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Uncertainty and the Dynamics of Multifactor Loadings and Pricing Errors

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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.

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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, experience significant variation over time. Hence, risk loadings are commonly modeled as functions of observed macroeconomic and financial variables. 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. This note computes estimates of abnormal returns (alphas) and risk loadings (betas) 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, betas 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. Accordingly, this note holds that changes in risk factor returns effectively summarize the arrival of relevant information. Therefore, unlike 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 that yields monthly alpha and beta time series without relying on exogenous state variables or time/frequency assumptions. The core results of this note is that alphas and risk loadings do 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.

Section 2 introduces an empirical model 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. Model

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) added two more factors to the static market model:

$$R_t^{ei} = \alpha^i + \beta^i R_t^{eM} + s^i R_t^{SMB} + h^i R_t^{HML} + \varepsilon_t^i \tag{1}$$

Here R_t^{ei} is the return on asset i in excess of the one-month Treasury bill rate, R_t^{eM} is the excess return on the market, R_t^{SMB} and R_t^{HML} are the returns on the SMB and HML factor portfolios, respectively, and β^i, s^i and h^i are the asset's factor loadings. The idea in the literature is that fundamental risk factors, such as the market, growth opportunities and financial distress, as well as firm's size, drive the cross-section of risk and return. Using the sensitivity to changes in R_t^{SMB} to explain returns is in line with the evidence (see for instance Cochrane, 2005) that there is co-variation in the returns on small stocks that is not captured by the market return and is compensated in average returns. 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.

The key hypothesis of this note is that investors engage in a systematic learning activity on observed asset returns, aimed at extracting and updating forecasts of undiversifiable and idiosyncratic risk components. The conditional expectation of R_t^{ei}, under uncertainty, becomes

$$E\left(R_t^{ei}\middle|\psi_{t-1}\right) = \textstyle\sum_{j=1}^{K} E\left(\beta^{ij}\middle|\psi_{t-1}\right) \cdot E\left(x^j\middle|\psi_{t-1}\right) \tag{2}$$

Here ψ is the information set, x^j are the risk premia, i.e., expected returns on mimicking portfolios for *K* risk factors, and β^{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, in which the intercept and slope coefficients, stacked up in the coefficient vector β_t^i, change over time according to an autoregressive dynamics:

$$R_t^{ei} = X_t'\beta_t^i + \varepsilon_t^i, t = 1, 2, \dots, T \tag{3}$$
$$\beta_t^i = \widetilde{\beta^\iota} + F^i\beta_{t-1}^i + \upsilon_t^i, \tag{4}$$

where $\varepsilon_t^i \sim IIDN(0, S)$ and $\upsilon_t^i \sim IIDN(0, Q)$. Importantly, ε_t^i and υ_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 here are not assumed to be conditional on any exogenous variable. The parameters are estimated through the Kalman filter (KF). The KF 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. The KF computes a minimum mean-squared-error estimate of β_t^i conditional on ψ. 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 β_t^i 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.

The impact of time variation and uncertainty on the market's assessment of risk has been analyzed 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. In these cases, 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. Also, idiosyncratic risk is rarely allowed to vary over time. In contrast, the main advantages of this note’s methodology are its simplicity and its ability to adapt to assets' or portfolios' actual sensitivities to risk factors in a way that constant-coefficient, but also popular rolling- or fixed-window regressions, simply do not permit to. Unlike some recent contributions, this note's joint estimates of each period's conditional alphas and betas are obtained without making any assumption about period-to-period variation in betas.

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. 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. 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 note endogenizes pricing errors and prevents future information from affecting today's forecasts.

3. Estimated time-varying alphas and betas

Our test assets are 10 US industry-sorted portfolios[1]. 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 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 (see the Data Appendix).

OLS-based parameters of the three-factor model (not shown but available upon request) exhibit higher R^2s and lower idiosyncratic risk than simple 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. All this confirms that the Fama-French model is better than the CAPM at pricing industry-sorted portfolios.

Several interesting findings emerge from the KF estimates of volatility parameters for the 10 industry portfolios (available on request). 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 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. Also, a formal test in Trecroci (2010) confirms that the TVK estimation procedure yields more accurate factor loadings than competing time-varying approaches.

[1] 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.

