row) using the Full method rather than the Short method and (in the second row) from using the Full method rather than the portfolio-by-portfolio adjusted moment method, which, for each portfolio, uses only the factor moments and the moments for that TNA-style portfolio, constructed using all available data for the factors, the instruments and the returns on that portfolio. Panel B reports the p-values for Wald tests of joint significance based on the Newey-West covariances. The Wald tests for the Short and Reg methods only use data from 1/72 to 12/07. Further details of the methodologies employed are in section 4.

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel A: Abnormal performance: $e$ parameters (% per month) | | | | | | | | | | | | | | | | |
| GRI-*Sm* | -0.144 | -0.100 | 30.6 | -0.105 | -0.041 | -0.164 | 12.6 | -0.163 | -0.050 | -0.064 | 29.7 | -0.069 | -0.084 | -0.131 | 13.6 | -0.132 |
| | *0.066* | *0.095* | 0.0 | *0.030* | *0.061* | *0.069* | 0.0 | *0.068* | *0.064* | *0.091* | 0.0 | *0.029* | *0.063* | *0.073* | 0.0 | *0.071* |
| GRI-*Lg* | -0.112 | -0.063 | 31.6 | -0.068 | -0.008 | -0.127 | 13.2 | -0.125 | -0.040 | -0.044 | 31.4 | -0.047 | -0.075 | -0.111 | 13.8 | -0.110 |
| | *0.066* | *0.096* | 0.0 | *0.027* | *0.058* | *0.066* | 0.0 | *0.067* | *0.062* | *0.090* | 0.0 | *0.023* | *0.058* | *0.068* | 0.0 | *0.067* |
| GRO-*Sm* | -0.003 | -0.034 | 26.8 | -0.040 | 0.185 | 0.111 | 13.4 | 0.109 | 0.004 | -0.048 | 27.0 | -0.053 | 0.074 | 0.037 | 13.0 | 0.036 |
| | *0.079* | *0.108* | 0.0 | *0.040* | *0.088* | *0.102* | 0.0 | *0.084* | *0.080* | *0.109* | 0.0 | *0.039* | *0.079* | *0.091* | 0.0 | *0.074* |
| GRO-*Lg* | -0.036 | -0.039 | 29.1 | -0.043 | 0.152 | 0.106 | 14.3 | 0.105 | -0.043 | -0.057 | 29.2 | -0.060 | 0.028 | 0.028 | 14.1 | 0.029 |
| | *0.070* | *0.099* | 0.0 | *0.034* | *0.082* | *0.096* | 0.0 | *0.084* | *0.072* | *0.101* | 0.0 | *0.035* | *0.073* | *0.085* | 0.0 | *0.075* |
| CGM-*Sm* | 0.030 | -0.121 | 22.9 | -0.126 | -0.337 | -0.255 | 10.5 | -0.263 | -0.124 | -0.220 | 24.2 | -0.221 | -0.234 | -0.244 | 10.4 | -0.240 |
| | *0.091* | *0.118* | 1.5 | *0.077* | *0.098* | *0.109* | 1.0 | *0.103* | *0.109* | *0.144* | 1.7 | *0.079* | *0.085* | *0.095* | 0.9 | *0.085* |
| CGM-*Lg* | 0.111 | 0.042 | 25.6 | 0.038 | -0.217 | -0.093 | 10.9 | -0.099 | -0.045 | -0.060 | 27.2 | -0.062 | -0.205 | -0.209 | 11.0 | -0.215 |
| | *0.084* | *0.113* | 1.3 | *0.068* | *0.078* | *0.087* | 1.0 | *0.080* | *0.096* | *0.133* | 1.3 | *0.060* | *0.076* | *0.085* | 1.0 | *0.072* |
| INC-*Sm* | -0.115 | -0.087 | 27.6 | -0.090 | -0.008 | -0.052 | 7.1 | -0.052 | -0.012 | -0.027 | 26.3 | -0.032 | 0.011 | 0.043 | 10.2 | 0.038 |
| | *0.068* | *0.093* | 1.1 | *0.041* | *0.079* | *0.085* | 1.5 | *0.084* | *0.063* | *0.085* | 1.2 | *0.040* | *0.088* | *0.098* | 1.3 | *0.085* |
| INC-*Lg* | -0.056 | 0.011 | 23.5 | 0.005 | 0.066 | 0.046 | 4.5 | 0.044 | 0.119 | 0.067 | 19.9 | 0.056 | 0.156 | 0.137 | 8.9 | 0.126 |
| | *0.072* | *0.094* | 0.7 | *0.058* | *0.079* | *0.083* | 2.2 | *0.090* | *0.071* | *0.088* | 1.6 | *0.057* | *0.087* | *0.095* | 2.0 | *0.089* |
| Average $e$ | -0.041 | -0.049 | | -0.054 | -0.026 | -0.053 | | -0.056 | -0.024 | -0.057 | | -0.061 | -0.041 | -0.056 | | -0.059 |
| Panel B: Null hypotheses and test p-values | | | | | | | | | | | | | | | | |
| All $e = 0$ | 0.000 | 0.013 | | 0.002 | 0.000 | 0.002 | | 0.002 | 0.007 | 0.068 | | 0.021 | 0.000 | 0.000 | | 0.001 |
| All $e$ same | 0.000 | 0.007 | | 0.011 | 0.000 | 0.003 | | 0.005 | 0.004 | 0.050 | | 0.023 | 0.000 | 0.006 | | 0.006 |
| Avg $e = 0$ | 0.551 | 0.622 | | 0.077 | 0.551 | 0.302 | | 0.264 | 0.738 | 0.583 | | 0.046 | 0.351 | 0.282 | | 0.216 |

Table 6: Unconditional fund performance relative to a conditional factor model with term spread as the instrument.
This table reports performance results for the following fund styles: Growth and Income (GRI), Growth (GRO), Maximum Capital Gains (CGM), Income (INC). The mutual fund data is from CRSP's mutual fund database, and is free of survivorship bias. Return data is available from 1/62 to 12/07 for GRI and GRO, from 1/69 to 12/07 for CGM and from 1/72 to 12/07 for INC. Factor and instrument data are available from 1/27 to 12/07. *Sm* (*Lg*) refers to the portfolio of funds with beginning of year TNA below (above) the median for the specified fund style. Performance results are reported relative to the Fama-French pricing model in the first 8 columns and relative to the Carhart pricing model in the last 8 columns. For each pricing model, performance results are reported for return in excess of the riskfree rate in the first 4 columns, and in excess of return on a portfolio matched on the basis of Fama-French loadings in the last 4 columns. Panel A reports the abnormal performance parameter $e$ for the fund-style portfolios, where $e$ measures unconditional performance. When parameter $e$ is identified by moment conditions (21) and (23), it is estimated for each fund-style portfolio using the adjusted moment (Full) method that uses all available data, and using the standard GMM method (Short) that only uses data from 1/72 to 12/07. Standard errors for both are calculated using the adjusted-moment coefficients. For each fund-style portfolio, parameter $e$ is also estimated for the regression-based (Reg) approach of Ferson and Harvey (1996) using data from 1/72 to 12/07 and setting $f = 0$ in the regression. Newey-West standard errors for the parameter estimates of all 3 are in italics. In the % Reduction column (% Red), we report the percent reduction in the coefficient standard error from (in the first row) using the Full method rather than the Short method and (in the second row) from using the Full method rather than the portfolio-by-portfolio adjusted moment method, which, for each portfolio, uses only the factor moments and the moments for that TNA-style portfolio, constructed using all available data for the factors, the instruments and the returns on that portfolio. Panel B reports the p-values for Wald tests of joint significance based on the Newey-West covariances. The Wald tests for the Short and Reg methods only use data from 1/72 to 12/07. Further details of the methodologies employed are in section 4.

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel A: Abnormal performance: $e$ parameters (% per month) | | | | | | | | | | | | | | | | |
| GRI-*Sm* | -0.052 | -0.117 | 30.7 | -0.117 | -0.072 | 0.030 | 16.3 | 0.034 | -0.033 | -0.075 | 30.0 | -0.075 | 0.041 | 0.010 | 15.6 | 0.015 |
| | *0.067* | *0.097* | 0.0 | *0.033* | *0.078* | *0.093* | 0.0 | *0.087* | *0.068* | *0.097* | 0.0 | *0.030* | *0.072* | *0.085* | 0.0 | *0.077* |
| GRI-*Lg* | -0.058 | -0.071 | 32.0 | -0.071 | -0.181 | -0.128 | 15.3 | -0.128 | -0.031 | -0.042 | 31.5 | -0.042 | -0.019 | -0.106 | 13.8 | -0.107 |
| | *0.069* | *0.102* | 0.0 | *0.030* | *0.061* | *0.072* | 0.0 | *0.069* | *0.067* | *0.098* | 0.0 | *0.028* | *0.057* | *0.067* | 0.0 | *0.068* |
| GRO-*Sm* | -0.009 | -0.067 | 26.9 | -0.065 | -0.030 | 0.081 | 16.2 | 0.087 | 0.031 | -0.065 | 27.2 | -0.063 | 0.105 | 0.020 | 15.3 | 0.028 |
| | *0.080* | *0.110* | 0.0 | *0.038* | *0.095* | *0.113* | 0.0 | *0.097* | *0.080* | *0.111* | 0.0 | *0.039* | *0.084* | *0.099* | 0.0 | *0.082* |
| GRO-*Lg* | -0.045 | -0.073 | 29.1 | -0.073 | -0.065 | 0.074 | 16.4 | 0.078 | -0.036 | -0.084 | 29.1 | -0.083 | 0.038 | 0.002 | 15.9 | 0.007 |
| | *0.073* | *0.103* | 0.0 | *0.034* | *0.089* | *0.106* | 0.0 | *0.096* | *0.074* | *0.104* | 0.0 | *0.035* | *0.079* | *0.094* | 0.0 | *0.082* |
| CGM-*Sm* | 0.080 | -0.099 | 23.3 | -0.101 | -0.245 | -0.192 | 9.3 | -0.198 | -0.076 | -0.197 | 24.0 | -0.198 | -0.258 | -0.289 | 12.3 | -0.294 |
| | *0.093* | *0.121* | 1.3 | *0.078* | *0.103* | *0.113* | 1.3 | *0.116* | *0.102* | *0.134* | 1.9 | *0.078* | *0.098* | *0.112* | 1.3 | *0.106* |
| CGM-*Lg* | 0.082 | -0.002 | 25.5 | 0.001 | -0.247 | -0.096 | 10.4 | -0.096 | -0.017 | -0.089 | 26.8 | -0.084 | -0.193 | -0.181 | 11.3 | -0.181 |
| | *0.086* | *0.116* | 1.4 | *0.065* | *0.080* | *0.089* | 1.2 | *0.077* | *0.095* | *0.129* | 1.5 | *0.062* | *0.077* | *0.087* | 1.3 | *0.070* |
| INC-*Sm* | -0.009 | -0.059 | 28.0 | -0.061 | 0.021 | 0.089 | 18.6 | 0.090 | 0.021 | -0.016 | 27.8 | -0.019 | 0.171 | 0.064 | 14.8 | 0.059 |
| | *0.072* | *0.100* | 0.9 | *0.043* | *0.091* | *0.112* | 7.2 | *0.096* | *0.071* | *0.099* | 1.0 | *0.043* | *0.097* | *0.114* | 0.9 | *0.099* |
| INC-*Lg* | -0.189 | -0.077 | 26.6 | -0.073 | -0.180 | -0.018 | 8.8 | -0.015 | -0.054 | -0.025 | 23.3 | -0.021 | 0.060 | 0.054 | 10.5 | 0.057 |
| | *0.080* | *0.109* | 0.4 | *0.054* | *0.086* | *0.094* | 2.8 | *0.095* | *0.076* | *0.099* | 0.9 | *0.057* | *0.086* | *0.096* | 1.8 | *0.090* |
| Average $e$ | -0.025 | -0.071 | | -0.070 | -0.125 | -0.020 | | -0.018 | -0.024 | -0.074 | | -0.073 | -0.007 | -0.053 | | -0.052 |
| Panel B: Null hypotheses and test p-values | | | | | | | | | | | | | | | | |
| All $e = 0$ | 0.002 | 0.069 | | 0.006 | 0.000 | 0.002 | | 0.007 | 0.000 | 0.091 | | 0.029 | 0.000 | 0.026 | | 0.023 |
| All $e$ same | 0.001 | 0.049 | | 0.062 | 0.024 | 0.098 | | 0.099 | 0.000 | 0.057 | | 0.060 | 0.000 | 0.140 | | 0.122 |
| Avg $e = 0$ | 0.734 | 0.510 | | 0.013 | 0.025 | 0.769 | | 0.764 | 0.739 | 0.483 | | 0.014 | 0.886 | 0.369 | | 0.312 |

Table 7: Conditional fund performance relative to a conditional factor model with dividend yield as the instrument.

