MULTIFACTOR RISK LOADINGS AND ABNORMAL RETURNS UNDER UNCERTAINTY AND LEARNING

By

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Abstract
This paper considers an environment where investors have limited knowledge of true systematic risks and therefore continuously re-estimate the forecasting model that they use to form expectations. Based on a parsimonious specification with learning and no conditioning information, I extract time-varying factor loadings, pricing errors, and a measure of pricing uncertainty for the Fama-French three-factor model. Estimated parameters display significant fluctuations over time, both short-run and long-term, along patterns that vary across industry portfolios. Besides being markedly variable across portfolios and over time, abnormal returns and risk loadings also display strong systematic correlations with market conditions and business-cycle developments. Overall, the estimates convey the idea that over the past two decades stocks have experienced a pervasive increase in the variability of their exposure to fundamental risks.

Keywords: Multifactor models, Time-varying alphas, Time-varying betas.
JEL Codes: G12, G31, C51.

1 Introduction

Recent asset pricing literature shows that the key components of expected returns, i.e., risk premia and assets’ sensitivities to risk factors, or risk loadings, are likely to experience significant variation over time. This evidence has directed researchers toward specifications in which expected returns depend on investors’ unobservable and time-varying information set. Hence, risk loadings are commonly modelled as functions of observed macroeconomic and financial variables. However, formal tests based on such hypothesis are strictly valid

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only if the econometrician knows the full set of state variables available to investors. In practice, several real-world factors are likely to play a significant role in the determination of risk loadings. One of them is investors’ uncertainty. Presumably, investors’ forecasts of risk loadings and risk premia are the result of some complex learning process that reflects uncertainty about the distributional characteristics of those and other quantities. Therefore, changes in the structure of the economy and in financial markets make reasonable to model risk sensitivities as varying over time, particularly over long samples and at business-cycle frequencies. This paper provides estimates of abnormal returns and risk loadings that are endogenous with respect to the level of uncertainty and studies their relationship with market conditions and business-cycle developments.

More in detail, I construct and estimate a specification of the Fama-French three-factor model based on time-varying alphas, risk loadings and idiosyncratic risk, and an endogenous measure of uncertainty, for ten US industry portfolios. Operationally, uncertainty is defined as the conditional error variance of the optimal forecast of alphas and betas. This setting seeks to replicate the learning activity of rational investors, who must infer the risk loadings from available information, and optimally update them as new information becomes available. Cognitive limitations or shortage of degrees of freedom are likely to force investors to under-parameterize their forecasting models. Accordingly, this paper holds that changes in risk factor returns effectively summarize the arrival of relevant information. Therefore, in contrast with much of the existing literature, the estimated risk loadings do not rely on conditioning information.

The parsimonious model that I specify allows for changes in perceived risks due to factors unobserved by the econometrician, such as shifts in the quantity of undiversifiable risk that might be learning-induced. To capture the time variation in the parameters I follow an approach based on the Kalman filter. This methodology (hereafter dubbed TVK) yields monthly alpha and beta time series without relying on exogenous state variables or time/frequency assumptions. The core results of the paper reveal that alphas and risk loadings experience significant fluctuations over time; this confirms that investors update their forecasts on a more frequent and systematic basis than existing analyses entertain. Subsequently, I study whether pricing errors and risk sensitivities evolve according to some cyclical
pattern, finding evidence of clear-cut relationships with market conditions.

The rest of the paper is structured as follows. Section 2 briefly sets out the literature background to the empirical exercise in this paper. Section 3 introduces a specification of the Kalman filter that accounts for the learning problem of investors under uncertainty. Section 4 presents estimates of time-varying alphas, betas and pricing uncertainty, while Section 5 evaluates the association of time-varying alphas and betas with business-cycle indicators. Section 6 concludes.

2 Motivations and review of the literature

Researchers have identified two broad channels through which fundamental risk factors drive asset returns (see among others Campbell and Vuolteenaho, 2004; Bansal et al., 2005). First, asset risk depends on the co-variation of the asset’s cash flows with fluctuations of the market return, or with changes in the economy’s rate of growth. In addition, the present value of cash flows is contingent on the aggregate discount rate: depending on the time profile of cash flows, shocks to the discount rate drive changes in asset returns. Consequently, the sensitivity to cash-flow risk and discount-rate risk determines an asset’s risk-return trade-off.

Now, there are no reasons to think that the exposures to undiversifiable risks vary across assets, i.e., across claims to different cash flows, but not over time, i.e., when the information set and economic circumstances driving the valuation of those cash flows possibly change. Also, if the variance of market return or its covariance with asset returns is time-varying, an asset’s sensitivity to risk factors will shift over time. Indeed, there is ample evidence on the persistence and heteroskedasticity of market returns at business-cycle frequencies (Schwert, 1989a, b). There are also substantial proofs of time variation in market premia (see for instance Ang and Bekaert, 2007; Cooper and Priestley, 2009), and of a similar behaviour by market betas (Fama and French, 1997; Lewellen and Nagel, 2006; Ghysels and Jacquier, 2006; Ang and Chen, 2007; Trecroci, 2009). Finally, even assuming that individual stocks had time-invariant risk loadings, changes in portfolio weights imply that portfolio returns satisfy a linear factor model, but one with time-varying coefficients and a heteroskedastic disturbance term (see Mamaysky et al., 2008).

1 Santos and Veronesi (2004) build a general-equilibrium model that explains the time variation of betas.
Empirical evidence dating back at least to Fama and French (1997) shows that time-invariant regression techniques yield risk loadings that are imprecisely estimated because true betas experience substantial variation through time. Mis-specified beta dynamics can negatively affect asset pricing tests as well as portfolio and capital budgeting choices. To model such dynamics, two competing approaches have emerged. One could employ short-window (rolling-sample) OLS regressions (like Lewellen and Nagel, 2006, or Fama and French, 2006). Alternatively, one could impose more or less complex parametric relationships between risk loadings and a set of state variables proxying for the state of the economy, like in Ferson and Harvey (1999), or Ang and Chen (2007).

In both cases the results are far from satisfying. For instance, Ghysels (1998) shows that simple constant betas outperform several parametric beta models, while Jostova and Philipov (2005) and Ang and Chen (2007) find substantial evidence of inconsistency in conditional CAPM coefficients estimated through constant-parameter and rolling regressions. Again in the CAPM context, Trecroci (2009) shows that TVK market-risk sensitivities have superior predictive ability for portfolio returns against constant and rolling-window OLS estimates. Apparently, the lack of precision of estimates from classical regression approaches is matched by a pervasive lack of robustness in models based on conditioning information. Tests based on parametric approaches are strictly valid only if the econometrician knows the full set of state variables available to investors. But even if this were the case, the complexity of the structural relationships would make unfeasible their direct estimation. Indeed, Ghysels and Jacquier (2006) show that estimated time-varying betas from time-series models outperform those based on conditioning information.