Turning to point estimates, Figures 1-3 plot the time series of risk loadings from the Fama-French model estimated via the TVK algorithm. To avoid cluttering the charts, I do not report here confidence bands. Graphs with confidence bands are available upon request. 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 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 ($\hat{\beta}$), Figure 1 shows this beta as experiencing a very long-term upward trend in some industries (TELCM, HLTH) and a downward one in others (UTILS, DURBL). 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 ($\hat{s}$), Figure 2 confirms broadly upward trends for TELCM, HLTH, MANUF and SHPS. HITEC and TELCM betas on SMB have higher volatility. 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 ($\hat{h}$, Figure 3) portraits 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 4 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.

4. 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[2] (CAPE), the consumption-to-wealth ratio by Lettau and Ludvigson[3] (2001) (CAY) and the log of the PMI Composite Index (PMI). These variables are designed to capture fluctuations in expectations of the business cycle. 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[4]. Each of them is standardized, 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)

Alpha-centred estimates, reported in Table I, 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^2s 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 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 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 for the other state variables, TBILL, DEF, CAY and TERM all appear to have some 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 degree than all other indicators.

Turning now to regressions of TVK portfolio betas on state variables, estimates in Table II yield several interesting insights. First, R^2s 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.

[2] The series is calculated by R. Shiller, http://www.econ.yale.edu/~shiller/data.htm. The dividend-price ratio was also tested, with less clear results as to its correlation with alphas and betas

[3] CAY is available only at the quarterly frequency. I computed monthly observations from the original data using linear interpolation.

[4] Due to data constraints, the estimation sample here starts in May 1953.

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. 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, 2010), 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 behavior. 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. 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.

5. 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 actual 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.

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
10. OTHER, Other -- Mines, Construction, Building Materials, Transportation, Hotels, Business Services, Entertainment, Finance

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).

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Table I – OLS regressions of alphas on state variables

This table contains OLS estimates for the intercept and R² 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 at the monthly frequency, and the sample is from May 1953 to August 2008 (653 observations).

	mkt	tbill	term	def	cape	cay	pmi	R^2
NODUR	−0.02	−0.22***	0.02	0.2***	−0.52***	−0.02	0.09***	0.27
DURBL	0.00	0.00	0.00	−0.02***	−0.29***	−0.01***	0.01***	0.41
MANUF	0.00	0.03***	0.02***	−0.01	−0.02	0.00	−0.01*	0.03
ENRGY	0.00	0.01***	0.00	0.00	−0.37***	−0.03***	0.00	0.74
TELCM	0.00	0.07***	0.04***	0.01***	0.42***	0.05***	0.00	0.75
HITEC	−0.03*	0.04*	0.05**	0.09***	1.62***	−0.09***	−0.08***	0.24
UTILS	0.00	0.01***	0.00*	0.00	0.09***	0.00	0.00	0.13
HLTH	−0.05	−0.13*	−0.01	0.08	0.5	0.01	−0.21***	0.07
SHPS	0.00	−0.08***	−0.05***	−0.02***	−0.76***	−0.01***	0.02***	0.59
OTHER	0.00	0.02***	0.02***	0.01***	0.16***	−0.02***	0.02	0.48

Table II – OLS regressions of betas on state variables

This table contains OLS estimates for the slope and R² 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 at the monthly frequency, and the sample is from May 1953 to August 2008 (653 observations).