This table reports performance results for the following fund styles: Energy (ENR), Financial (FIN), Health (HLT), Technology (TCH), Utilities (UTL). The mutual fund data is from CRSP's mutual fund database, and is free of survivorship bias. Return data is available from 1/91 for all 5 fund styles and from dates earlier than 1/91 for other fund styles: growth and income (GRI), growth (GRO), maximum capital gains (CGM), and income (INC). Factor and instrument data are available from 1/27 to 12/07. Factor and instrument data are available from 1/27 to 12/07. *Sm* (*Lg*) refers to the portfolio of funds with beginning of year TNA below (above) the median for the specified fund style. Performance results are reported relative to the Fama-French pricing model in the first 8 columns and relative to the Carhart pricing model in the last 8 columns. For each pricing model, performance results are reported for return in excess of the riskfree rate in the first 4 columns, and in excess of return on a portfolio matched on the basis of Fama-French loadings in the last 4 columns. Panels A and B report the abnormal performance parameters $e$ and $f$ respectively for the fund-style portfolios, where $e$ measures mean conditional performance and $f$ measures the extent to which the conditional performance varies with the information variable. When parameters $e$ and $f$ are identified by moment conditions (21) and (22), they are estimated for each fund-style portfolio using the adjusted moment (Full) method that uses all available data, and using the standard GMM method (Short) that only uses data from 1/91 to 12/07. Standard errors for both are calculated using the adjusted-moment coefficients. For each fund-style portfolio, parameters $e$ and $f$ are also estimated for the regression-based (Reg) approach of Ferson and Harvey (1996) using data from 1/91 to 12/07. Newey-West standard errors for the parameter estimates of all 3 are in italics. In the % Reduction column (% Red), we report the percent reduction in the coefficient standard error from (in the first row) using the Full method rather than the Short method and (in the second row) from using the Full method rather than the portfolio-by-portfolio adjusted moment method, which, for each portfolio, uses only the factor moments and the moments for that TNA-style portfolio, constructed using all available data for the factors, the instruments and the returns on that portfolio. Panel C reports the p-values for Wald tests of joint significance based on the Newey-West covariances. The Wald tests for the Short and Reg methods only use data from 1/91 to 12/07. Further details of the methodologies employed are in section 4.

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel A: Abnormal performance: $e$ parameters (% per month) | | | | | | | | | | | | | | | | |
| ENR-*Sm* | 2.148 | 0.026 | 46.4 | 0.069 | 0.225 | 0.027 | 38.2 | 0.011 | 0.652 | -0.075 | 24.5 | -0.038 | 0.814 | 0.055 | 31.9 | -0.137 |
| | *0.307* | *0.572* | 10.9 | *0.313* | *0.285* | *0.460* | 16.0 | *0.289* | *0.206* | *0.273* | 16.7 | *0.306* | *0.243* | *0.356* | 9.1 | *0.284* |
| ENR-*Lg* | 2.119 | 0.120 | 45.0 | 0.184 | 0.319 | 0.120 | 37.1 | 0.125 | 0.783 | 0.025 | 26.9 | 0.085 | 1.035 | 0.155 | 32.0 | -0.014 |
| | *0.295* | *0.536* | 10.8 | *0.317* | *0.278* | *0.441* | 14.8 | *0.294* | *0.215* | *0.295* | 17.6 | *0.309* | *0.250* | *0.368* | 10.5 | *0.288* |
| FIN-*Sm* | -0.696 | 0.053 | 49.1 | 0.061 | -0.355 | 0.158 | 32.9 | 0.159 | -0.359 | 0.038 | 45.3 | 0.051 | -0.299 | 0.078 | 31.5 | 0.081 |
| | *0.225* | *0.443* | 7.4 | *0.165* | *0.147* | *0.219* | 13.1 | *0.199* | *0.195* | *0.356* | 7.3 | *0.158* | *0.144* | *0.210* | 9.9 | *0.197* |
| FIN-*Lg* | -0.982 | -0.056 | 50.0 | -0.050 | -0.516 | 0.049 | 35.9 | 0.047 | -0.348 | -0.035 | 45.4 | -0.024 | -0.318 | 0.005 | 29.8 | 0.006 |
| | *0.241* | *0.482* | 5.3 | *0.169* | *0.145* | *0.226* | 10.7 | *0.215* | *0.191* | *0.350* | 6.2 | *0.169* | *0.136* | *0.194* | 10.4 | *0.215* |
| HLT-*Sm* | 0.159 | 0.231 | 44.3 | 0.203 | 0.454 | 0.087 | 30.0 | 0.037 | -0.439 | 0.207 | 47.3 | 0.213 | -0.288 | 0.022 | 25.0 | -0.007 |
| | *0.407* | *0.730* | 20.7 | *0.238* | *0.207* | *0.296* | 22.1 | *0.240* | *0.298* | *0.566* | 9.4 | *0.258* | *0.168* | *0.224* | 20.7 | *0.247* |
| HLT-*Lg* | 0.453 | 0.379 | 45.2 | 0.344 | 0.505 | 0.235 | 29.6 | 0.178 | -0.303 | 0.263 | 48.6 | 0.251 | -0.226 | 0.078 | 26.6 | 0.030 |
| | *0.418* | *0.763* | 19.4 | *0.197* | *0.185* | *0.263* | 19.8 | *0.221* | *0.268* | *0.521* | 6.9 | *0.210* | *0.163* | *0.223* | 16.0 | *0.220* |
| TCH-*Sm* | 0.351 | 0.041 | 49.3 | 0.059 | 0.115 | -0.103 | 32.9 | 0.259 | 1.410 | 0.142 | 49.4 | 0.170 | 0.366 | -0.043 | 38.9 | 0.315 |
| | *0.287* | *0.566* | 8.9 | *0.195* | *0.163* | *0.243* | 13.9 | *0.221* | *0.322* | *0.636* | 7.7 | *0.198* | *0.187* | *0.306* | 8.3 | *0.209* |
| TCH-*Lg* | 0.648 | 0.182 | 48.9 | 0.196 | 0.296 | 0.038 | 34.0 | 0.396 | 1.296 | 0.213 | 49.5 | 0.240 | 0.236 | 0.028 | 36.9 | 0.385 |
| | *0.287* | *0.563* | 9.8 | *0.190* | *0.155* | *0.234* | 15.1 | *0.222* | *0.306* | *0.606* | 6.8 | *0.184* | *0.175* | *0.277* | 9.0 | *0.204* |
| UTL-*Sm* | -0.015 | -0.009 | 41.3 | -0.005 | 0.758 | 0.349 | 37.5 | 0.328 | -0.479 | -0.058 | 42.1 | -0.048 | 0.353 | 0.196 | 25.5 | 0.224 |
| | *0.185* | *0.314* | 17.9 | *0.189* | *0.190* | *0.304* | 8.4 | *0.179* | *0.178* | *0.308* | 13.7 | *0.189* | *0.174* | *0.233* | 10.6 | *0.193* |
| UTL-*Lg* | 0.061 | 0.066 | 39.8 | 0.065 | 0.814 | 0.268 | 38.4 | 0.398 | -0.372 | 0.036 | 41.7 | 0.042 | 0.447 | 0.184 | 28.8 | 0.315 |
| | *0.155* | *0.257* | 14.7 | *0.177* | *0.167* | *0.271* | 18.4 | *0.169* | *0.171* | *0.293* | 13.7 | *0.182* | *0.157* | *0.221* | 18.5 | *0.190* |
| Average $e$ | 0.425 | 0.103 | | 0.113 | 0.262 | 0.123 | | 0.194 | 0.184 | 0.076 | | 0.094 | 0.212 | 0.076 | | 0.120 |