The impact of time variation and uncertainty on market’s assessment of risk has been analysed in various ways in the literature. Most contributions employ models in which betas are allowed to change over time and constant alphas are extracted via numerical optimization. More importantly, the models tested tend to be richly parameterized and often rely on strict priors about time variation in the mean and volatility of the conditional risk premia. In contrast, the main advantages of this paper’s methodology are its simplicity and its ability to adapt to assets’ or portfolios’ actual sensitivities to risk factors in a way

\footnote{Ghysels and Jacquier (2006) is a compromise between the two routes.}

\footnote{Also, idiosyncratic risk is rarely allowed to vary over time.}
that constant-coefficient, but also popular rolling- or fixed-window regressions, simply do not permit to. Unlike some recent contributions, this paper’s joint estimates of each period’s conditional alphas and betas are obtained without making any assumption about period-to-period variation in betas.

Methodologically, this empirical exercise accounts for two sources of uncertainty: uncertainty associated to future idiosyncratic risk, and uncertainty arising because of evolution in the risk loadings. Conditional uncertainty is therefore directly tied to observed returns, which contain and update the information relevant for investment choices. This framework proxies for a more complex environment in which investors face uncertainty about their model specification and choose parsimonious trading strategies. Consequently, the model allows for both time variation in the mean and homoskedastic stochastic components of the alpha and beta processes, thus combining features that the existing literature does not consider jointly\(^4\). Crucially, the time-varying, Kalman-filter based estimates that I obtain depend only on portfolio and market returns and appear to be precisely estimated.

3 A parsimonious representation with uncertainty, learning and time variation

Modern finance explains risk premia with the relationship between stock characteristics and fluctuations in aggregate consumption or wealth (see for instance Zhang, 2005). Fama and French (1992a) augmented the static CAPM specification by adding two more factors:

\[
R_{it}^{e_i} = \alpha^i + \beta^i R_{it}^{EM} + s^i R_{it}^{SMB} + h^i R_{it}^{HML} + \varepsilon_{it}^i
\]  

Here \(R_{it}^{e_i}\) is the return on test asset \(i\) in excess of the one-month Treasury bill rate, \(R_{it}^{EM}\) is the excess return on the market, \(R_{it}^{SMB}\) and \(R_{it}^{HML}\) are the returns on the SMB and HML factor portfolios, respectively, and \(\beta^i\), \(s^i\) and \(h^i\) are the asset’s factor loadings. The idea is that the dynamics of fundamental risk factors, such as the market, growth opportunities and financial distress, as well as firm’s size, drives the cross-section of risk and return. Indeed, Fama and French show that their three-factor model captures much of the spread in the

\(^4\)Jostova and Philipov’s (2005) study based on Monte Carlo Markov Chain is the only exception, but it focuses on a one-factor model.
cross-section of average returns. Using the sensitivity to changes in $R_t^{SMB}$ to explain returns is in line with the evidence that there is co-variation in the returns on small stocks that is not captured by the market return and is compensated in average return. Similarly, the sensitivity to changes in $R_t^{HML}$ captures the return co-variation related to financial distress (proxied here by BE/ME, the ratio of the book value of common equity to its market value) that is missed by the market return and is compensated in average returns. Fragile firms with low profits tend to have high BE/ME ratios and positive $h^i$; strong firms with persistently high earnings have low BE/ME ratios and negative $h^i$.

Liew and Vassalou (2000) provide evidence that $R_t^{SMB}$ and $R_t^{HML}$ are positively related to future economic growth. Therefore, it is of primary interest to understand whether the sensitivity of portfolio returns to those risks shifts over time too and in relation to which market conditions\(^5\). For instance, in the case of an industry that becomes distressed, one result of distress could be an increase in $h^i$, the industry’s loading on HML. Conversely, the loadings on the SMB factor may change following bad surprises about an industry’s future cash flows. Accordingly, I evaluate the association of TVK alphas and betas with key state variables and macroeconomic indicators, obtaining fresh evidence on the dynamics of pricing errors and risk sensitivities at business-cycle frequency.

3.1 The Kalman hypothesis

The key hypothesis of this paper is that the arrival of new information and investors’ uncertainty have defined implications on the pricing of risk. Investors are assumed to engage in a systematic learning activity on observed asset returns, aimed at extracting and updating forecasts of undiversifiable and idiosyncratic risk components. To allow for these effects, I write the conditional expectation of $R_t^{i}$, asset $i$’s excess return, under uncertainty, as

$$\mathbb{E} \left[ R_t^{i} | \psi_{t-1} \right] = \sum_{j=1}^{K} \mathbb{E} \left( \beta_{ij} | \psi_{t-1} \right) \cdot \mathbb{E} \left( x^j | \psi_{t-1} \right)$$

Here $\psi$ is the information set, $x^j$ are risk premia, i.e., expected returns on mimicking portfolios for $K$ risk factors, and $\beta_{ij}$ are conditional regression slopes of the asset return on the risk factors. Now, let us assume that realized returns follow a linear regression model,

\(^5\)This paper defers to future investigation the complex implications for expected returns.
in which the intercept and slope coefficients, stacked up in the coefficient vector $\beta_t^i$, change over time according to an autoregressive dynamics:

$$
R_t^i = X_t^i \beta_t^i + \epsilon_t^i, \quad t = 1, 2, \ldots, T
$$

(3)

$$
\beta_t^i = \bar{\beta}^i + F^i \beta_{t-1}^i + v_t^i
$$

(4)

where

$$
\epsilon_t^i \sim IIDN (0, S)
$$

(5)

$$
v_t^i \sim IIDN (0, Q)
$$

(6)

Importantly, $\epsilon_t^i$ and $v_t^i$ are mutually independent and $X_t$ contains a constant and the returns on the $K$ risk factors. Unlike most of the available literature (see for instance Adrian and Franzoni, 2009, and the references therein), alphas and betas are not assumed to be conditional on any exogenous variable. To spare notation, I drop the superscript "$i$" to denote asset $i$’s return, coefficients, etc.

If investors were fully informed and under no uncertainty, all parameters ($\tilde{\beta}, F, S, Q$) would be known. If this were really the case, a sequence of GLS regressions would deliver an estimate of the state vector. However, such approach tends to be extremely inefficient. Besides, we have already discussed plausible reasons to hold that investors are uncertain about the true values of those parameters and therefore need to update systematically their forecasts. Finally, if only some of the hyperparameters were not known, they would have to be estimated anyway before making any inference about $\beta_t$. All this leads quite naturally to consider the Kalman filter (KF, henceforth) to make inferences about $\beta_t$.