		mkt	*tbill*	*term*	*def*	*cape*	*cay*	*pmi*	R^2
	β_t	0.00	0.02***	0.01**	−0.01**	0.08***	0.01**	0.01***	0.11
NODUR	s_t	0.00	0.05***	0.04***	−0.03***	−0.9***	0.00	0.01**	0.14
	h_t	−0.01	−0.06***	−0.02**	0.02*	−0.08	−0.02***	−0.02***	0.07
	β_t	−0.01***	−0.06***	−0.02***	−0.01	−0.38***	−0.02***	0.00	0.42
DURBL	s_t	0.00	0.02	0.1***	−0.06***	−0.8***	0.02**	0.0	0.24
	h_t	0.00	−0.08***	−0.03**	0.04***	0.38***	0.04	0.00	0.14
	β_t	0.00	−0.09***	−0.06***	0.01	−0.13***	0.00	0.00	0.55
MANUF	s_t	0.00	0.11***	0.06***	0.00	0.00	0.00	0.02***	0.49
	h_t	0.00	−0.05***	−0.02	−0.01	0.41***	−0.01*	0.02***	0.24
	β_t	−0.02***	−0.09***	−0.13***	0.1***	−0.18***	−0.07***	−0.01*	0.51
ENRGY	s_t	0.00	0.24***	0.07***	0.05**	1.61***	−0.04***	0.01	0.47
	h_t	−0.02	−0.03	0.03	−0.16***	1.45***	−0.09***	−0.07***	0.39
	β_t	−0.01**	−0.02***	0.01*	0.02**	0.44***	−0.04***	0.00	0.47
TELCM	s_t	0.02**	−0.08***	0.00	0.00	−0.37***	0.09***	−0.01	0.28
	h_t	0.03***	−0.12***	−0.15***	−0.03	−1.40***	0.15***	0.06***	0.47
	β_t	−0.01	−0.14***	−0.03***	0.03***	−0.22***	−0.03***	0.01*	0.29
HITEC	s_t	0.01	0.15***	0.19***	−0.05*	−0.02	−0.04*	−0.02	0.09
	h_t	0.02*	−0.02	0.01	−0.17***	−2.00***	0.06***	0.03**	0.46
	β_t	0.00	−0.04***	−0.02***	−0.01***	−0.55***	−0.02***	0.00	0.71
UTILS	s_t	−0.01	−0.18***	−0.07***	0.00	0.54***	−0.02**	0.02**	0.27
	h_t	0.00	0.29***	0.12***	0.07***	1.45***	−0.07***	−0.01	0.55
	β_t	0.01***	−0.01	0.01**	−0.04***	−0.11*	0.01	0.02***	0.15
HLTH	s_t	0.00	0.39***	0.30***	−0.01	1.24***	0.08***	0.00	0.62
	h_t	0.00	−0.01***	0.00	−0.01	−0.01	0.2***	0.01***	0.20
	β_t	0.00	0.04***	0.04***	−0.16	0.01***	0.01**	0.01***	0.28
SHPS	s_t	0.00	0.12***	0.13***	−0.05***	−0.33***	−0.02**	0.02**	0.38
	h_t	−0.01	−0.06***	−0.02	0.10***	0.39***	0.00	0.06	0.08
	β_t	0.01**	−0.04***	−0.03***	−0.02***	−0.31***	0.02***	0.01**	0.28
OTHER	s_t	0.00	0.08***	0.11***	−0.08***	−0.80***	−0.02**	0.10	0.30
	h_t	0.00	−0.06***	0.00	−0.05**	0.30***	0.08***	−0.02*	0.28

Figure 1 - Time-varying loadings from the three-factor model for 10 industry portfolios: loading on the market, 1928M6-2009M9.

The panels plot estimated time-varying slopes from the model $R_t^{ei} = \alpha^i + \beta^i R_t^{eM} + s^i R_t^{SMB} + h^i R_t^{HML} + \varepsilon_t^i$, where R_t^{ei} is the return on test portfolio i in excess of the one-month Treasury bill rate, R_t^{eM} is the excess return on the market, and R_t^{SMB} and R_t^{HML} are the simple returns on the SMB and HML portfolios, respectively.