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel B: Abnormal performance: $f$ parameters (% per month) | | | | | | | | | | | | | | | | |
| ENR-*Sm* | 2.383 | 0.220 | 47.4 | 0.425 | 1.968 | 0.386 | 46.3 | 0.283 | 0.563 | 0.112 | 34.4 | 0.291 | 0.432 | 0.028 | 38.1 | 0.158 |
| | *0.423* | *0.803* | 20.5 | *0.275* | *0.341* | *0.635* | 19.3 | *0.258* | *0.200* | *0.305* | 21.6 | *0.332* | *0.232* | *0.374* | 14.6 | *0.310* |
| ENR-*Lg* | 2.136 | 0.104 | 46.3 | 0.409 | 1.763 | 0.270 | 45.2 | 0.266 | 0.358 | -0.024 | 32.3 | 0.263 | 0.136 | -0.108 | 34.6 | 0.129 |
| | *0.396* | *0.737* | 20.3 | *0.309* | *0.321* | *0.585* | 18.4 | *0.295* | *0.231* | *0.341* | 20.4 | *0.373* | *0.256* | *0.391* | 15.7 | *0.349* |
| FIN-*Sm* | -0.440 | -0.060 | 51.7 | -0.021 | -0.070 | -0.248 | 32.5 | 0.020 | 0.110 | -0.060 | 49.8 | 0.003 | -0.073 | -0.201 | 35.8 | 0.033 |
| | *0.269* | *0.557* | 4.6 | *0.155* | *0.131* | *0.194* | 7.3 | *0.176* | *0.201* | *0.400* | 3.2 | *0.176* | *0.137* | *0.214* | 6.3 | *0.175* |
| FIN-*Lg* | -0.657 | -0.055 | 51.6 | -0.028 | -0.424 | -0.243 | 39.4 | 0.013 | 0.050 | -0.049 | 49.4 | 0.005 | -0.224 | -0.189 | 34.2 | 0.035 |
| | *0.314* | *0.650* | 5.7 | *0.171* | *0.157* | *0.259* | 6.8 | *0.209* | *0.210* | *0.414* | 3.5 | *0.202* | *0.145* | *0.221* | 8.4 | *0.211* |
| HLT-*Sm* | -2.779 | 0.172 | 46.2 | 0.041 | 0.094 | 0.392 | 27.4 | 0.157 | -0.776 | 0.287 | 47.6 | 0.313 | 0.152 | 0.475 | 29.6 | 0.334 |
| | *0.582* | *1.081* | 13.3 | *0.305* | *0.236* | *0.325* | 17.7 | *0.301* | *0.361* | *0.689* | 6.8 | *0.333* | *0.188* | *0.266* | 17.2 | *0.326* |
| HLT-*Lg* | -3.117 | -0.012 | 46.6 | -0.178 | -0.208 | 0.209 | 29.0 | -0.061 | -0.922 | 0.086 | 48.2 | 0.025 | 0.013 | 0.274 | 33.4 | 0.046 |
| | *0.604* | *1.131* | 13.5 | *0.266* | *0.219* | *0.309* | 16.5 | *0.275* | *0.335* | *0.647* | 6.4 | *0.273* | *0.187* | *0.281* | 13.9 | *0.278* |
| TCH-*Sm* | -0.718 | -0.489 | 49.9 | -0.400 | -0.068 | -0.269 | 31.2 | -0.347 | -0.052 | -0.474 | 51.1 | -0.337 | -0.026 | -0.285 | 42.2 | -0.241 |
| | *0.324* | *0.646* | 10.5 | *0.307* | *0.193* | *0.281* | 19.3 | *0.358* | *0.377* | *0.772* | 6.7 | *0.316* | *0.213* | *0.368* | 14.1 | *0.350* |
| TCH-*Lg* | -0.861 | -0.380 | 49.9 | -0.311 | 0.009 | -0.160 | 29.4 | -0.257 | -0.032 | -0.377 | 51.4 | -0.250 | 0.125 | -0.189 | 39.6 | -0.154 |
| | *0.328* | *0.655* | 10.2 | *0.281* | *0.183* | *0.259* | 17.3 | *0.340* | *0.352* | *0.725* | 4.9 | *0.274* | *0.194* | *0.322* | 13.0 | *0.320* |
| UTL-*Sm* | -0.883 | 0.158 | 47.1 | 0.180 | 0.770 | 0.176 | 43.5 | 0.353 | -0.347 | 0.194 | 46.6 | 0.241 | 0.001 | 0.198 | 35.3 | 0.423 |
| | *0.222* | *0.421* | 11.4 | *0.195* | *0.265* | *0.469* | 12.7 | *0.239* | *0.179* | *0.336* | 11.4 | *0.204* | *0.200* | *0.309* | 11.0 | *0.246* |
| UTL-*Lg* | -0.509 | 0.157 | 46.6 | 0.155 | 0.187 | 0.226 | 44.1 | 0.328 | -0.231 | 0.210 | 46.9 | 0.240 | 0.018 | 0.323 | 40.1 | 0.423 |
| | *0.168* | *0.315* | 9.8 | *0.161* | *0.183* | *0.328* | 18.4 | *0.201* | *0.161* | *0.303* | 9.4 | *0.175* | *0.158* | *0.263* | 17.8 | *0.215* |
| Panel C: Null hypotheses and test p-values | | | | | | | | | | | | | | | | |
| All $e = 0$ | 0.000 | 0.025 | | 0.083 | 0.000 | 0.067 | | 0.017 | 0.000 | 0.178 | | 0.113 | 0.000 | 0.860 | | 0.134 |
| All $e$ same | 0.000 | 0.024 | | 0.120 | 0.000 | 0.077 | | 0.098 | 0.000 | 0.134 | | 0.174 | 0.000 | 0.852 | | 0.188 |
| Avg $e = 0$ | 0.004 | 0.718 | | 0.198 | 0.000 | 0.279 | | 0.025 | 0.217 | 0.807 | | 0.275 | 0.000 | 0.392 | | 0.148 |
| All $f = 0$ | 0.000 | 0.642 | | 0.457 | 0.000 | 0.571 | | 0.360 | 0.000 | 0.173 | | 0.385 | 0.003 | 0.299 | | 0.191 |
| All $f$ same | 0.000 | 0.662 | | 0.367 | 0.000 | 0.476 | | 0.329 | 0.000 | 0.159 | | 0.375 | 0.002 | 0.225 | | 0.214 |
| Av $f = 0$ | 0.000 | 0.833 | | 0.147 | 0.000 | 0.590 | | 0.313 | 0.030 | 0.890 | | 0.427 | 0.237 | 0.915 | | 0.659 |
| Av $f_{\text{ENR}}$ = Av $f_{\text{rest}}$ | 0.000 | 0.876 | | 0.132 | 0.000 | 0.612 | | 0.365 | 0.013 | 0.908 | | 0.449 | 0.277 | 0.740 | | 0.782 |
| Av $f = 0$ | 0.059 | 0.924 | | 0.876 | 0.074 | 0.256 | | 0.929 | 0.694 | 0.894 | | 0.982 | 0.281 | 0.358 | | 0.856 |
| Av $f_{\text{FIN}}$ = Av $f_{\text{rest}}$ | 0.160 | 0.934 | | 0.819 | 0.000 | 0.382 | | 0.914 | 0.224 | 0.927 | | 0.850 | 0.192 | 0.426 | | 0.901 |
| Av $f = 0$ | 0.000 | 0.942 | | 0.806 | 0.798 | 0.333 | | 0.863 | 0.014 | 0.780 | | 0.568 | 0.648 | 0.161 | | 0.520 |
| Av $f_{\text{HLT}}$ = Av $f_{\text{rest}}$ | 0.000 | 0.864 | | 0.741 | 0.003 | 0.599 | | 0.967 | 0.002 | 0.543 | | 0.620 | 0.992 | 0.331 | | 0.624 |
| Av $f = 0$ | 0.014 | 0.502 | | 0.221 | 0.873 | 0.419 | | 0.383 | 0.908 | 0.569 | | 0.313 | 0.805 | 0.486 | | 0.551 |
| Av $f_{\text{TCH}}$ = Av $f_{\text{rest}}$ | 0.807 | 0.217 | | 0.168 | 0.001 | 0.322 | | 0.276 | 0.502 | 0.357 | | 0.208 | 0.829 | 0.286 | | 0.393 |
| Av $f = 0$ | 0.000 | 0.668 | | 0.342 | 0.021 | 0.592 | | 0.119 | 0.088 | 0.526 | | 0.201 | 0.954 | 0.324 | | 0.065 |
| Av $f_{\text{UTL}}$ = Av $f_{\text{rest}}$ | 0.414 | 0.560 | | 0.322 | 0.306 | 0.668 | | 0.082 | 0.628 | 0.550 | | 0.227 | 0.573 | 0.258 | | 0.056 |
| Av $f_{Sm} = 0$ | 0.008 | 0.999 | | 0.685 | 0.000 | 0.677 | | 0.469 | 0.572 | 0.975 | | 0.445 | 0.238 | 0.760 | | 0.279 |
| Av $f_{Lg} = 0$ | 0.002 | 0.925 | | 0.929 | 0.001 | 0.652 | | 0.644 | 0.381 | 0.934 | | 0.663 | 0.848 | 0.853 | | 0.447 |
| Av $f_{Sm}$ =Av $f_{Lg}$ | 0.000 | 0.454 | | 0.328 | 0.000 | 0.800 | | 0.328 | 0.039 | 0.309 | | 0.226 | 0.047 | 0.753 | | 0.226 |
| All $f_{Sm} = f_{Lg}$ | 0.000 | 0.286 | | 0.483 | 0.000 | 0.314 | | 0.483 | 0.003 | 0.151 | | 0.305 | 0.002 | 0.191 | | 0.305 |
| $f_{\text{ENR-Sm}} = f_{\text{ENR-Lg}}$ | 0.001 | 0.314 | | 0.877 | 0.004 | 0.248 | | 0.877 | 0.012 | 0.246 | | 0.796 | 0.001 | 0.312 | | 0.796 |
| $f_{\text{FIN-Sm}} = f_{\text{FIN-Lg}}$ | 0.002 | 0.969 | | 0.927 | 0.000 | 0.973 | | 0.927 | 0.247 | 0.885 | | 0.985 | 0.015 | 0.907 | | 0.985 |
| $f_{\text{HLT-Sm}} = f_{\text{HLT-Lg}}$ | 0.000 | 0.147 | | 0.103 | 0.001 | 0.162 | | 0.103 | 0.070 | 0.083 | | 0.034 | 0.127 | 0.085 | | 0.034 |
| $f_{\text{TCH-Sm}} = f_{\text{TCH-Lg}}$ | 0.094 | 0.349 | | 0.328 | 0.324 | 0.256 | | 0.328 | 0.812 | 0.429 | | 0.414 | 0.086 | 0.428 | | 0.414 |
| $f_{\text{UTL-Sm}} = f_{\text{UTL-Lg}}$ | 0.000 | 0.995 | | 0.687 | 0.002 | 0.870 | | 0.687 | 0.002 | 0.764 | | 0.997 | 0.918 | 0.577 | | 0.997 |

Table 8: Conditional fund performance relative to a conditional factor model with term spread as the instrument.

This table reports performance results for the following fund styles: Energy (ENR), Financial (FIN), Health (HLT), Technology (TCH), Utilities (UTL). The mutual fund data is from CRSP's mutual fund database, and is free of survivorship bias. Return data is available from 1/91 for all 5 fund styles and from dates earlier than 1/91 for other fund styles: growth and income (GRI), growth (GRO), maximum capital gains (CGM), and income (INC). Factor and instrument data are available from 1/27 to 12/07. Factor and instrument data are available from 1/27 to 12/07. *Sm* (*Lg*) refers to the portfolio of funds with beginning of year TNA below (above) the median for the specified fund style. Performance results are reported relative to the Fama-French pricing model in the first 8 columns and relative to the Carhart pricing model in the last 8 columns. For each pricing model, performance results are reported for return in excess of the riskfree rate in the first 4 columns, and in excess of return on a portfolio matched on the basis of Fama-French loadings in the last 4 columns. Panels A and B report the abnormal performance parameters $e$ and $f$ respectively for the fund-style portfolios, where $e$ measures mean conditional performance and $f$ measures the extent to which the conditional performance varies with the information variable. When parameters $e$ and $f$ are identified by moment conditions (21) and (22), they are estimated for each fund-style portfolio using the adjusted moment (Full) method that uses all available data, and using the standard GMM method (Short) that only uses data from 1/91 to 12/07. Standard errors for both are calculated using the adjusted-moment coefficients. For each fund-style portfolio, parameters $e$ and $f$ are also estimated for the regression-based (Reg) approach of Ferson and Harvey (1996) using data from 1/91 to 12/07. Newey-West standard errors for the parameter estimates of all 3 are in italics. In the % Reduction column (% Red), we report the percent reduction in the coefficient standard error from (in the first row) using the Full method rather than the Short method and (in the second row) from using the Full method rather than the portfolio-by-portfolio adjusted moment method, which, for each portfolio, uses only the factor moments and the moments for that TNA-style portfolio, constructed using all available data for the factors, the instruments and the returns on that portfolio. Panel C reports the p-values for Wald tests of joint significance based on the Newey-West covariances. The Wald tests for the Short and Reg methods only use data from 1/91 to 12/07. Further details of the methodologies employed are in section 4.