The Kalman filter is a recursive procedure for computing the estimator of a time-$t$ unobservable component, based only on information available up to time $t$. When the shocks to the model and the initial unobserved variables are normally distributed, the KF allows the computation of the likelihood function through prediction error decomposition\(^6\). The KF computes a minimum mean-squared-error estimate of $\beta_t$ conditional on $\psi$. Depending on the information set used, one obtains filtered or smoothed estimates. The filter, which

is used in this paper, refers to an estimate of $\beta_t$ based on information available up to time $t$, whereas the smoothing version of the Kalman algorithm yields an estimate of the state vector based on all the available information in the sample through time $T$. The latter is employed in Adrian and Franzoni (2009), who hence assume that investors know the true value of hyperparameters -like the long-run level of beta- when they form forecasts of time-varying parameters.

Now, I define $\beta_{t|t-1} = \mathbb{E}[\beta_t|\psi_{t-1}]$ as the expected value of $\beta_t$ conditional on $\psi_{t-1}$, whereas $\beta_{t|t} = \mathbb{E}[\beta_t|\psi_t]$ represents the estimate of $\beta_t$ conditional on $\psi_t$, and therefore on the realization of the prediction error. Let us also define $P_{t|t-1} = \mathbb{E}\left[\left(\beta_t - \beta_{t|t-1}\right)\left(\beta_t - \beta_{t|t-1}\right)^\prime\right]$, and $P_{t|t} = \mathbb{E}\left[\left(\beta_t - \beta_{t|t}\right)\left(\beta_t - \beta_{t|t}\right)^\prime\right]$ as their respective covariance matrices\(^7\).

The asset’s expected excess return, which represents an optimal forecast given information up to time $t - 1$, is $R_{t|t-1} = \mathbb{E}\left[R_t|\psi_{t-1}\right] = X_t\beta_{t|t-1}$. This forecast has prediction error equal to $\eta_{t|t-1} = R_t - R_{t|t-1}$, in turn characterised by conditional variance $f_{t|t-1} = \mathbb{E}\left[\eta_{t|t-1}^2\right]$.

The timing assumption of the model is straightforward. At the beginning of time $t$, $X_t$ becomes available; at the end of time $t$ a new realization of $R_t$ becomes public knowledge. As a consequence, the basic KF involves two steps:

**Step 1** At the beginning of time $t$, investors formulate an optimal prediction of the expected asset return $R_{t|t-1}$, based on information up to $t - 1$. To this end, investors need to compute $\beta_{t|t-1}$:

$$\beta_{t|t-1} = \tilde{\beta} + F\beta_{t-1|t-1} \quad (7)$$
$$P_{t|t-1} = FP_{t-1|t-1}F^\prime + Q \quad (8)$$
$$\eta_{t|t-1} = R_t - R_{t|t-1} = X_t^\prime\beta_{t|t-1} \quad (9)$$
$$f_{t|t-1} = X_tP_{t|t-1}X_t^\prime + S \quad (10)$$

Besides $\beta_{t|t-1}$, the KF algorithm therefore generates an estimate of the conditional variance of forecast errors, eq. (10). This equation shows that the model accounts for two sources of uncertainty: uncertainty arising from future idiosyncratic risk, and uncertainty arising because of evolution in the model’s coefficients. In this simple way,\(^7\)For smoothed Kalman estimates, we have $\beta_{t|T} = \mathbb{E}[\beta_t|\psi_T]$ and $P_{t|T} = \mathbb{E}\left[\left(\beta_t - \beta_{t|T}\right)\left(\beta_t - \beta_{t|T}\right)^\prime\right]$, respectively.
conditional uncertainty is directly associated with observed returns, which contain and update the information relevant for investment choices.

**Step 2** Once $R_t^e$ is realized at the end of time $t$, the prediction error can be calculated: $\eta_{t|t-1} = R_t^e - R_{t|t-1}$. This contains new information about the model’s coefficients $\beta_t$, beyond that contained in $\beta_{t|t-1}$. Thus, after observing $R_t^e$, a more accurate inference about $\beta_t$ can be made. $\beta_{t|t}$, an inference of $\beta_t$ based on information up to time $t$, has the following form

$$
\beta_{t|t} = \beta_{t|t-1} + K_t \eta_{t|t-1}
$$

(11)

$$
P_{t|t} = P_{t|t-1} - K_t X_t P_{t|t-1}
$$

(12)

The quantity

$$
K_t = P_{t|t-1} X_t f_{t|t-1}^{-1}
$$

(13)

is the so-called Kalman gain, which determines the weight assigned to new information about $\beta_t$ contained in the prediction error.

The specification above is deliberately general, as priors about relevant aspects, like the law of motion of alpha and betas, remain far from obvious. That said, tests of structural changes on unconditional betas (Trecroci, 2009) provide evidence supporting the presence of multiple breaks in risk loadings. Indeed, Engle and Watson (1985) suggested to model as unit root processes the regression coefficients of relationships based on the hypothesis that agents update their estimates only when new information becomes available, which is exactly our case. There is also a broad consensus in the literature, both theoretical (Santos and Veronesi, 2004) and empirical (Ghysels and Jacquier, 2006), that betas are likely to be highly persistent quantities, essentially because they are functions of shocks that have permanent effects. In the context of CAPM betas, Ang and Chen (2007) model them as quasi-unit root AR(1) processes. Adrian and Franzoni (2009) share the random walk assumption in their priors, whereas Fama and French (2006) do not. Lo and MacKinlay (1998) and Lo (2007) contain further empirical and theoretical support to the unit-root hypothesis. Hence, I assume that the regression coefficients in $\beta_t$ follow a random walk, and in the following set $F = I_k$. I alternatively estimate my model by positing an autocorrelation of 0.95, obtaining
no qualitatively different results. On the one hand, none of the TVK parameters displays exploding behaviour (see below). On the other hand, some evidence shows that specifying the betas as explicit mean-reverting processes places costly restrictions on their dynamics. Indeed, this is what seems to happen in Jostova and Philipov (2005), where most estimated CAPM betas are not statistically different from unity and display very limited time variation.

In equation (7), an inference on coefficients $\beta_t$ given information up to time $t - 1$ is a function of the inference on $\beta_{t-1}$ given information up to time $t - 1$, due to the law of motion of the state vector. Thus, uncertainty underlying $\beta_{t|t-1}$ is a function of the uncertainty underlying $\beta_{t-1|t-1}$ and $Q$, the covariance of the shocks to $\beta_t$. This is shown in equation (8).

