Horizon-specific risk, higher moments, and asset prices.

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Outline

- Motivation
  - Higher moments of distribution
  - Horizon-specific risk
  - Systemic risk vs. Idiosyncratic risk
- Model derivation
- Estimation
- Results
- Conclusions

Motivation

- Solution to portfolio choice can be expressed in terms of Euler equation

$$E(M_{t+1}R^i_{t+1} \mid \Omega_t) = 1$$

- Hence asset returns directly depend on the pricing kernel, or stochastic discount factor, M_{t+1}.
- Although we don't know the precise structure of M_{t+1}, we should be able to approximate it with some factors.
- Decades of research following the emergence of CAPM created an enormous set of potentially significant risk factors.
- Which are the "proper" factors?

Motivation - cont.

- Are all the discovered factors outcomes of fundamental asset pricing relationships?
- Recent out-of-sample and post publication testing indicates that majority of these relationships are spurious, or at least corrected by arbitrageurs following their publication.
- In light of such discoveries, attention should be turned to theoretical factors capturing the fundaments of asset returns.
  - Moments of distribution are a good candidate.

Motivation - higher moments

- Second, third and fourth moment capture different aspects of asset riskiness.
- We shouldn't limit our attention in terms of asset riskiness to volatility.
- Skewness and kurtosis contain information about the tails of distribution that should be crucial for risk averse investors.
- Accounting for volatility risk, skewness risk, and kurtosis risk should provide better representation of investors' preferences.
- How accurate will this representation be?

Motivation - horizon-specific risk

- Are investors that have different tastes, and are following different investment strategies, would be interested in same investment horizon?
  - Probably NOT!
- Hence by aggregating investors across investments horizons we are throwing away large portion of information.
- Frequency domain analysis allows us to incorporate the heterogeneity of investment horizons.
- The model we derive considers information contained in higher moments, and allows them to operate separately at different frequencies.

Motivation - Market versus Idiosyncratic risk

- It is assumed that idiosyncratic risk is not important for investors, since it can be diversified away.
  - Empirical evidence suggests that idiosyncratic volatility and skewness risk plays a role in determination of asset returns, e.g. Jondeau, Zhang, and Zhu (2019) or Amaya et al. (2015).
- There are several reasons idiosyncratic risk is relevant for investors.
  - Exposure to idiosyncratic risks due to asymmetric connectedness in the network of assets.
  - Deliberate underdiversification due to preference for lottery-like stocks .
- We should consider idiosyncratic risk in excess to market risk.

Model derivation

General utility function

Expected return of asset i is determined by

$$E(M_{t+1}R^i_{t+1} \mid \Omega_t) = 1,$$

the stochastic discount factor M_{t+1} can be expressed as

$$M_{t+1} = \frac{U'(W_{t+1})}{U'(W_t)}.$$

Following Maheu, McCurdy, and Zhao (2013), and Dittmar (2002), we model $U(W_{t+1})$ by assuming a general utility function of wealth and taking the Taylor expansion up to the N-th order, i.e.

$$\begin{aligned} U(W_{t+1}) &\approx \sum_{n=0}^{N} \frac{U^{(n)}(W_t(1+C_t))}{n!}(W_{t+1} - W_t(1+C_t))^n \\ &= \sum_{n=0}^{N} \frac{U^{(n)}(W_t(1+C_t))}{n!}(W_t(R^w_{t+1} - C_t))^n, \end{aligned} \tag{1}$$

where C_t is an arbitrary return.

Pricing kernel

Dittmar (2002) shows that $N = 4$ is needed to avoid counterintuitive risk taking.

Without loss of generality we can assume $W_t = 1$, then the pricing kernel becomes

$$\begin{aligned} M_{t+1} &\approx \sum_{n=0}^{3} \frac{U^{(n+1)}(1+C_t)}{U'(1)n!}(R^w_{t+1} - C_t)^n \\ &= g_{0,t} + g_{1,t}(R^w_{t+1} - C_t) + g_{2,t}(R^w_{t+1} - C_t)^2 + g_{3,t}(R^w_{t+1} - C_t)^3, \end{aligned} \tag{2}$$

where $g_{n,t} = [U^{(n+1)}(1+C_t)/U'(1)][1/n!] = [U^{(n+1)}(1+C_t)/U'(1+C_t)n!][U'(1+C_t)/U'(1)]$.

Market risk premia

Let's assume that the investor decides between investing into the pool of risky assets which yields return on aggregate wealth R_t^w, and the risk-free asset yielding R_t^f. Then the Euler equation is

$$E_t[M_{t+1}R_{t+1}^w \mid \Omega_t] = 1.$$

If we now apply the pricing kernel from Equation (2) to the above Euler equation we get

$$\begin{aligned} E_t(R_{t+1}^w) - R_t^f &= \theta_{1,t} cov(R_{t+1}^w, R_{t+1}^w - C_t) \\ &+ \theta_{2,t} cov(R_{t+1}^w, [R_{t+1}^w - C_t]^2) \\ &+ \theta_{3,t} cov(R_{t+1}^w, [R_{t+1}^w - C_t]^3), \end{aligned} \tag{3}$$

where R_t^f is the risk free rate for period t, $\theta_{n,t} = -R_t^f g_{n,t}$.