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel A: Abnormal performance: $e$ parameters (% per month) | | | | | | | | | | | | | | | | |
| ENR-*Sm* | 0.818 | -0.207 | 33.8 | -0.211 | -0.037 | -0.150 | 21.9 | -0.077 | -0.183 | -0.160 | 27.6 | -0.164 | -0.227 | -0.167 | 20.9 | -0.065 |
| | *0.268* | *0.405* | 23.9 | *0.365* | *0.220* | *0.282* | 9.9 | *0.315* | *0.264* | *0.365* | 20.7 | *0.349* | *0.208* | *0.263* | 14.7 | *0.275* |
| ENR-*Lg* | 1.001 | -0.097 | 34.5 | -0.097 | -0.167 | -0.160 | 23.7 | -0.144 | 0.040 | -0.046 | 29.8 | -0.049 | -0.340 | -0.129 | 24.1 | -0.123 |
| | *0.286* | *0.437* | 25.6 | *0.391* | *0.232* | *0.303* | 18.1 | *0.358* | *0.265* | *0.378* | 23.5 | *0.382* | *0.234* | *0.308* | 20.6 | *0.331* |
| FIN-*Sm* | 0.045 | -0.037 | 45.2 | -0.108 | 0.315 | -0.002 | 31.0 | 0.026 | -0.248 | -0.085 | 44.7 | -0.186 | 0.044 | -0.129 | 28.7 | -0.087 |
| | *0.174* | *0.317* | 9.8 | *0.172* | *0.129* | *0.187* | 5.2 | *0.176* | *0.168* | *0.305* | 14.2 | *0.157* | *0.124* | *0.174* | 8.6 | *0.169* |
| FIN-*Lg* | -0.168 | -0.155 | 45.1 | -0.217 | 0.072 | -0.120 | 26.5 | -0.083 | -0.294 | -0.154 | 44.0 | -0.230 | -0.081 | -0.199 | 25.8 | -0.132 |
| | *0.170* | *0.309* | 8.1 | *0.168* | *0.127* | *0.173* | 4.8 | *0.184* | *0.165* | *0.295* | 12.8 | *0.165* | *0.122* | *0.165* | 8.2 | *0.185* |
| HLT-*Sm* | 1.022 | 0.406 | 29.9 | 0.346 | 0.754 | 0.279 | 32.5 | 0.226 | 0.263 | 0.339 | 44.2 | 0.319 | 0.587 | 0.209 | 31.9 | 0.205 |
| | *0.260* | *0.371* | 18.8 | *0.330* | *0.269* | *0.398* | 21.3 | *0.321* | *0.228* | *0.408* | 12.6 | *0.295* | *0.200* | *0.294* | 15.5 | *0.290* |
| HLT-*Lg* | 0.858 | 0.605 | 34.2 | 0.541 | 0.486 | 0.478 | 34.7 | 0.421 | 0.308 | 0.478 | 43.5 | 0.449 | 0.355 | 0.348 | 36.1 | 0.334 |
| | *0.206* | *0.313* | 13.9 | *0.278* | *0.210* | *0.322* | 15.3 | *0.298* | *0.192* | *0.341* | 10.7 | *0.245* | *0.201* | *0.315* | 13.4 | *0.263* |
| TCH-*Sm* | -0.021 | 0.128 | 45.6 | 0.164 | -0.425 | 0.001 | 34.4 | 0.298 | 0.871 | 0.263 | 49.1 | 0.308 | 0.264 | 0.133 | 37.9 | 0.394 |
| | *0.252* | *0.463* | 10.6 | *0.283* | *0.189* | *0.288* | 15.7 | *0.353* | *0.352* | *0.692* | 6.3 | *0.289* | *0.206* | *0.331* | 12.7 | *0.318* |
| TCH-*Lg* | 0.117 | 0.255 | 46.4 | 0.273 | -0.050 | 0.128 | 34.2 | 0.391 | 1.003 | 0.324 | 49.4 | 0.346 | 0.338 | 0.194 | 39.5 | 0.432 |
| | *0.230* | *0.428* | 10.0 | *0.242* | *0.172* | *0.262* | 12.2 | *0.306* | *0.341* | *0.672* | 4.8 | *0.240* | *0.188* | *0.310* | 13.1 | *0.282* |
| UTL-*Sm* | 0.244 | -0.003 | 24.9 | 0.009 | 0.418 | 0.103 | 35.9 | 0.155 | -0.089 | -0.025 | 34.0 | -0.002 | 0.327 | 0.037 | 27.0 | 0.093 |
| | *0.160* | *0.214* | 13.5 | *0.196* | *0.190* | *0.297* | 23.4 | *0.254* | *0.179* | *0.271* | 17.5 | *0.178* | *0.165* | *0.225* | 18.6 | *0.222* |
| UTL-*Lg* | 0.092 | 0.098 | 28.8 | 0.123 | 0.235 | 0.204 | 34.4 | 0.269 | -0.063 | 0.076 | 34.7 | 0.117 | 0.326 | 0.138 | 25.5 | 0.212 |
| | *0.140* | *0.197* | 9.9 | *0.169* | *0.177* | *0.271* | 22.2 | *0.231* | *0.167* | *0.255* | 15.8 | *0.157* | *0.157* | *0.211* | 19.7 | *0.206* |
| Average $e$ | 0.401 | 0.099 | | 0.082 | 0.160 | 0.076 | | 0.148 | 0.161 | 0.101 | | 0.091 | 0.159 | 0.044 | | 0.126 |

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel B: Abnormal performance: $f$ parameters (% per month) | | | | | | | | | | | | | | | | |
| ENR-*Sm* | 1.181 | -0.023 | 35.7 | -0.034 | 0.147 | -0.093 | 24.7 | 0.080 | -0.449 | -0.031 | 33.3 | -0.042 | 0.141 | -0.105 | 24.7 | 0.086 |
| | *0.227* | *0.353* | 21.1 | *0.319* | *0.158* | *0.211* | 13.5 | *0.293* | *0.216* | *0.324* | 20.2 | *0.295* | *0.164* | *0.218* | 17.2 | *0.245* |
| ENR-*Lg* | 1.383 | 0.018 | 35.7 | 0.016 | 0.535 | -0.063 | 29.5 | -0.018 | -0.205 | 0.017 | 34.2 | 0.008 | 0.028 | -0.055 | 23.7 | -0.017 |
| | *0.247* | *0.383* | 21.0 | *0.337* | *0.192* | *0.272* | 16.1 | *0.316* | *0.204* | *0.310* | 22.3 | *0.314* | *0.185* | *0.242* | 20.3 | *0.273* |
| FIN-*Sm* | -0.137 | -0.235 | 43.8 | -0.438 | -0.864 | -0.514 | 28.2 | -0.323 | 0.145 | -0.135 | 43.0 | -0.421 | -0.769 | -0.400 | 23.4 | -0.294 |
| | *0.119* | *0.213* | 11.2 | *0.171* | *0.126* | *0.176* | 9.8 | *0.180* | *0.122* | *0.214* | 14.1 | *0.141* | *0.118* | *0.154* | 13.8 | *0.165* |
| FIN-*Lg* | -0.137 | -0.220 | 43.1 | -0.396 | -0.859 | -0.499 | 27.3 | -0.282 | -0.010 | -0.179 | 41.1 | -0.396 | -0.755 | -0.444 | 21.9 | -0.268 |
| | *0.118* | *0.208* | 12.3 | *0.158* | *0.125* | *0.172* | 10.2 | *0.180* | *0.116* | *0.197* | 15.2 | *0.146* | *0.123* | *0.157* | 14.7 | *0.178* |
| HLT-*Sm* | 0.285 | 0.201 | 25.4 | 0.031 | 0.623 | 0.207 | 35.0 | 0.058 | 0.405 | 0.103 | 40.4 | 0.046 | 0.240 | 0.083 | 32.8 | 0.072 |
| | *0.238* | *0.319* | 17.5 | *0.295* | *0.252* | *0.387* | 20.6 | *0.284* | *0.200* | *0.335* | 12.9 | *0.235* | *0.195* | *0.291* | 19.6 | *0.232* |
| HLT-*Lg* | 0.036 | 0.149 | 26.1 | -0.033 | 0.243 | 0.155 | 40.3 | -0.006 | 0.363 | 0.086 | 39.0 | 0.001 | 0.298 | 0.066 | 37.7 | 0.027 |
| | *0.187* | *0.253* | 11.6 | *0.261* | *0.205* | *0.343* | 15.5 | *0.257* | *0.169* | *0.278* | 10.6 | *0.194* | *0.176* | *0.283* | 16.1 | *0.206* |
| TCH-*Sm* | 0.073 | 0.135 | 47.7 | 0.239 | -0.190 | 0.141 | 36.3 | 0.354 | -0.108 | 0.076 | 51.4 | 0.204 | -0.380 | 0.057 | 45.6 | 0.137 |
| | *0.237* | *0.454* | 8.5 | *0.194* | *0.163* | *0.256* | 12.8 | *0.256* | *0.361* | *0.742* | 6.8 | *0.189* | *0.186* | *0.341* | 13.6 | *0.218* |
| TCH-*Lg* | 0.398 | 0.138 | 47.2 | 0.188 | -0.134 | 0.144 | 32.8 | 0.110 | 0.240 | 0.111 | 51.4 | 0.173 | -0.347 | 0.091 | 44.9 | 0.106 |
| | *0.239* | *0.453* | 11.3 | *0.188* | *0.157* | *0.234* | 14.6 | *0.243* | *0.355* | *0.731* | 5.9 | *0.183* | *0.178* | *0.323* | 13.1 | *0.211* |
| UTL-*Sm* | 0.869 | 0.239 | 40.3 | 0.273 | 0.045 | 0.129 | 39.3 | 0.138 | 1.368 | 0.218 | 42.0 | 0.283 | 0.810 | 0.082 | 34.3 | 0.163 |
| | *0.150* | *0.251* | 17.4 | *0.180* | *0.150* | *0.247* | 20.8 | *0.209* | *0.187* | *0.322* | 19.0 | *0.154* | *0.130* | *0.198* | 21.7 | *0.163* |
| UTL-*Lg* | 0.692 | 0.206 | 42.8 | 0.277 | -0.083 | 0.095 | 36.5 | 0.141 | 1.163 | 0.170 | 43.3 | 0.284 | 0.594 | 0.034 | 34.2 | 0.165 |
| | *0.143* | *0.250* | 13.4 | *0.174* | *0.146* | *0.231* | 18.6 | *0.207* | *0.173* | *0.306* | 18.0 | *0.150* | *0.124* | *0.189* | 21.2 | *0.165* |
| Panel C: Null hypotheses and test p-values | | | | | | | | | | | | | | | | |
| All $e = 0$ | 0.000 | 0.004 | | 0.000 | 0.000 | 0.154 | | 0.129 | 0.000 | 0.046 | | 0.000 | 0.001 | 0.663 | | 0.094 |
| All $e$ same | 0.000 | 0.003 | | 0.000 | 0.000 | 0.127 | | 0.205 | 0.000 | 0.034 | | 0.000 | 0.001 | 0.570 | | 0.145 |
| Avg $e = 0$ | 0.001 | 0.650 | | 0.518 | 0.028 | 0.510 | | 0.326 | 0.238 | 0.709 | | 0.426 | 0.006 | 0.598 | | 0.273 |
| All $f = 0$ | 0.000 | 0.691 | | 0.096 | 0.000 | 0.054 | | 0.049 | 0.000 | 0.935 | | 0.075 | 0.000 | 0.067 | | 0.237 |
| All $f$ same | 0.000 | 0.627 | | 0.225 | 0.000 | 0.603 | | 0.275 | 0.000 | 0.924 | | 0.090 | 0.000 | 0.496 | | 0.205 |
| Av $f = 0$ | 0.000 | 0.995 | | 0.978 | 0.043 | 0.736 | | 0.917 | 0.115 | 0.982 | | 0.956 | 0.615 | 0.717 | | 0.890 |
| Av $f_{\text{ENR}}$ = Av $f_{\text{rest}}$ | 0.001 | 0.745 | | 0.959 | 0.008 | 0.896 | | 0.945 | 0.002 | 0.872 | | 0.933 | 0.525 | 0.963 | | 0.917 |
| Av $f = 0$ | 0.245 | 0.276 | | 0.010 | 0.000 | 0.003 | | 0.089 | 0.565 | 0.440 | | 0.004 | 0.000 | 0.006 | | 0.099 |
| Av $f_{\text{FIN}}$ = Av $f_{\text{rest}}$ | 0.000 | 0.187 | | 0.021 | 0.000 | 0.071 | | 0.087 | 0.038 | 0.514 | | 0.004 | 0.000 | 0.094 | | 0.076 |
| Av $f = 0$ | 0.441 | 0.530 | | 0.996 | 0.052 | 0.611 | | 0.922 | 0.033 | 0.755 | | 0.909 | 0.133 | 0.789 | | 0.816 |
| Av $f_{\text{HLT}}$ = Av $f_{\text{rest}}$ | 0.005 | 0.810 | | 0.975 | 0.002 | 0.378 | | 0.950 | 0.645 | 0.896 | | 0.929 | 0.054 | 0.512 | | 0.827 |
| Av $f = 0$ | 0.318 | 0.762 | | 0.255 | 0.304 | 0.556 | | 0.330 | 0.853 | 0.899 | | 0.302 | 0.043 | 0.823 | | 0.567 |
| Av $f_{\text{TCH}}$ = Av $f_{\text{rest}}$ | 0.008 | 0.870 | | 0.259 | 0.646 | 0.488 | | 0.285 | 0.117 | 0.955 | | 0.330 | 0.040 | 0.580 | | 0.572 |
| Av $f = 0$ | 0.000 | 0.370 | | 0.117 | 0.896 | 0.636 | | 0.501 | 0.000 | 0.535 | | 0.061 | 0.000 | 0.761 | | 0.313 |
| Av $f_{\text{UTL}}$ = Av $f_{\text{rest}}$ | 0.554 | 0.457 | | 0.070 | 0.575 | 0.299 | | 0.420 | 0.000 | 0.650 | | 0.049 | 0.000 | 0.397 | | 0.264 |
| Av $f_{Sm} = 0$ | 0.000 | 0.770 | | 0.897 | 0.508 | 0.815 | | 0.663 | 0.020 | 0.844 | | 0.864 | 0.885 | 0.488 | | 0.712 |
| Av $f_{Lg} = 0$ | 0.000 | 0.781 | | 0.921 | 0.320 | 0.720 | | 0.936 | 0.007 | 0.859 | | 0.845 | 0.448 | 0.376 | | 0.976 |
| Av $f_{Sm}$ =Av $f_{Lg}$ | 0.441 | 0.887 | | 0.900 | 0.725 | 0.875 | | 0.113 | 0.111 | 0.863 | | 0.995 | 0.171 | 0.918 | | 0.389 |
| All $f_{Sm} = f_{Lg}$ | 0.000 | 0.986 | | 0.926 | 0.000 | 0.989 | | 0.646 | 0.000 | 0.950 | | 0.964 | 0.000 | 0.809 | | 0.897 |
| $f_{\text{ENR-Sm}} = f_{\text{ENR-Lg}}$ | 0.000 | 0.549 | | 0.456 | 0.000 | 0.842 | | 0.433 | 0.000 | 0.541 | | 0.471 | 0.256 | 0.699 | | 0.445 |
| $f_{\text{FIN-Sm}} = f_{\text{FIN-Lg}}$ | 0.991 | 0.742 | | 0.479 | 0.885 | 0.745 | | 0.479 | 0.000 | 0.447 | | 0.592 | 0.706 | 0.339 | | 0.592 |
| $f_{\text{HLT-Sm}} = f_{\text{HLT-Lg}}$ | 0.013 | 0.715 | | 0.575 | 0.001 | 0.744 | | 0.575 | 0.608 | 0.887 | | 0.708 | 0.552 | 0.907 | | 0.708 |
| $f_{\text{TCH-Sm}} = f_{\text{TCH-Lg}}$ | 0.000 | 0.979 | | 0.466 | 0.343 | 0.974 | | 0.113 | 0.000 | 0.711 | | 0.654 | 0.575 | 0.640 | | 0.654 |
| $f_{\text{UTL-Sm}} = f_{\text{UTL-Lg}}$ | 0.000 | 0.621 | | 0.933 | 0.005 | 0.614 | | 0.933 | 0.000 | 0.436 | | 0.962 | 0.000 | 0.443 | | 0.962 |