More importantly, the prediction error in the time-varying-parameter model consists of two parts: the component due to error in making an inference about $\beta_t$ (i.e., $\beta_t - \beta_{t|t-1}$), which is related to systematic risk, and the prediction error due to $\varepsilon_t$, the random shock to excess return $R_e$. Therefore, in equation (10), the conditional variance of the prediction error is a function of uncertainty associated with $\beta_{t|t-1}$ and of $S$, the variance of $\varepsilon_t$. The updating equation in (11) suggests that $\beta_{t|t}$ is formed as a combination of $\beta_{t|t-1}$ and new information contained in the prediction error $\eta_{t|t-1}$, the weight assigned to new information being the Kalman gain. Examining $K_t$ more carefully, we notice that it is an inverse function of $S$, the variance of $\varepsilon_t$: the larger the idiosyncratic risk component, the smaller the weight assigned to new information about $\beta_t$ contained in the prediction error. For given risk premia in $X_t$, $K_t$ is increasing in the uncertainty surrounding $\beta_{t|t-1}$. To simplify, let us assume that $\beta_t$ and $X_t$ are $1 \times 1$; then the Kalman gain can be rewritten as

$$K_t = \frac{1}{X_t} \frac{P_{t|t-1}X_t^2}{P_{t|t-1}X_t^2 + S}$$  \hspace{1cm} (14)

where $P_{t|t-1}X_t^2$ is the portion of prediction error variance due to uncertainty in $\beta_{t|t-1}$ and $S$ is the component due to the random shock $\varepsilon_t$. We can easily see that

$$\left| \frac{\partial K_t}{\partial (P_{t|t-1}X_t^2)} \right| > 0$$  \hspace{1cm} (15)

suggesting that, when uncertainty associated with $\beta_{t|t-1}$ increases, relatively more weight is placed on new information from the prediction error, $\eta_{t|t-1}$. Intuitively, the algorithm
interprets an increase of uncertainty about $\beta_{t|t-1}$ as a deterioration of the information content of $\beta_{t|t-1}$ relative to that of $\eta_{t|t-1}$.

Overall, the approach aims at striking a novel balance in the parameterization/robustness trade-off observed in the existing literature. First, the TVK methodology accounts for investors’ uncertainty about asset risk in a straightforward way, as it entails a simple learning process on the model’s coefficients: rational investors must infer the risk sensitivities from observable portfolio returns and past prediction errors. The uncertainty they face depends upon the error variance of their past optimal forecast\(^8\). Second, it is methodologically parsimonious, as its implementation requires narrow parameterization compared with, say, multi-equation settings, or alternative state-space models with regime-switching. Third, estimation is not based on conditioning information or strong assumptions about period-to-period variation in betas. For instance, this exercise does not employ restrictive assumptions as to the frequency of actual betas and of their changes\(^9\). Fourth, it is consistent with a time-varying representation of multifactor risk in which uncertainty about current betas directly feeds into changing conditional variance of returns. Finally, whereas most existing studies do not deal directly with the issue of parameter uncertainty and limited information on abnormal returns, the approach in this paper endogenizes pricing errors and prevents future information from affecting today’s forecasts.

4 Time variation in factor loadings and pricing errors

To set the stage, Table I provides basic statistics and unconditional one-factor (CAPM) estimates for 10 industry-sorted portfolios and the three factor returns\(^10\). The use of relatively coarse, industry-sorted portfolios rather than more traditional portfolios formed on underlying risk factors like HML and SMB is motivated by arguments in Lewellen, Nagel and Shanken (2010), who argue for employing test assets that minimize the risk of dealing with spurious factor structures. The portfolios consist of NYSE, AMEX, and NASDAQ stocks

\(^8\)Obviously, forecasts are optimal in the sense that forecast errors are orthogonal to the information set.

\(^9\)Ozoguz (2009) considers a two-state regime-switching model of the aggregate market return, based on the idea that the economy fluctuates between two states. While interesting, this intuition however rests on a relatively rigid assumption on the number and nature of the states. See also Anderson et al. (2009).

\(^10\)The industry return series are obtained from Kenneth French’s Web site data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The Data Appendix contains a list of sectors and keys for portfolios’ acronyms.
assigned to each basket at the end of June of year \( t \) based on their four-digit SIC code at that
time. Returns are then computed from July of \( t \) to June of \( t + 1 \). The sample period spans
from July 1926 to September 2009. Portfolios’ labels hint at their sectoral classification,
further detailed in the Data Appendix.

Overall, and in line with existing studies, the statistics are not particularly support-
ive of the unconditional CAPM. The most volatile returns (standard deviation in excess
of 9% monthly) and market loadings (1.43) are for HITEC and DURBL portfolios, but
while HITEC has the highest average return, DURBL has the lowest one. As to uncondi-
tional CAPM pricing errors (\( \hat{\alpha} \)), they are significant and positive across all portfolios except
DURBL, and sizeable, as they fall between 19 (SHOPS) and 44 (ENRGY) basis points per
month. Risk loadings seem to be precisely estimated, as standard errors of market slopes
are tiny. Idiosyncratic risk \( (\sigma (\hat{\varepsilon} t)) \) is lowest for NODUR and MANUF portfolios (around
3.30%), and highest again for DURBL and HITEC. The regressions’ goodness of fit (adjusted
\( R^2 \)) hovers between 0.57 and 0.82.

Estimated parameters of the three-factor model (reported in Table II) confirm that the
Fama-French model is better than the CAPM at pricing industry-sorted portfolios. \( R^2 \)s are
higher and idiosyncratic risk lower for each portfolio compared with one-factor regressions.
Slopes on market, size and distress risk factors are always statistical significant. HITEC,
TELCM and HTLH have negative loadings on HML. More importantly, abnormal returns
are smaller and even become insigniﬁcant for 6 out of the 10 portfolios.

The KF methodology adopted in this paper yields endogenous volatilities for alphas,
betas, and idiosyncratic risk, rather than relying on simulation or other approximations to
recover them as in alternative exercises. The analysis of estimated TVK parameters therefore
starts by assessing their variability. Table III reports the KF estimates of volatility param-
eters for the 10 industry portfolios (respective standard errors are in parentheses). Several
interesting ﬁndings emerge. First of all, alphas are very smooth. The standard deviations
of most abnormal returns resulting from the TVK algorithm are in the 0.01%-0.07% range
per month, with HLTH (0.28%) and NODUR (0.13%) as exceptions. Alphas’ volatilities
are therefore on average much smaller than those estimated, for instance, by Glabadanidis
(2009) using GLS. Apparently, the way in which the TVK methodology handles uncertainty
and learning, far from introducing excess variation in the coefficients, instead yields tightly estimated parameters. This seems to apply to most risk loadings as well. Interestingly, idiosyncratic risk too is for each portfolio remarkably lower than what obtained with time-invariant OLS. This fits in well with findings by Ang and Chen (2007), who employ asymptotic theory to prove that standard OLS inference provides misleading estimates, precisely because of time variation in the quantity of market risk.