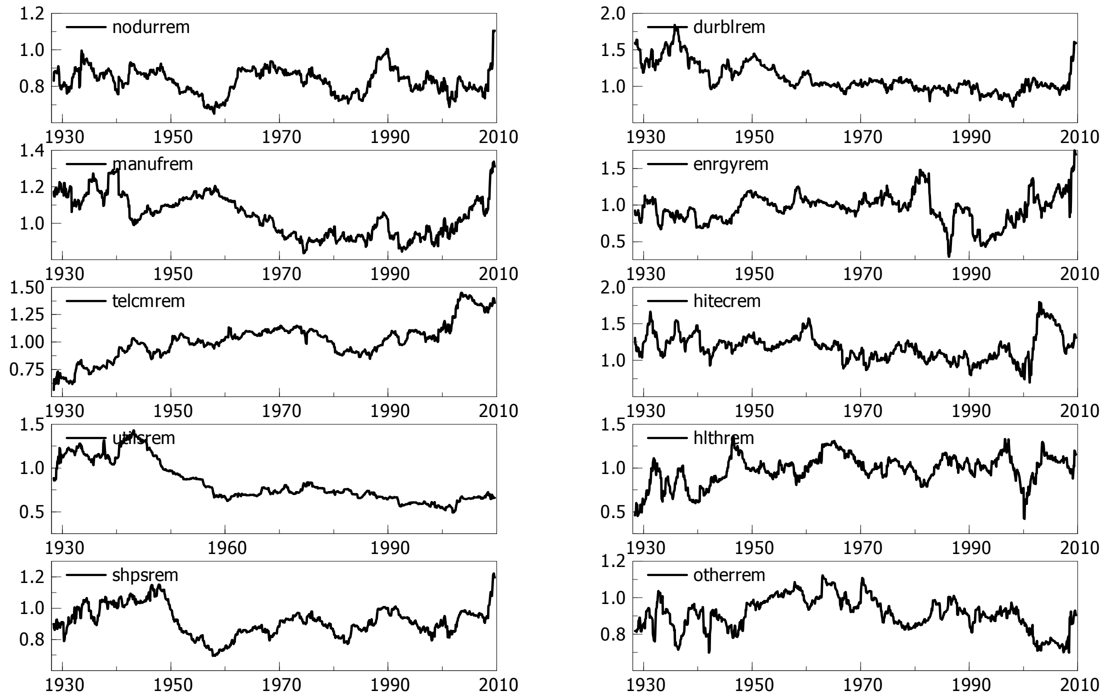

Figure 2 - Time-varying loadings from the three-factor model for 10 industry portfolios: loading on the SMB factor, 1928M6-2009M9.

The panels plot estimated time-varying slopes from the model $R_t^{ei} = \alpha^i + \beta^i R_t^{eM} + s^i R_t^{SMB} + h^i R_t^{HML} + \varepsilon_t^i$, where R_t^{ei} is the return on test portfolio i in excess of the one-month Treasury bill rate, R_t^{eM} is the excess return on the market, and R_t^{SMB} and R_t^{HML} are the simple returns on the SMB and HML portfolios, respectively.