Table 9: Conditional fund performance relative to a conditional factor model with dividend yield as the instrument.

This table reports performance results for the following fund styles: Small Cap Growth (SCG), Flexible (FLX), Mid-Cap Growth (MCG). The mutual fund data is from CRSP's mutual fund database, and is free of survivorship bias. Return data is available from 1/91 for SCG, from 1/93 from FLX, from 1/95 from MCG, and from dates earlier than 1/91 or 1/91 for other fund styles: growth and income (GRI), growth (GRO), maximum capital gains (CGM), income (INC), energy (ENR), financial (FIN), health(HLT), technology (TCH), and utilities (UTL). Factor and instrument data are available from 1/27 to 12/07. *Sm* (*Lg*) refers to the portfolio of funds with beginning of year TNA below (above) the median for the specified fund style. Performance results are reported relative to the Fama-French pricing model in the first 8 columns and relative to the Carhart pricing model in the last 8 columns. For each pricing model, performance results are reported for return in excess of the riskfree rate in the first 4 columns, and in excess of return on a portfolio matched on the basis of Fama-French loadings in the last 4 columns. Panels A and B report the abnormal performance parameters $e$ and $f$ respectively for the fund-style portfolios, where $e$ measures mean conditional performance and $f$ measures the extent to which the conditional performance varies with the information variable. When parameters $e$ and $f$ are identified by moment conditions (21) and (22), they are estimated for each fund-style portfolio using the adjusted moment (Full) method that uses all available data, and using the standard GMM method (Short) that only uses data from 1/95 to 12/07. Standard errors for both are calculated using the adjusted-moment coefficients. For each fund-style portfolio, parameters $e$ and $f$ are also estimated for the regression-based (Reg) approach of Ferson and Harvey (1996) using data from 1/95 to 12/07. Newey-West standard errors for the parameter estimates of all 3 are in italics. In the % Reduction column (% Red), we report the percent reduction in the coefficient standard error from (in the first row) using the Full method rather than the Short method and (in the second row) from using the Full method rather than the portfolio-by-portfolio adjusted moment method, which, for each portfolio, uses only the factor moments and the moments for that TNA-style portfolio, constructed using all available data for the factors, the instruments and the returns on that portfolio. Panel C reports the p-values for Wald tests of joint significance based on the Newey-West covariances. The Wald tests for the Short and Reg methods only use data from 1/95 to 12/07. Further details of the methodologies employed are in section 4.

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel A: Abnormal performance: $e$ parameters (% per month) | | | | | | | | | | | | | | | | |
| SCG-*Sm* | 0.097 | -0.021 | 58.6 | -0.021 | -0.124 | 0.267 | 41.1 | -0.105 | -0.069 | -0.073 | 58.7 | -0.072 | 0.041 | 0.140 | 30.0 | -0.191 |
| | *0.165* | *0.399* | 4.5 | *0.096* | *0.083* | *0.141* | 13.8 | *0.125* | *0.170* | *0.411* | 5.7 | *0.105* | *0.074* | *0.106* | 11.6 | *0.135* |
| SCG-*Lg* | -0.042 | -0.075 | 58.6 | -0.074 | -0.272 | 0.213 | 41.7 | -0.158 | -0.156 | -0.144 | 59.0 | -0.143 | -0.040 | 0.069 | 32.8 | -0.262 |
| | *0.192* | *0.463* | 5.9 | *0.087* | *0.087* | *0.149* | 15.9 | *0.130* | *0.180* | *0.440* | 3.6 | *0.094* | *0.066* | *0.099* | 10.1 | *0.137* |
| FLX-*Sm* | 0.010 | -0.078 | 58.3 | -0.078 | -0.070 | -0.162 | 53.7 | -0.038 | -0.141 | -0.108 | 58.9 | -0.108 | -0.263 | -0.226 | 54.3 | -0.145 |
| | *0.077* | *0.186* | 4.6 | *0.041* | *0.067* | *0.144* | 22.6 | *0.127* | *0.091* | *0.222* | 2.7 | *0.040* | *0.068* | *0.148* | 21.0 | *0.128* |
| FLX-*Lg* | 0.131 | -0.093 | 58.5 | -0.093 | 0.093 | -0.177 | 55.8 | -0.054 | -0.035 | -0.089 | 59.1 | -0.089 | -0.215 | -0.207 | 54.5 | -0.126 |
| | *0.074* | *0.179* | 3.0 | *0.033* | *0.076* | *0.173* | 21.5 | *0.138* | *0.089* | *0.218* | 1.8 | *0.032* | *0.069* | *0.152* | 22.3 | *0.137* |
| MCG-*Sm* | -0.142 | 0.096 | 59.2 | 0.097 | 0.086 | 0.115 | 48.8 | -0.095 | -0.104 | 0.031 | 59.3 | 0.032 | -0.168 | -0.053 | 43.2 | -0.214 |
| | *0.209* | *0.513* | 5.1 | *0.108* | *0.145* | *0.284* | 28.9 | *0.103* | *0.242* | *0.595* | 5.2 | *0.107* | *0.100* | *0.175* | 21.0 | *0.089* |
| MCG-*Lg* | -0.290 | 0.095 | 59.1 | 0.096 | -0.266 | -0.097 | 52.7 | -0.097 | -0.185 | 0.021 | 59.4 | 0.022 | -0.520 | -0.224 | 55.0 | -0.224 |
| | *0.236* | *0.578* | 5.4 | *0.109* | *0.104* | *0.220* | 25.7 | *0.099* | *0.267* | *0.657* | 4.2 | *0.107* | *0.104* | *0.230* | 19.9 | *0.090* |
| Average $e$ | -0.040 | -0.013 | | -0.012 | -0.092 | 0.026 | | -0.091 | -0.115 | -0.060 | | -0.060 | -0.194 | -0.083 | | -0.194 |