Turning to point estimates, Figures I-III plot the time series of risk loadings from the Fama-French model estimated via the TVK algorithm. Projected over the length of the estimation sample, all betas exhibit marked medium-term variation, typically through intervals of one to two years. Starting with Fama and French (1997), there is clear evidence that risk loadings, from both one- and multi-factor representations, wander through time by an extent significantly in excess of average estimation error. This seems to occur largely because underlying risks too, and their perception by the market, wander, pushing industries from relative growth to relative distress and vice versa. Starting with the loading on the market \((\hat{\beta}_t^i)\), Figure I shows this beta as experiencing a very long-term upward trend in some industries (TELCM, HLTH) and a downward one in others (UTILS, DURBL), but the overall dynamics is quite rich, with persistent fluctuations apparently occurring at business-cycle-like frequencies. The latter part of the sample is characterized by more dramatic swings. Interestingly, for many portfolios the market loading trends up toward the end of the sample, often sharply so, right at the onset of the 2007-2009 financial crisis. This is particularly clear for NODUR, DURBL, ENRGY, OTHER, MANUF and SHPS industries, whose market betas also display a broadly cyclical pattern.

Turning to loadings on the SMB factor \((\hat{s}_t^i)\), Figure II confirms broadly upward trends for TELCM, HLTH, MANUF and SHPS, and that HITEC and TELCM betas on SMB have higher variability. However, with the exception of SHPS, NODUR and DURBL, these loadings do not shoot up in correspondence of notable episodes of financial distress. HITEC and ENRGY show significant shocks around 1999-2000, consistently with major upsets in these sectors.

As expected, the dynamics of the loadings on the HML factor \((\hat{h}_t^i)\), Figure III) portraits

\(^{11}\)Betas are very tightly estimated, as seen in Table III. To avoid cluttering the charts, I do not report here confidence bands. Graphs with confidence bands are available upon request.
a dramatically different picture. Despite being smaller than all other loadings, these betas experience large swings in the run-up and aftermath of episodes of financial distress. Interestingly, this pattern literally dominates the last 20 years of data. As to the 2007-2009 turmoil, the overwhelming effect seems to be a remarkable increase of HML loadings in the years preceding it, followed by a sharp decline. Overall, these estimates convey the idea that over the past two decades stocks have experienced a pervasive increase in the variability of their exposure to fundamental risks.

Finally, Figure IV plots the time series of alphas. Here two distinctive long-term patterns emerge. For some portfolios, notably NODUR, MANUF, HLTH and HITEC, abnormal returns reach sizeable values but undergo several switches from positive to negative and vice versa, within intervals of a few years, over most of the sample. On the contrary, all other portfolios show smaller but more persistent alphas throughout the sample, especially for ENRGY, TELCM, UTILS, SHPS, mostly positive, and DURBL and OTHER, mostly negative. Strikingly, alphas of ENRGY, TELCM and UTILS, albeit very different in size, display positive values and inertial behaviour at least over the latter 50 years of data. These differences in the dynamics of pricing errors call for further investigation of the link between alphas and business cycle indicators.

5 Alphas, betas and the business cycle

Are risk loadings and pricing errors tied to economic activity and market conditions? The answer to this question holds important implications for asset pricing, portfolio choice and capital budgeting issues, stemming from the rich temporal and cross-sectional variation revealed by TVK estimates. To evaluate the interplay between time-varying parameters and economic fluctuations, I perform two complementary exercises. First, I run simple regressions of each portfolio’s TVK alpha on a battery of state variables. Second, I repeat the exercise using TVK betas as dependent variables.

In both regressions, the explanatory variables are the following: the value-weighted excess return on the market (MKT), the one-month Treasury bill rate (TBILL), the yield spread between ten-year and one-year Treasury bonds (TERM), the yield spread between Moody’s seasoned Baa and Aaa corporate bonds (DEF), the log of the ratio of the value-weighted
market index to the 10-year-trailing average of earnings, or cyclically-adjusted price/earnings ratio\textsuperscript{12} (CAPE), the consumption-to-wealth ratio by Lettau and Ludvigson (2001) (CAY)\textsuperscript{13} and the log of the PMI Composite Index (PMI). The aim of this exercise is to capture the marginal explanatory content of state variables for alphas and betas; therefore, I include as regressors one lag of all the variables jointly. Each of them is standardised, so that the resulting coefficient can be interpreted as the change in the TVK alpha or beta predicted by a one-standard-deviation change in the regressor. Computed standard errors are autocorrelation-and heteroskedasticity-consistent, following Andrews (1991)\textsuperscript{14}.

Alpha-centred estimates, reported in Table IV, show that the response of abnormal returns to changes in the state variables, and hence in business and market conditions, varies a lot across industries. TVK alphas for portfolios of TELCM, ENRGY and SHPS stocks appear to be closely tied to those variables, as $R^2$s for these portfolios range from about 0.60 up to 0.75. On the contrary, market conditions explain very little of the overall variability of alphas in MANUF, HLTH and UTILS portfolios, revealing that pricing errors in those industries have no significant correlations with indicators of market conditions. A related result, which applies to all industry portfolios, is that abnormal returns appear to be orthogonal to the market return. This lack of significant feedback from market return onto TVK parameters will show up also in the results for the betas, and confirms that the TVK technique does a satisfactory job at purging factor loadings and pricing errors from any remaining correlation with unadjusted market returns. In contrast, market valuation ratios seem to hold significant predictive content for alphas. Changes in CAPE, the cyclically-adjusted price/earnings ratio, are by far the strongest single determinant of alpha dynamics. Its slope coefficient is the largest in all but one regression, and almost always highly significant. This suggests that alphas are mainly driven by fundamental measures of firms’ cash flows. Also, noting that CAPE tends to rise (fall) during bull (bear) market conditions, the regression results point to alphas as being strongly pro-cyclical for HITEC and TELCM, and strongly counter-cyclical for SHPS, NODUR, ENRGY, DURBL.