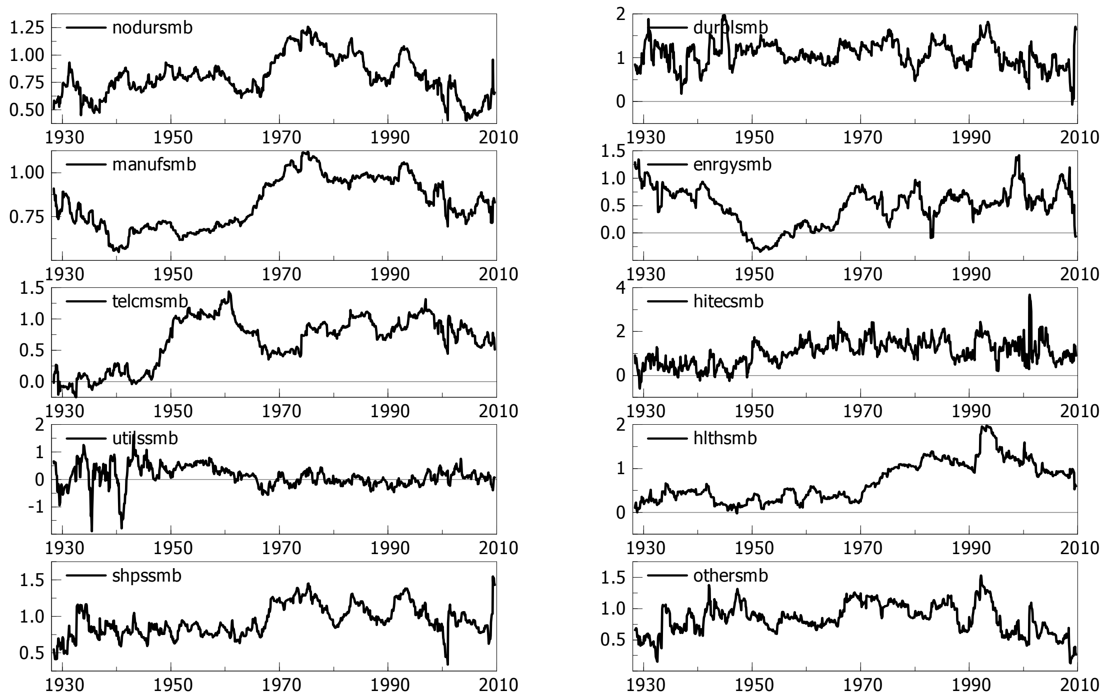

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Figure 3 - Time-varying loadings from the three-factor model for 10 industry portfolios: loading on the HML factor, 1928M6-2009M9.

The panels plot estimated time-varying slopes from the model $R_t^{ei} = \alpha^i + \beta^i R_t^{eM} + s^i R_t^{SMB} + h^i R_t^{HML} + \varepsilon_t^i$, where R_t^{ei} is the return on test portfolio i in excess of the one-month Treasury bill rate, R_t^{eM} is the excess return on the market, and R_t^{SMB} and R_t^{HML} are the simple returns on the SMB and HML portfolios, respectively.

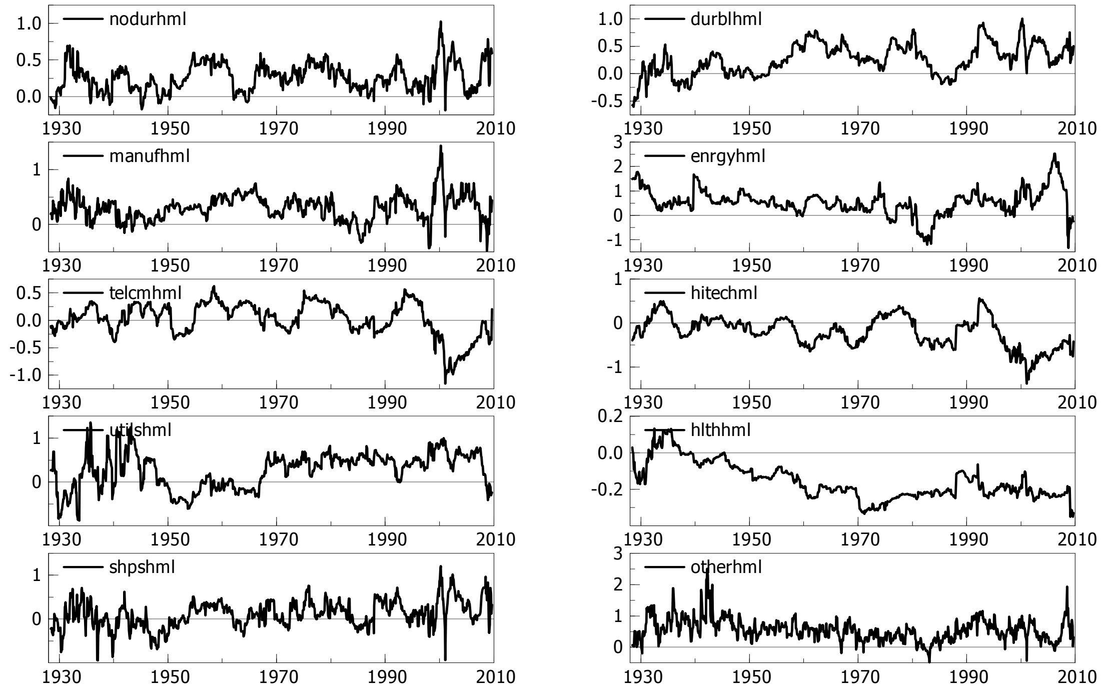

Figure 4 - Time-varying abnormal returns from the three-factor model for 10 industry portfolio, 1928M6-2009M9.

The panels plot estimated time-varying intercepts from the model $R_t^{ei} = \alpha^i + \beta^i R_t^{eM} + s^i R_t^{SMB} + h^i R_t^{HML} + \varepsilon_t^i$, where R_t^{ei} is the return on test portfolio i in excess of the one-month Treasury bill rate, R_t^{eM} is the excess return on the market, and R_t^{SMB} and R_t^{HML} are the simple returns on the SMB and HML portfolios, respectively.