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel B: Abnormal performance: $f$ parameters (% per month) | | | | | | | | | | | | | | | | |
| SCG-*Sm* | -0.170 | -0.013 | 58.8 | 0.056 | 0.081 | 0.058 | 39.1 | -0.109 | -0.010 | -0.046 | 59.0 | 0.032 | 0.035 | 0.044 | 41.2 | -0.122 |
| | *0.178* | *0.433* | 3.7 | *0.102* | *0.084* | *0.138* | 13.2 | *0.131* | *0.186* | *0.452* | 3.7 | *0.115* | *0.077* | *0.131* | 7.5 | *0.124* |
| SCG-*Lg* | -0.485 | 0.020 | 58.7 | 0.113 | -0.062 | 0.091 | 40.7 | -0.052 | -0.111 | 0.013 | 59.3 | 0.153 | 0.000 | 0.103 | 47.5 | -0.001 |
| | *0.221* | *0.535* | 4.6 | *0.102* | *0.099* | *0.167* | 13.8 | *0.145* | *0.205* | *0.504* | 2.2 | *0.105* | *0.086* | *0.163* | 4.9 | *0.125* |
| FLX-*Sm* | -0.010 | 0.000 | 58.9 | 0.018 | -0.067 | -0.162 | 55.8 | 0.042 | -0.048 | -0.022 | 59.1 | -0.015 | -0.050 | -0.155 | 56.8 | -0.015 |
| | *0.089* | *0.217* | 3.3 | *0.046* | *0.081* | *0.183* | 20.3 | *0.159* | *0.106* | *0.258* | 2.7 | *0.044* | *0.075* | *0.173* | 16.2 | *0.145* |
| FLX-*Lg* | 0.066 | 0.019 | 58.2 | 0.000 | 0.011 | -0.143 | 56.7 | 0.025 | -0.011 | 0.030 | 58.9 | 0.009 | 0.033 | -0.102 | 56.4 | 0.009 |
| | *0.083* | *0.198* | 5.3 | *0.040* | *0.101* | *0.234* | 20.3 | *0.162* | *0.102* | *0.248* | 2.6 | *0.042* | *0.084* | *0.194* | 19.1 | *0.160* |
| MCG-*Sm* | -0.644 | -0.277 | 59.1 | -0.137 | -1.297 | -0.198 | 54.4 | -0.006 | -0.326 | -0.283 | 59.4 | -0.116 | -0.434 | -0.182 | 52.5 | -0.089 |
| | *0.244* | *0.597* | 5.3 | *0.131* | *0.218* | *0.479* | 27.1 | *0.112* | *0.268* | *0.660* | 3.7 | *0.128* | *0.139* | *0.293* | 18.1 | *0.108* |
| MCG-*Lg* | -0.493 | -0.019 | 59.1 | 0.121 | 0.640 | 0.265 | 54.9 | 0.252 | -0.140 | -0.035 | 59.5 | 0.161 | 0.415 | 0.233 | 56.5 | 0.188 |
| | *0.272* | *0.666* | 6.0 | *0.152* | *0.119* | *0.263* | 20.3 | *0.108* | *0.298* | *0.735* | 2.8 | *0.137* | *0.115* | *0.265* | 15.8 | *0.107* |
| Panel C: Null hypotheses and test p-values | | | | | | | | | | | | | | | | |
| All $e = 0$ | 0.000 | 0.140 | | 0.000 | 0.000 | 0.405 | | 0.602 | 0.000 | 0.062 | | 0.000 | 0.000 | 0.585 | | 0.008 |
| All $e$ same | 0.000 | 0.499 | | 0.005 | 0.000 | 0.301 | | 0.731 | 0.000 | 0.490 | | 0.002 | 0.000 | 0.468 | | 0.657 |
| Avg $e = 0$ | 0.826 | 0.977 | | 0.855 | 0.050 | 0.751 | | 0.146 | 0.568 | 0.904 | | 0.383 | 0.000 | 0.262 | | 0.001 |
| All $f = 0$ | 0.000 | 0.000 | | 0.000 | 0.000 | 0.191 | | 0.000 | 0.000 | 0.000 | | 0.000 | 0.000 | 0.057 | | 0.000 |
| All $f$ same | 0.000 | 0.000 | | 0.000 | 0.000 | 0.128 | | 0.000 | 0.000 | 0.000 | | 0.000 | 0.000 | 0.069 | | 0.000 |
| Av $f = 0$ | 0.099 | 0.994 | | 0.392 | 0.916 | 0.610 | | 0.553 | 0.756 | 0.973 | | 0.386 | 0.826 | 0.608 | | 0.611 |
| Av $f_{\text{SCG}}$ = Av $f_{\text{rest}}$ | 0.120 | 0.446 | | 0.272 | 0.018 | 0.503 | | 0.402 | 0.134 | 0.652 | | 0.309 | 0.813 | 0.551 | | 0.575 |
| Av $f = 0$ | 0.739 | 0.964 | | 0.772 | 0.753 | 0.461 | | 0.831 | 0.775 | 0.987 | | 0.924 | 0.917 | 0.479 | | 0.981 |
| Av $f_{\text{FLX}}$ = Av $f_{\text{rest}}$ | 0.018 | 0.871 | | 0.894 | 0.212 | 0.561 | | 0.874 | 0.525 | 0.855 | | 0.591 | 0.912 | 0.483 | | 0.995 |
| Av $f = 0$ | 0.027 | 0.815 | | 0.956 | 0.000 | 0.858 | | 0.254 | 0.409 | 0.819 | | 0.862 | 0.888 | 0.845 | | 0.642 |
| Av $f_{\text{MCG}}$ = Av $f_{\text{rest}}$ | 0.000 | 0.222 | | 0.827 | 0.016 | 0.732 | | 0.278 | 0.000 | 0.104 | | 0.965 | 0.900 | 0.806 | | 0.620 |
| Av $f_{Sm} = 0$ | 0.146 | 0.835 | | 0.799 | 0.000 | 0.537 | | 0.750 | 0.542 | 0.821 | | 0.695 | 0.017 | 0.479 | | 0.213 |
| Av $f_{Lg} = 0$ | 0.154 | 0.990 | | 0.336 | 0.002 | 0.558 | | 0.400 | 0.705 | 0.996 | | 0.165 | 0.000 | 0.363 | | 0.362 |
| Av $f_{Sm}$ =Av $f_{Lg}$ | 0.378 | 0.181 | | 0.001 | 0.000 | 0.411 | | 0.001 | 0.207 | 0.102 | | 0.000 | 0.000 | 0.233 | | 0.000 |
| All $f_{Sm} = f_{Lg}$ | 0.000 | 0.000 | | 0.000 | 0.000 | 0.415 | | 0.000 | 0.000 | 0.000 | | 0.000 | 0.000 | 0.321 | | 0.000 |
| $f_{\text{SCG-Sm}} = f_{\text{SCG-Lg}}$ | 0.000 | 0.804 | | 0.238 | 0.001 | 0.711 | | 0.238 | 0.009 | 0.492 | | 0.019 | 0.325 | 0.453 | | 0.019 |
| $f_{\text{FLX-Sm}} = f_{\text{FLX-Lg}}$ | 0.028 | 0.772 | | 0.758 | 0.028 | 0.790 | | 0.758 | 0.227 | 0.345 | | 0.653 | 0.006 | 0.355 | | 0.653 |
| $f_{\text{MCG-Sm}} = f_{\text{MCG-Lg}}$ | 0.000 | 0.002 | | 0.000 | 0.000 | 0.494 | | 0.000 | 0.000 | 0.006 | | 0.000 | 0.000 | 0.400 | | 0.000 |

Table 10: Conditional fund performance relative to a conditional factor model with term spread as the instrument.

This table reports performance results for the following fund styles: Small Cap Growth (SCG), Flexible (FLX), Mid-Cap Growth (MCG). The mutual fund data is from CRSP's mutual fund database, and is free of survivorship bias. Return data is available from 1/91 for SCG, from 1/93 from FLX, from 1/95 from MCG, and from dates earlier than 1/91 or 1/91 for other fund styles: growth and income (GRI), growth (GRO), maximum capital gains (CGM), income (INC), energy (ENR), financial (FIN), health(HLT), technology (TCH), and utilities (UTL). Factor and instrument data are available from 1/27 to 12/07. *Sm* (*Lg*) refers to the portfolio of funds with beginning of year TNA below (above) the median for the specified fund style. Performance results are reported relative to the Fama-French pricing model in the first 8 columns and relative to the Carhart pricing model in the last 8 columns. For each pricing model, performance results are reported for return in excess of the riskfree rate in the first 4 columns, and in excess of return on a portfolio matched on the basis of Fama-French loadings in the last 4 columns. Panels A and B report the abnormal performance parameters $e$ and $f$ respectively for the fund-style portfolios, where $e$ measures mean conditional performance and $f$ measures the extent to which the conditional performance varies with the information variable. When parameters $e$ and $f$ are identified by moment conditions (21) and (22), they are estimated for each fund-style portfolio using the adjusted moment (Full) method that uses all available data, and using the standard GMM method (Short) that only uses data from 1/95 to 12/07. Standard errors for both are calculated using the adjusted-moment coefficients. For each fund-style portfolio, parameters $e$ and $f$ are also estimated for the regression-based (Reg) approach of Ferson and Harvey (1996) using data from 1/95 to 12/07. Newey-West standard errors for the parameter estimates of all 3 are in italics. In the % Reduction column (% Red), we report the percent reduction in the coefficient standard error from (in the first row) using the Full method rather than the Short method and (in the second row) from using the Full method rather than the portfolio-by-portfolio adjusted moment method, which, for each portfolio, uses only the factor moments and the moments for that TNA-style portfolio, constructed using all available data for the factors, the instruments and the returns on that portfolio. Panel C reports the p-values for Wald tests of joint significance based on the Newey-West covariances. The Wald tests for the Short and Reg methods only use data from 1/95 to 12/07. Further details of the methodologies employed are in section 4.

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel A: Abnormal performance: $e$ parameters (% per month) | | | | | | | | | | | | | | | | |
| SCG-*Sm* | 0.031 | -0.139 | 57.1 | -0.139 | 0.255 | 0.069 | 37.1 | -0.017 | -0.157 | -0.129 | 56.8 | -0.129 | 0.353 | 0.005 | 37.9 | -0.064 |
| | *0.147* | *0.343* | 7.8 | *0.091* | *0.094* | *0.150* | 12.9 | *0.167* | *0.171* | *0.395* | 10.9 | *0.098* | *0.106* | *0.171* | 10.0 | *0.137* |
| SCG-*Lg* | -0.031 | -0.218 | 57.7 | -0.218 | 0.128 | -0.010 | 39.1 | -0.258 | -0.312 | -0.228 | 57.9 | -0.228 | 0.104 | -0.094 | 42.9 | -0.299 |
| | *0.153* | *0.363* | 6.5 | *0.090* | *0.107* | *0.176* | 16.5 | *0.146* | *0.176* | *0.418* | 7.0 | *0.083* | *0.090* | *0.158* | 7.2 | *0.119* |
| FLX-*Sm* | -0.015 | -0.064 | 56.3 | -0.064 | -0.071 | -0.103 | 49.1 | 0.059 | -0.088 | -0.093 | 58.0 | -0.093 | 0.022 | -0.164 | 52.0 | -0.028 |
| | *0.070* | *0.160* | 8.1 | *0.037* | *0.083* | *0.162* | 28.4 | *0.149* | *0.084* | *0.199* | 5.5 | *0.039* | *0.069* | *0.143* | 26.4 | *0.136* |
| FLX-*Lg* | -0.115 | -0.063 | 57.8 | -0.063 | -0.105 | -0.103 | 51.3 | 0.059 | -0.102 | -0.064 | 58.5 | -0.064 | 0.056 | -0.134 | 51.5 | 0.001 |
| | *0.071* | *0.168* | 5.3 | *0.032* | *0.080* | *0.164* | 29.8 | *0.153* | *0.081* | *0.195* | 5.4 | *0.032* | *0.072* | *0.149* | 30.2 | *0.143* |
| MCG-*Sm* | 0.334 | -0.058 | 57.8 | -0.057 | -0.029 | 0.189 | 42.6 | -0.127 | 0.273 | -0.074 | 58.4 | -0.074 | 0.094 | 0.033 | 42.4 | -0.174 |
| | *0.145* | *0.344* | 12.7 | *0.108* | *0.140* | *0.244* | 21.1 | *0.110* | *0.187* | *0.450* | 8.3 | *0.102* | *0.100* | *0.174* | 25.2 | *0.095* |
| MCG-*Lg* | 0.190 | -0.089 | 58.0 | -0.089 | -0.133 | -0.159 | 49.1 | -0.159 | 0.106 | -0.108 | 59.1 | -0.108 | -0.348 | -0.209 | 54.4 | -0.209 |
| | *0.161* | *0.383* | 12.0 | *0.116* | *0.067* | *0.131* | 29.2 | *0.113* | *0.202* | *0.495* | 5.8 | *0.100* | *0.085* | *0.186* | 19.6 | *0.096* |
| Average $e$ | 0.066 | -0.105 | | -0.105 | 0.008 | -0.020 | | -0.074 | -0.047 | -0.116 | | -0.116 | 0.047 | -0.094 | | -0.129 |