As to the other state variables, TBILL, DEF, CAY and TERM all appear to have some

\textsuperscript{12}The series is calculated by R. Shiller, http://www.econ.yale.edu/~shiller/data.htm
\textsuperscript{13}CAY is available only at the quarterly frequency. I computed monthly observations from the original data using linear interpolation.
\textsuperscript{14}Due to data constraints, the estimation sample here starts in May 1953.
explanatory power for alphas, though it is especially changes in TBILL and DEF that display the most sizeable influence. As is well known, DEF tends to be correlated with financial distress on the markets, so the sign of its estimated coefficients broadly confirms the cyclical nature of most alphas, as already apparent in their association with CAPE. Finally, PMI seems to have some predictive power, but to a more limited extent than all other indicators.

Turning now to regressions of TVK portfolio betas on state variables, estimates in Table V yield several interesting insights.

First, $R^2$s vary substantially across industries and loadings. They are generally higher when the dependent variable is the loading on the market, and for portfolios whose alphas are less correlated with state variables. They reach 0.71 for UTILS’ market beta, while state variables explain only 7% of the variability in NODUR’s loading on HML. Apparently, the loadings of UTILS, MANUF, ENRGY and TELCM are more tightly predicted by developments in market conditions.

Second, the value-weighted excess return on the market seems to be almost orthogonal to betas, besides rare and very small correlations with the market and HML loadings in few industries. Third, CAPE here too stands out as the variable most highly and systematically correlated with the dependent variable. Its regression slope is almost always very significant and sizeable, pointing to a strong feedback from adjusted market valuations of cash flows on to risk loadings. That said, the sign of this relationship does switch across industries and risk factors. For instance, HML loadings fall by 140% and 200% following a one-standard-deviation change in CAPE in the cases of TELCM and HITEC, respectively, while they rise by 145% for ENRGY and UTILS. Instead, the exposure to this underlying risk factor appears to be much lighter for HLTH and NODUR, signalling once again the counter-cyclical nature of these industries.

Fourth, TBILL and the yield spreads (TERM and DEF) also have strong predictive power for risk loadings. Market and HML betas almost invariably fall following a unit change in TBILL (and almost as often in TERM too), whereas the loading on SMB responds with a rise. TBILL and TERM is often found to have strong predictive power for economic activity or the state of investment opportunities. This is additional and more detailed evidence that HML and market-risk loadings of portfolios tend to move pro-cyclically (see also Trecroci,
a finding also supported by their positive associations with PMI.

Finally, CAY too appears to hold significant predictive power for most betas. Lettau and Ludvigson (2001) claim that their CAY indicator is broadly counter-cyclical. Trecroci (2009) finds that CAY exhibits a strong and negative relationship with market betas, pointing to a pro-cyclical behaviour. The results here broadly confirm such finding, but also highlight important differences across industries.

Taken together, these results say that the correlation of alphas and risk loadings with business cycle variables, although differentiated, is substantial and pervasive across portfolios. Moreover, state variables commonly used as leading indicators of business cycle or market valuations, also hold some useful information for developments in TVK parameters. This is in contrast with the evidence collected for quarterly betas by Ghysels and Jacquier (2006). The variation over time in portfolio risk loadings on, say, HML, correctly reflects periods of industry strength or distress. For instance, fragile industries have strong positive HML loadings in bad times and negative loadings when times are good. These are valuable findings, for at least two reasons. First, TVK risk loadings were explicitly derived to account for the effects of uncertainty and time variation, but are based only on asset and market return data. Second, despite showing ample fluctuations over time, these parameters reveal strong correlations with business-cycle and market conditions, which are therefore the fundamental driver of changes in asset risk.

6 Conclusions

The aim of this study was to investigate whether the loadings of fundamental risk factors HML, SMB, and the market experience significant time-variation and can be linked to future economic growth. Using data from industry portfolios, I estimate a parsimonious three-factor model with time-varying alphas and betas that are endogenous with respect to the uncertainty surrounding their true values. The estimated alphas and risk loadings are not conditional on exogenous state variables, but interestingly they display fluctuations that are variously correlated with changes in market conditions and the business environment. Also, they evolve according to different and intuitive cyclical patterns across industry portfolios. This confirms that industry betas and pricing errors change through time, not least as to
reflect changing industry fundamentals and/or regulation.

7 Data Appendix

Fama and French assign each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June of year \( t \) based on its four-digit SIC code at that time. For further details please refer to French’s data library at:

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

Industry classification:

1. NODUR, Consumer NonDurables — Food, Tobacco, Textiles, Apparel, Leather, Toys
2. DURBL, Consumer Durables — Cars, TV’s, Furniture, Household Appliances
3. MANUF, Manufacturing — Machinery, Trucks, Planes, Chemicals, Off Furn, Paper, Com Printing
4. ENRGY, Oil, Gas, and Coal Extraction and Products
5. HITEC, Business Equipment — Computers, Software, and Electronic Equipment
6. TELCM, Telephone and Television Transmission
7. SHPS, Wholesale, Retail, and Some Services (Laundries, Repair Shops)
8. HLTH, Healthcare, Medical Equipment, and Drugs
9. UTILS, Utilities

The Fama/French factors are constructed using the 6 value-weight portfolios formed on size and book-to-market. SMB (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios. HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios. The excess return on the market is the value-weight return on all NYSE, AMEX,
and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates). The excess return on the market is the value-weight return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates).
References


Table I
Summary statistics and unconditional CAPM parameters for 10 industry portfolios and risk factors REM, SMB, HML: 1926-2009

The table contains summary statistics for the simple returns of 10 industry portfolios and the REM, SMB and HML factors of Fama and French (1993). The table also reports OLS estimates for the intercept, slope, $R^2$ and standard error of fitted residuals of the OLS regression $R^{ei}_t = \alpha^i + \beta^i R^M_t + \varepsilon^i_t$, where $R^{ei}_t = R^e_i - R^f_t$ is the return on test portfolio $i$ in excess of the one-month Treasury bill rate and $R^e_t = R^e_t - R^f_t$ is the excess return on the market. $t$-values are constructed using HAC standard errors, following Andrews (1991). Standard errors are in parentheses. Data are sampled at the monthly frequency and cover the period July 1926 to September 2009 (999 observations).