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel B: Abnormal performance: $f$ parameters (% per month) | | | | | | | | | | | | | | | | |
| SCG-*Sm* | 0.483 | 0.154 | 56.2 | 0.090 | -0.638 | -0.318 | 45.3 | 0.170 | 0.507 | 0.194 | 56.8 | 0.105 | 0.064 | -0.191 | 42.3 | 0.235 |
| | *0.126* | *0.288* | 13.9 | *0.097* | *0.094* | *0.172* | 11.4 | *0.210* | *0.134* | *0.310* | 9.6 | *0.089* | *0.078* | *0.135* | 16.3 | *0.183* |
| SCG-*Lg* | 0.297 | 0.019 | 56.5 | 0.019 | -0.794 | -0.454 | 44.4 | -0.101 | 0.387 | 0.070 | 57.7 | 0.064 | -0.048 | -0.315 | 47.4 | -0.034 |
| | *0.127* | *0.291* | 13.1 | *0.128* | *0.102* | *0.184* | 10.0 | *0.214* | *0.145* | *0.343* | 7.6 | *0.089* | *0.073* | *0.139* | 12.4 | *0.158* |
| FLX-*Sm* | 0.150 | -0.046 | 56.9 | -0.074 | -0.463 | -0.271 | 50.4 | 0.007 | 0.172 | -0.024 | 58.6 | -0.073 | -0.079 | -0.262 | 53.5 | 0.057 |
| | *0.061* | *0.142* | 7.5 | *0.040* | *0.081* | *0.163* | 22.9 | *0.171* | *0.079* | *0.191* | 3.8 | *0.043* | *0.066* | *0.141* | 24.2 | *0.163* |
| FLX-*Lg* | 0.244 | 0.023 | 57.8 | -0.003 | -0.361 | -0.203 | 50.2 | 0.077 | 0.210 | 0.007 | 58.4 | -0.002 | -0.096 | -0.231 | 54.1 | 0.128 |
| | *0.074* | *0.175* | 9.4 | *0.030* | *0.069* | *0.138* | 28.2 | *0.171* | *0.091* | *0.218* | 6.3 | *0.031* | *0.066* | *0.145* | 25.9 | *0.165* |
| MCG-*Sm* | 0.398 | 0.077 | 55.9 | 0.044 | -0.721 | 0.016 | 47.6 | -0.026 | 0.485 | 0.132 | 58.3 | 0.077 | 0.117 | 0.012 | 54.0 | 0.004 |
| | *0.130* | *0.295* | 20.0 | *0.098* | *0.123* | *0.234* | 17.6 | *0.075* | *0.192* | *0.460* | 8.7 | *0.081* | *0.112* | *0.244* | 19.4 | *0.080* |
| MCG-*Lg* | 0.384 | 0.014 | 56.7 | 0.010 | -0.190 | -0.038 | 53.2 | -0.060 | 0.469 | 0.064 | 59.0 | 0.055 | -0.244 | -0.008 | 58.4 | -0.018 |
| | *0.138* | *0.318* | 19.8 | *0.120* | *0.058* | *0.123* | 14.0 | *0.079* | *0.216* | *0.527* | 5.9 | *0.082* | *0.132* | *0.318* | 6.7 | *0.062* |
| Panel C: Null hypotheses and test p-values | | | | | | | | | | | | | | | | |
| All $e = 0$ | 0.000 | 0.327 | | 0.001 | 0.000 | 0.427 | | 0.329 | 0.000 | 0.179 | | 0.000 | 0.000 | 0.071 | | 0.044 |
| All $e$ same | 0.000 | 0.257 | | 0.016 | 0.000 | 0.337 | | 0.423 | 0.000 | 0.321 | | 0.001 | 0.000 | 0.377 | | 0.604 |
| Avg $e = 0$ | 0.608 | 0.736 | | 0.099 | 0.905 | 0.878 | | 0.417 | 0.765 | 0.762 | | 0.058 | 0.234 | 0.219 | | 0.091 |
| All $f = 0$ | 0.000 | 0.056 | | 0.027 | 0.000 | 0.017 | | 0.070 | 0.000 | 0.052 | | 0.048 | 0.000 | 0.045 | | 0.049 |
| All $f$ same | 0.000 | 0.147 | | 0.014 | 0.000 | 0.011 | | 0.181 | 0.000 | 0.077 | | 0.026 | 0.001 | 0.061 | | 0.046 |
| Av $f = 0$ | 0.002 | 0.765 | | 0.620 | 0.000 | 0.029 | | 0.857 | 0.001 | 0.686 | | 0.325 | 0.913 | 0.058 | | 0.499 |
| Av $f_{\text{SCG}}$ = Av $f_{\text{rest}}$ | 0.033 | 0.448 | | 0.531 | 0.806 | 0.200 | | 0.833 | 0.307 | 0.767 | | 0.284 | 0.150 | 0.717 | | 0.522 |
| Av $f = 0$ | 0.003 | 0.942 | | 0.196 | 0.000 | 0.111 | | 0.805 | 0.023 | 0.968 | | 0.238 | 0.179 | 0.081 | | 0.570 |
| Av $f_{\text{FLX}}$ = Av $f_{\text{rest}}$ | 0.004 | 0.727 | | 0.284 | 0.000 | 0.619 | | 0.761 | 0.006 | 0.684 | | 0.139 | 0.620 | 0.797 | | 0.606 |
| Av $f = 0$ | 0.003 | 0.881 | | 0.795 | 0.000 | 0.931 | | 0.545 | 0.019 | 0.843 | | 0.388 | 0.122 | 0.983 | | 0.914 |
| Av $f_{\text{MCG}}$ = Av $f_{\text{rest}}$ | 0.172 | 0.910 | | 0.779 | 0.000 | 0.014 | | 0.542 | 0.606 | 0.992 | | 0.377 | 0.998 | 0.120 | | 0.648 |
| Av $f_{Sm} = 0$ | 0.002 | 0.810 | | 0.750 | 0.000 | 0.284 | | 0.680 | 0.012 | 0.788 | | 0.506 | 0.639 | 0.352 | | 0.356 |
| Av $f_{Lg} = 0$ | 0.008 | 0.946 | | 0.916 | 0.000 | 0.058 | | 0.822 | 0.040 | 0.912 | | 0.471 | 0.001 | 0.018 | | 0.780 |
| Av $f_{Sm}$ =Av $f_{Lg}$ | 0.072 | 0.236 | | 0.761 | 0.000 | 0.653 | | 0.248 | 0.229 | 0.378 | | 0.924 | 0.022 | 0.816 | | 0.236 |
| All $f_{Sm} = f_{Lg}$ | 0.000 | 0.070 | | 0.019 | 0.000 | 0.018 | | 0.099 | 0.000 | 0.030 | | 0.055 | 0.001 | 0.244 | | 0.076 |
| $f_{\text{SCG-Sm}} = f_{\text{SCG-Lg}}$ | 0.000 | 0.004 | | 0.252 | 0.000 | 0.004 | | 0.118 | 0.000 | 0.030 | | 0.386 | 0.002 | 0.049 | | 0.113 |
| $f_{\text{FLX-Sm}} = f_{\text{FLX-Lg}}$ | 0.002 | 0.238 | | 0.065 | 0.001 | 0.197 | | 0.065 | 0.132 | 0.490 | | 0.067 | 0.484 | 0.448 | | 0.067 |
| $f_{\text{MCG-Sm}} = f_{\text{MCG-Lg}}$ | 0.682 | 0.292 | | 0.576 | 0.000 | 0.840 | | 0.576 | 0.712 | 0.456 | | 0.695 | 0.119 | 0.971 | | 0.695 |

Table 11: Conditional fund performance relative to a conditional factor model with NBER recession indicator as the instrument.

This table reports performance results for the following fund styles: Growth and Income (GRI), Growth (GRO), Maximum Capital Gains (CGM), Income (INC). The mutual fund data is from CRSP's mutual fund database, and is free of survivorship bias. Return data is available from 1/62 to 12/07 for GRI and GRO, from 1/69 to 12/07 for CGM and from 1/72 to 12/07 for INC. Factor and instrument data are available from 1/27 to 12/07. *Sm* (*Lg*) refers to the portfolio of funds with beginning of year TNA below (above) the median for the specified fund style. Performance results are reported relative to the Fama-French pricing model in the first 8 columns and relative to the Carhart pricing model in the last 8 columns. For each pricing model, performance results are reported for return in excess of the riskfree rate in the first 4 columns, and in excess of return on a portfolio matched on the basis of Fama-French loadings in the last 4 columns. Panels A and B report the abnormal performance parameters $e$ and $f$ respectively for the fund-style portfolios, where $e$ measures mean conditional performance and $f$ measures the extent to which the conditional performance varies with the information variable. When parameters $e$ and $f$ are identified by moment conditions (21) and (22), they are estimated for each fund-style portfolio using the adjusted moment (Full) method that uses all available data, and using the standard GMM method (Short) that only uses data from 1/72 to 12/07. Standard errors for both are calculated using the adjusted-moment coefficients. For each fund-style portfolio, parameters $e$ and $f$ are also estimated for the regression-based (Reg) approach of Ferson and Harvey (1996) using data from 1/72 to 12/07. Newey-West standard errors for the parameter estimates of all 3 are in italics. In the % Reduction column (% Red), we report the percent reduction in the coefficient standard error from (in the first row) using the Full method rather than the Short method and (in the second row) from using the Full method rather than the portfolio-by-portfolio adjusted moment method, which, for each portfolio, uses only the factor moments and the moments for that TNA-style portfolio, constructed using all available data for the factors, the instruments and the returns on that portfolio. Panel C reports the p-values for Wald tests of joint significance based on the Newey-West covariances. The Wald tests for the Short and Reg methods only use data from 1/72 to 12/07. Further details of the methodologies employed are in section 4.

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel A: Abnormal performance: $e$ parameters (% per month) | | | | | | | | | | | | | | | | |
| GRI-*Sm* | -0.051 | -0.118 | 29.8 | -0.118 | 0.026 | 0.006 | 15.9 | 0.006 | -0.039 | -0.074 | 29.4 | -0.074 | -0.017 | -0.003 | 14.2 | -0.003 |
| | *0.071* | *0.101* | 0.0 | *0.037* | *0.084* | *0.099* | 0.0 | *0.091* | *0.068* | *0.097* | 0.0 | *0.034* | *0.076* | *0.088* | 0.0 | *0.083* |
| GRI-*Lg* | -0.069 | -0.085 | 31.3 | -0.085 | 0.086 | -0.001 | 14.0 | -0.001 | -0.035 | -0.052 | 31.0 | -0.052 | -0.039 | 0.035 | 13.7 | 0.035 |
| | *0.070* | *0.101* | 0.0 | *0.030* | *0.067* | *0.077* | 0.0 | *0.079* | *0.065* | *0.095* | 0.0 | *0.028* | *0.072* | *0.083* | 0.0 | *0.081* |
| GRO-*Sm* | 0.119 | -0.067 | 26.6 | -0.067 | 0.197 | 0.058 | 14.3 | 0.058 | 0.009 | -0.063 | 27.1 | -0.063 | 0.031 | 0.007 | 13.0 | 0.007 |
| | *0.087* | *0.118* | 0.0 | *0.040* | *0.102* | *0.120* | 0.0 | *0.104* | *0.089* | *0.122* | 0.0 | *0.043* | *0.089* | *0.102* | 0.0 | *0.089* |
| GRO-*Lg* | -0.001 | -0.065 | 28.7 | -0.065 | 0.076 | 0.059 | 15.0 | 0.059 | -0.049 | -0.074 | 28.6 | -0.074 | -0.027 | -0.004 | 14.2 | -0.004 |
| | *0.077* | *0.109* | 0.0 | *0.035* | *0.096* | *0.113* | 0.0 | *0.104* | *0.080* | *0.112* | 0.0 | *0.038* | *0.084* | *0.098* | 0.0 | *0.089* |
| CGM-*Sm* | -0.016 | -0.116 | 24.7 | -0.116 | -0.189 | -0.178 | 9.2 | -0.178 | -0.087 | -0.184 | 24.1 | -0.184 | -0.207 | -0.200 | 10.0 | -0.200 |
| | *0.106* | *0.141* | 1.0 | *0.085* | *0.110* | *0.121* | 1.1 | *0.116* | *0.120* | *0.158* | 1.9 | *0.089* | *0.089* | *0.099* | 1.4 | *0.092* |
| CGM-*Lg* | 0.063 | -0.012 | 27.2 | -0.012 | -0.110 | -0.075 | 9.4 | -0.075 | -0.091 | -0.085 | 27.6 | -0.085 | -0.159 | -0.145 | 11.4 | -0.145 |
| | *0.100* | *0.137* | 0.8 | *0.067* | *0.080* | *0.088* | 0.6 | *0.070* | *0.112* | *0.155* | 1.2 | *0.068* | *0.077* | *0.087* | 0.6 | *0.063* |
| INC-*Sm* | 0.048 | -0.061 | 26.2 | -0.061 | 0.194 | 0.021 | 20.2 | 0.021 | 0.010 | -0.023 | 25.2 | -0.023 | 0.033 | 0.047 | 18.1 | 0.047 |
| | *0.068* | *0.092* | 1.1 | *0.047* | *0.097* | *0.122* | 1.3 | *0.081* | *0.063* | *0.085* | 1.3 | *0.044* | *0.097* | *0.119* | 7.2 | *0.094* |
| INC-*Lg* | -0.183 | -0.102 | 26.8 | -0.102 | -0.051 | -0.018 | 12.3 | -0.018 | -0.021 | -0.058 | 24.0 | -0.058 | -0.065 | 0.029 | 13.0 | 0.029 |
| | *0.078* | *0.106* | 0.6 | *0.054* | *0.079* | *0.090* | 7.5 | *0.090* | *0.074* | *0.098* | 1.1 | *0.056* | *0.082* | *0.094* | 7.1 | *0.089* |
| Average $e$ | -0.011 | -0.078 | | -0.078 | 0.029 | -0.016 | | -0.016 | -0.038 | -0.077 | | -0.077 | -0.056 | -0.029 | | -0.029 |