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>$\hat{\alpha}_i$</th>
<th>$\hat{\beta}_i$</th>
<th>$\sigma (\hat{\varepsilon}_i^t)$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nodur</td>
<td>1.15</td>
<td>6.67</td>
<td>0.20**</td>
<td>1.06***</td>
<td>3.27</td>
<td>0.76</td>
</tr>
<tr>
<td>Durbl</td>
<td>1.19</td>
<td>9.06</td>
<td>0.02</td>
<td>1.43***</td>
<td>4.58</td>
<td>0.74</td>
</tr>
<tr>
<td>Manuf</td>
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<td>7.87</td>
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<td>1.31***</td>
<td>3.31</td>
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<td>Energy</td>
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<td>1.17***</td>
<td>5.53</td>
<td>0.57</td>
</tr>
<tr>
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<td>9.05</td>
<td>0.28**</td>
<td>1.43***</td>
<td>4.58</td>
<td>0.74</td>
</tr>
<tr>
<td>Telcm</td>
<td>1.23</td>
<td>7.16</td>
<td>0.29**</td>
<td>1.04***</td>
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<td>0.63</td>
</tr>
<tr>
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<td>1.16***</td>
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<tr>
<td>Hlth</td>
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<td>1.05***</td>
<td>4.19</td>
<td>0.65</td>
</tr>
<tr>
<td>Utils</td>
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<td>0.94***</td>
<td>4.37</td>
<td>0.58</td>
</tr>
<tr>
<td>Other</td>
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<td>0.24**</td>
<td>1.24***</td>
<td>4.23</td>
<td>0.72</td>
</tr>
<tr>
<td>$R^e_t^M$(REM)</td>
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<td>5.48</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>SMB</td>
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<td>0.20***</td>
<td>3.17</td>
<td>0.10</td>
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<tr>
<td>HML</td>
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<td>0.01</td>
<td>0.15***</td>
<td>3.50</td>
<td>0.05</td>
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Table II
Estimated three-factor model parameters for 10 industry portfolios: 1926-2009

The table reports OLS estimates for the intercept, slope, $R^2$ and standard error of fitted residuals of the OLS regression $R_{it}^i = \alpha^i + \beta^i R_{it}^{eM} + s^i SMB_t + h^i HML_t + \varepsilon_t$, where $R_{it}^i = R_i - R_t^f$ is the return on test portfolio $i$ in excess of the one-month Treasury bill rate, $R_{it}^{eM} = R_{it}^{eM} - R_t^f$ is the excess return on the market, and $SMB_t$ and $HML_t$ are the simple returns on the SMB and HML portfolios, respectively. $t$-values are constructed using HAC standard errors, following Andrews (1991). Standard errors are in parentheses. Data are sampled at the monthly frequency and cover the period July 1926 to September 2009 (999 observations).

<table>
<thead>
<tr>
<th></th>
<th>$\hat{\alpha}^i$</th>
<th>$\hat{\beta}^i$</th>
<th>$\hat{s}^i$</th>
<th>$\hat{h}^i$</th>
<th>$\sigma(\hat{\varepsilon}_t)$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nodur</td>
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<td>0.87***</td>
<td>0.72***</td>
<td>0.35***</td>
<td>1.98</td>
<td>0.91</td>
</tr>
<tr>
<td>Durbl</td>
<td>-0.23***</td>
<td>1.17***</td>
<td>1.01***</td>
<td>0.40***</td>
<td>2.95</td>
<td>0.89</td>
</tr>
<tr>
<td>Manuf</td>
<td>0.00</td>
<td>1.10***</td>
<td>0.76***</td>
<td>0.40***</td>
<td>1.75</td>
<td>0.95</td>
</tr>
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<td>Enrgy</td>
<td>0.21</td>
<td>0.98***</td>
<td>0.57***</td>
<td>0.50***</td>
<td>4.92</td>
<td>0.66</td>
</tr>
<tr>
<td>Hitec</td>
<td>0.22**</td>
<td>1.26***</td>
<td>0.98***</td>
<td>-0.18***</td>
<td>3.33</td>
<td>0.86</td>
</tr>
<tr>
<td>Telcm</td>
<td>0.30**</td>
<td>0.97***</td>
<td>0.52***</td>
<td>-0.22***</td>
<td>3.97</td>
<td>0.69</td>
</tr>
<tr>
<td>Shops</td>
<td>0.03</td>
<td>0.95***</td>
<td>0.89***</td>
<td>0.19***</td>
<td>2.70</td>
<td>0.87</td>
</tr>
<tr>
<td>Hlth</td>
<td>0.42***</td>
<td>0.94***</td>
<td>0.73***</td>
<td>-0.25***</td>
<td>3.41</td>
<td>0.77</td>
</tr>
<tr>
<td>Utils</td>
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<td>0.83***</td>
<td>0.16*</td>
<td>0.50***</td>
<td>3.97</td>
<td>0.65</td>
</tr>
<tr>
<td>Other</td>
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<td>0.97***</td>
<td>0.84***</td>
<td>0.68***</td>
<td>2.22</td>
<td>0.92</td>
</tr>
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</table>
Table III
Volatilities of time-varying parameters for 10 industry portfolios: 1926-2009

The table contains estimated time-varying parameter estimates from the model \( R_t = x_t \beta_t + \varepsilon_t \), where \( \beta_t = F_\beta_{t-1} + \nu_t \), and \( \sigma_\alpha \), \( \sigma_\beta \) and \( \sigma_\varepsilon \) are conditional estimates of the standard deviations of three-factor regression coefficients and disturbance. \( R_t \) is the return on industry portfolio \( i \) in excess of the one-month Treasury bill rate. Standard errors are in parentheses. Data are sampled at the monthly frequency and cover the period July 1926 to September 2009 (999 observations).

<table>
<thead>
<tr>
<th></th>
<th>( \sigma_\alpha )</th>
<th>( \sigma_\beta )</th>
<th>( \sigma_s )</th>
<th>( \sigma_h )</th>
<th>( \sigma_\varepsilon )</th>
</tr>
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<tbody>
<tr>
<td>Nodur</td>
<td>0.13(0.03)</td>
<td>0.02(–)</td>
<td>0.03(0.01)</td>
<td>0.07(0.02)</td>
<td>1.53(0.05)</td>
</tr>
<tr>
<td>Durbl</td>
<td>0.01(0.01)</td>
<td>0.03(0.01)</td>
<td>0.1(0.03)</td>
<td>0.06(0.02)</td>
<td>2.34(0.07)</td>
</tr>
<tr>
<td>Manuf</td>
<td>0.02(0.01)</td>
<td>0.01(–)</td>
<td>0.01(–)</td>
<td>0.1(0.01)</td>
<td>1.31(0.04)</td>
</tr>
<tr>
<td>Energy</td>
<td>0.00(–)</td>
<td>0.04(0.01)</td>
<td>0.05(0.03)</td>
<td>0.13(0.03)</td>
<td>4.33(0.11)</td>
</tr>
<tr>
<td>Hitec</td>
<td>0.07(0.03)</td>
<td>0.04(0.01)</td>
<td>0.22(0.03)</td>
<td>0.06(0.01)</td>
<td>2.21(0.07)</td>
</tr>
<tr>
<td>Telec</td>
<td>0.00(–)</td>
<td>0.02(–)</td>
<td>0.04(0.01)</td>
<td>0.06(0.01)</td>
<td>3.39(0.08)</td>
</tr>
<tr>
<td>Shops</td>
<td>0.01(0.01)</td>
<td>0.01(–)</td>
<td>0.05(0.02)</td>
<td>0.14(0.04)</td>
<td>2.1(0.07)</td>
</tr>
<tr>
<td>Hlth</td>
<td>0.28(0.06)</td>
<td>0.04(0.01)</td>
<td>0.04(0.01)</td>
<td>0.01(–)</td>
<td>2.77(0.08)</td>
</tr>
<tr>
<td>Util</td>
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<td>0.02(–)</td>
<td>0.15(0.05)</td>
<td>0.11(0.03)</td>
<td>3.07(0.1)</td>
</tr>
<tr>
<td>Other</td>
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<td>0.02(0.01)</td>
<td>0.06(0.01)</td>
<td>0.19(0.03)</td>
<td>1.41(0.05)</td>
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</table>
Table IV