| | Fama-French | | | | | | | | Carhart | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Excess of $r_f$ | | | | Excess of matched portfolio | | | | Excess of $r_f$ | | | | Excess of matched portfolio | | | |
| | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. | Full | Short | % Red | Reg. |
| Panel B: Abnormal performance: $f$ parameters (% per month) | | | | | | | | | | | | | | | | |
| GRI-*Sm* | -0.091 | -0.039 | 32.0 | -0.039 | 0.043 | 0.048 | 21.6 | 0.048 | -0.145 | -0.088 | 32.1 | -0.088 | -0.001 | 0.060 | 21.8 | 0.060 |
| | *0.234* | *0.344* | 0.0 | *0.095* | *0.202* | *0.258* | 0.0 | *0.219* | *0.234* | *0.344* | 0.0 | *0.092* | *0.201* | *0.257* | 0.0 | *0.216* |
| GRI-*Lg* | 0.062 | 0.080 | 31.9 | 0.080 | -0.055 | 0.044 | 17.9 | 0.044 | -0.051 | 0.022 | 32.2 | 0.022 | -0.035 | 0.083 | 18.7 | 0.083 |
| | *0.239* | *0.352* | 0.0 | *0.088* | *0.225* | *0.274* | 0.0 | *0.262* | *0.240* | *0.355* | 0.0 | *0.075* | *0.231* | *0.283* | 0.0 | *0.287* |
| GRO-*Sm* | -0.305 | -0.065 | 30.1 | -0.065 | -0.171 | 0.021 | 20.8 | 0.021 | -0.209 | -0.084 | 30.5 | -0.084 | -0.064 | 0.064 | 21.6 | 0.064 |
| | *0.249* | *0.357* | 0.0 | *0.129* | *0.240* | *0.303* | 0.0 | *0.265* | *0.252* | *0.362* | 0.0 | *0.125* | *0.238* | *0.304* | 0.0 | *0.263* |
| GRO-*Lg* | -0.139 | -0.032 | 31.2 | -0.032 | -0.005 | 0.054 | 19.6 | 0.054 | -0.099 | -0.034 | 31.4 | -0.034 | 0.045 | 0.113 | 20.3 | 0.113 |
| | *0.243* | *0.354* | 0.0 | *0.111* | *0.223* | *0.278* | 0.0 | *0.253* | *0.250* | *0.364* | 0.0 | *0.105* | *0.223* | *0.279* | 0.0 | *0.257* |
| CGM-*Sm* | -0.078 | 0.034 | 25.5 | 0.034 | -0.240 | -0.295 | 10.1 | -0.295 | -0.163 | -0.022 | 27.4 | -0.022 | -0.165 | -0.044 | 16.1 | -0.044 |
| | *0.242* | *0.325* | 1.8 | *0.155* | *0.295* | *0.328* | 2.8 | *0.337* | *0.235* | *0.324* | 1.3 | *0.148* | *0.239* | *0.285* | 1.2 | *0.262* |
| CGM-*Lg* | -0.127 | -0.015 | 26.6 | -0.015 | -0.279 | -0.344 | 12.2 | -0.344 | -0.038 | -0.046 | 27.8 | -0.046 | -0.523 | -0.458 | 11.8 | -0.458 |
| | *0.243* | *0.331* | 2.4 | *0.168* | *0.278* | *0.316* | 3.2 | *0.315* | *0.242* | *0.335* | 2.0 | *0.166* | *0.270* | *0.306* | 2.3 | *0.316* |
| INC-*Sm* | 0.028 | 0.037 | 28.2 | 0.037 | -0.077 | -0.140 | 18.8 | -0.140 | 0.007 | 0.087 | 28.8 | 0.087 | 0.120 | 0.235 | 21.3 | 0.235 |
| | *0.235* | *0.327* | 1.5 | *0.134* | *0.302* | *0.372* | 3.5 | *0.300* | *0.235* | *0.330* | 1.6 | *0.140* | *0.227* | *0.288* | 6.1 | *0.245* |
| INC-*Lg* | -0.005 | 0.182 | 20.1 | 0.182 | -0.134 | 0.146 | 18.8 | 0.146 | -0.057 | 0.221 | 20.6 | 0.221 | 0.088 | 0.282 | 19.5 | 0.282 |
| | *0.249* | *0.312* | 4.4 | *0.205* | *0.355* | *0.437* | 7.4 | *0.381* | *0.246* | *0.310* | 4.7 | *0.219* | *0.358* | *0.445* | 7.4 | *0.416* |
| Panel C: Null hypotheses and test p-values | | | | | | | | | | | | | | | | |
| All $e=0$ | 0.000 | 0.424 | | 0.051 | 0.000 | 0.799 | | 0.538 | 0.023 | 0.536 | | 0.267 | 0.000 | 0.155 | | 0.190 |
| All $e$ same | 0.000 | 0.342 | | 0.335 | 0.000 | 0.785 | | 0.661 | 0.013 | 0.429 | | 0.428 | 0.003 | 0.253 | | 0.319 |
| Avg $e=0$ | 0.888 | 0.494 | | 0.011 | 0.611 | 0.819 | | 0.774 | 0.634 | 0.503 | | 0.025 | 0.303 | 0.655 | | 0.606 |
| All $f=0$ | 0.000 | 0.773 | | 0.718 | 0.004 | 0.751 | | 0.601 | 0.083 | 0.477 | | 0.406 | 0.000 | 0.018 | | 0.007 |
| All $f$ same | 0.000 | 0.740 | | 0.716 | 0.003 | 0.655 | | 0.493 | 0.059 | 0.517 | | 0.355 | 0.008 | 0.159 | | 0.021 |
| Av $f=0$ | 0.951 | 0.953 | | 0.798 | 0.973 | 0.840 | | 0.827 | 0.677 | 0.925 | | 0.643 | 0.922 | 0.756 | | 0.748 |
| Av $f_{\text{GRI}}=$ Av $f_{\text{rest}}$ | 0.826 | 0.959 | | 0.856 | 0.614 | 0.556 | | 0.524 | 0.671 | 0.836 | | 0.428 | 0.880 | 0.701 | | 0.683 |
| Av $f=0$ | 0.363 | 0.890 | | 0.677 | 0.700 | 0.895 | | 0.883 | 0.535 | 0.870 | | 0.599 | 0.966 | 0.759 | | 0.732 |
| Av $f_{\text{GRO}}=$ Av $f_{\text{rest}}$ | 0.156 | 0.741 | | 0.427 | 0.828 | 0.704 | | 0.688 | 0.432 | 0.749 | | 0.397 | 0.867 | 0.699 | | 0.671 |
| Av $f=0$ | 0.664 | 0.976 | | 0.947 | 0.356 | 0.312 | | 0.317 | 0.665 | 0.917 | | 0.812 | 0.082 | 0.280 | | 0.272 |
| Av $f_{\text{CGM}}=$ Av $f_{\text{rest}}$ | 0.686 | 0.994 | | 0.988 | 0.383 | 0.265 | | 0.255 | 0.725 | 0.859 | | 0.721 | 0.029 | 0.083 | | 0.106 |
| Av $f=0$ | 0.955 | 0.702 | | 0.305 | 0.666 | 0.992 | | 0.990 | 0.903 | 0.591 | | 0.156 | 0.668 | 0.414 | | 0.339 |
| Av $f_{\text{INC}}=$ Av $f_{\text{rest}}$ | 0.639 | 0.490 | | 0.222 | 0.794 | 0.891 | | 0.859 | 0.835 | 0.283 | | 0.063 | 0.390 | 0.250 | | 0.171 |
| Av $f_{Sm}=0$ | 0.624 | 0.980 | | 0.928 | 0.537 | 0.690 | | 0.641 | 0.580 | 0.937 | | 0.766 | 0.875 | 0.734 | | 0.690 |
| Av $f_{Lg}=0$ | 0.814 | 0.865 | | 0.642 | 0.588 | 0.926 | | 0.921 | 0.787 | 0.900 | | 0.719 | 0.636 | 0.985 | | 0.985 |
| Av $f_{Sm}=$Av $f_{Lg}$ | 0.479 | 0.511 | | 0.488 | 0.963 | 0.689 | | 0.685 | 0.420 | 0.471 | | 0.483 | 0.601 | 0.674 | | 0.669 |
| All $f_{Sm}=f_{Lg}$ | 0.003 | 0.655 | | 0.783 | 0.004 | 0.839 | | 0.850 | 0.068 | 0.698 | | 0.805 | 0.144 | 0.799 | | 0.674 |
| $f_{\text{GRI-Sm}}=f_{\text{GRI-Lg}}$ | 0.020 | 0.138 | | 0.196 | 0.675 | 0.988 | | 0.987 | 0.187 | 0.199 | | 0.231 | 0.887 | 0.934 | | 0.922 |
| $f_{\text{GRO-Sm}}=f_{\text{GRO-Lg}}$ | 0.018 | 0.704 | | 0.540 | 0.018 | 0.704 | | 0.540 | 0.109 | 0.555 | | 0.382 | 0.109 | 0.555 | | 0.382 |
| $f_{\text{CGM-Sm}}=f_{\text{CGM-Lg}}$ | 0.660 | 0.701 | | 0.723 | 0.730 | 0.701 | | 0.723 | 0.280 | 0.855 | | 0.861 | 0.265 | 0.257 | | 0.248 |
| $f_{\text{INC-Sm}}=f_{\text{INC-Lg}}$ | 0.899 | 0.612 | | 0.596 | 0.898 | 0.566 | | 0.555 | 0.804 | 0.643 | | 0.653 | 0.928 | 0.907 | | 0.910 |