This table contains OLS estimates for the slope and $R^2$ of the regression of each portfolio’s time-varying alphas on a constant and one lag of all of the state variables together. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively. HAC standard errors were computed, following Andrews (1991). Data are sampled at the monthly frequency, and the estimation sample is from May 1953 to August 2008 (653 observations).

<table>
<thead>
<tr>
<th></th>
<th>MKT</th>
<th>TBILL</th>
<th>TERM</th>
<th>DEF</th>
<th>CAPE</th>
<th>CAY</th>
<th>PMI</th>
<th>R^2</th>
</tr>
</thead>
<tbody>
<tr>
<td>NODUR</td>
<td>−0.02</td>
<td>−0.22***</td>
<td>0.02</td>
<td>0.2***</td>
<td>−0.52***</td>
<td>−0.02</td>
<td>0.09***</td>
<td>0.27</td>
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<tr>
<td>DURBL</td>
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<td>0.00</td>
<td>0.00</td>
<td>−0.02***</td>
<td>−0.29***</td>
<td>−0.01***</td>
<td>0.01***</td>
<td>0.41</td>
</tr>
<tr>
<td>MANUF</td>
<td>0.00</td>
<td>0.03***</td>
<td>0.02***</td>
<td>−0.01</td>
<td>−0.02</td>
<td>0.00</td>
<td>−0.01*</td>
<td>0.03</td>
</tr>
<tr>
<td>ENRGY</td>
<td>0.00</td>
<td>0.01***</td>
<td>0.00</td>
<td>0.00</td>
<td>−0.37***</td>
<td>−0.03***</td>
<td>0.00</td>
<td>0.74</td>
</tr>
<tr>
<td>TELCM</td>
<td>0.00</td>
<td>0.07***</td>
<td>0.04***</td>
<td>0.01***</td>
<td>0.42***</td>
<td>0.05***</td>
<td>0.00</td>
<td>0.75</td>
</tr>
<tr>
<td>HITEC</td>
<td>−0.03*</td>
<td>0.04*</td>
<td>0.05**</td>
<td>0.09***</td>
<td>1.62***</td>
<td>−0.09***</td>
<td>−0.08***</td>
<td>0.24</td>
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<td>UTILS</td>
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<td>0.01***</td>
<td>0.00*</td>
<td>0.00</td>
<td>0.09***</td>
<td>0.00</td>
<td>0.00</td>
<td>0.13</td>
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<tr>
<td>HLTH</td>
<td>−0.05</td>
<td>−0.13*</td>
<td>−0.01</td>
<td>0.08</td>
<td>0.5</td>
<td>0.01</td>
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<td>SHPS</td>
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<td>−0.08***</td>
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<td>−0.02***</td>
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<td>0.16***</td>
<td>−0.02***</td>
<td>0.02</td>
<td>0.48</td>
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Table V

This table contains OLS estimates for the slope and $R^2$ of the regression of each portfolio’s time-varying risk loadings on a constant and one lag of all of the state variables together. *, **, *** indicate significance at the 90%, 95% and 99% level, respectively. HAC standard errors were computed, following Andrews (1991). Data are sampled at the monthly frequency, and the estimation sample is from May 1953 to August 2008 (653 observations).

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Figure I
Time-varying loadings from the three-factor model for 10 industry portfolios:

The panels plot estimated time-varying slopes from the model $R_{it}^e = \alpha_i t + \beta_i R_{it}^M + s_i S M B_t + h_i H M L_t + \varepsilon_i t$, where $R_{it}^e = R_i t - R_f t$ is the return on test portfolio $i$ in excess of the one-month Treasury bill rate, $R_{it}^M = R_{it}^e - R_f t$ is the excess return on the market, and $S M B_t$ and $H M L_t$ are the simple returns on the SMB and HML portfolios, respectively.
Figure II

The panels plot estimated time-varying slopes from the model \( R_{\text{ei}}^{it} = \alpha_i + \beta_i R_{\text{eM}}^{it} + s_i \text{SMB}_t + h_i \text{HML}_t + \varepsilon_i^{it} \), where \( R_{\text{ei}}^{it} = R_{i}^{it} - R_{f}^{it} \) is the return on test portfolio \( i \) in excess of the one-month Treasury bill rate, \( R_{\text{eM}}^{it} = R_{eM}^{it} - R_{f}^{it} \) is the excess return on the market, and \( \text{SMB}_t \) and \( \text{HML}_t \) are the simple returns on the SMB and HML portfolios, respectively.
Figure III

The panels plot estimated time-varying slopes from the model

$$R_{ei}^t = \alpha_i^t + \beta_i^t R_{t}^{eM} + s_i^t SMB_t + h_i^t HML_t + \varepsilon_i^t,$$

where $R_{ei}^t = R_i^t - R_f^t$ is the return on test portfolio $i$ in excess of the one-month Treasury bill rate, $R_{t}^{eM} = R_{t}^{eM} - R_f^t$ is the excess return on the market, and $SMB_t$ and $HML_t$ are the simple returns on the SMB and HML portfolios, respectively.
Figure IV

The panels plot estimated time-varying intercepts from the model $R_{ei,t} = \alpha_i t + \beta_i R_{eM,t} + s_i SMB_t + h_i HML_t + \varepsilon_i t$, where $R_{ei,t} = R_{i,t} - R_{f,t}$ is the return on test portfolio $i$ in excess of the one-month Treasury bill rate, $R_{eM,t} = R_{eM,t} - R_{f,t}$ is the excess return on the market, and $SMB_t$ and $HML_t$ are the simple returns on the SMB and HML portfolios, respectively.
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