Expansion point C_t

We set $C_t = E(R^w_{t+1})$, thus we can rewrite $R^w_{t+1} - C_t$ as

$$R^w_{t+1} - C_t = R^w_{t+1} - E(R^w_{t+1}) = \epsilon_{t+1}.$$

If we simplify the notation so that

$$R^{i,e}_{t+1} = R^i_{t+1} - R^f_t,$$
$$R_{t+1} = R^w_{t+1} - R^f_t,$$

we can formulate ϵ_{t+1} in terms of excess returns

$$\epsilon_{t+1} = (R^w_{t+1} - R^f_t) - (E_t(R^w_{t+1}) - R^f_t) = R_{t+1} - E_t(R_{t+1}), \quad (4)$$

hence,

$$\begin{aligned} E_t(R_{t+1}) = \theta_{1,t} cov(R_{t+1}, \epsilon_{t+1}) + \theta_{2,t} cov(R_{t+1}, [\epsilon_{t+1}]^2) \\ + \theta_{3,t} cov(R_{t+1}, [\epsilon_{t+1}]^3). \end{aligned} \quad (5)$$

Decomposition of returns

Due to heterogeneity of investment horizons, returns operate at different scales. We are able to decompose returns (and other variables) to individual scales, for simplicity assume

$$R_{t+1} \equiv \sum_{j=1}^{N} R_{t+1}^{(j)} + R_{t+1}^{(>j)} = R_{t+1}^{(short)} + R_{t+1}^{(long)}, \tag{6}$$

where we assume $R_{t+1}^{(short)}$ and $R_{t+1}^{(long)}$ are orthogonal. Then Equation (4) becomes

$$\begin{aligned} \epsilon_{t+1} &= [R_{t+1}^{(short)} - E_t(R_{t+1}^{(short)})] + [R_{t+1}^{(long)} - E_t(R_{t+1}^{(long)})] \\ &= \epsilon_{t+1}^{(s)} + \epsilon_{t+1}^{(l)}. \end{aligned} \tag{7}$$

Decomposition of returns

For each i, we may assume that investors invest their whole wealth into asset i, hence $R_{t+1}^{i,e}$ and R_{t+1} can be treated as interchangeable. Hence,

$$\begin{aligned} E_t(R_{t+1}^{i,e}) &= \theta_{1,t} cov_t(R_{t+1}, \epsilon_{t+1}^{(s)} + \epsilon_{t+1}^{(l)}) \\ &+ \theta_{2,t} cov_t(R_{t+1}, [\epsilon_{t+1}^{(s)} + \epsilon_{t+1}^{(l)}]^2) \\ &+ \theta_{3,t} cov_t(R_{t+1}, [\epsilon_{t+1}^{(s)} + \epsilon_{t+1}^{(l)}]^3). \end{aligned} \tag{8}$$

Substituting R_{t+1} by equivalent $R_{t+1}^{(s)} + R_{t+1}^{(l)}$, Equation (8) becomes

$$\begin{aligned} E_t(R_{t+1}^{i,e}) &= \theta_{1,t}^{(s)} cov_t(R_{t+1}^{(s)}, \epsilon_{t+1}^{(s)}) + \theta_{1,t}^{(l)} cov_t(R_{t+1}^{(l)}, \epsilon_{t+1}^{(l)}) \\ &+ \theta_{2,t}^{(s)} cov_t(R_{t+1}^{(s)}, [\epsilon_{t+1}^{(s)}]^2) + \theta_{2,t}^{(l)} cov_t(R_{t+1}^{(l)}, [\epsilon_{t+1}^{(l)}]^2) \\ &+ \theta_{3,t}^{(s)} cov_t(R_{t+1}^{(s)}, [\epsilon_{t+1}^{(s)}]^3) + \theta_{3,t}^{(l)} cov_t(R_{t+1}^{(l)}, [\epsilon_{t+1}^{(l)}]^3). \end{aligned} \tag{9}$$

Decomposed centralized moments

It can be shown that

$$cov_t(R_{t+1}, [\epsilon_{t+1}]^n) = E_t([\epsilon_{t+1}]^{n+1}),$$

hence Equation (9) can be rewritten in terms of centralized moments of market returns distribution

$$\begin{aligned} E_t(R^{i,e}_{t+1}) &= \theta^{(s)}_{1,t} var_t(\epsilon^{(s)}_{t+1}) + \theta^{(l)}_{1,t} var_t(\epsilon^{(l)}_{t+1}) \\ &+ \theta^{(s)}_{2,t} E_t[(\epsilon^{(s)}_{t+1})^3] + \theta^{(l)}_{2,t} E_t[(\epsilon^{(l)}_{t+1})^3] \\ &+ \theta^{(s)}_{3,t} E_t[(\epsilon^{(s)}_{t+1})^4] + \theta^{(l)}_{3,t} E_t[(\epsilon^{(l)}_{t+1})^4], \end{aligned} \tag{10}$$

Estimation

Unconditional Estimates

The estimation is carried out in two stages. Firstly, the sensitivity of asset i returns to each of the risk factors is estimated. If we believe that these sensitivities are static, we can estimate the equations unconditionally in the following way

$$r_{i,t} = \alpha + \sum_{j=1}^{M} \beta_i^{(j)} x_{j,t} + \epsilon_t, \tag{11}$$

where $x_{j,t}$ is the value of risk factor j at time t, and $\beta_{i,t}^{(j)}$ is the sensitivity of returns of asset i to risk factor j. Then we conduct the second stage regression

$$\overline{r}_i = \omega + \sum_{j=1}^{M} \lambda_j \hat{\beta}_i^{(j)} + \eta_t,$$

where $\overline{r}_i$ is the mean return of asset i over the sample period, and $\hat{\beta}_i^{(j)}$ are the corresponding beta estimates from Equation (11).

Dynamic Estimation

- Equation (10) implies that the coefficients should be time specific, hence dynamic.
- There is evidence in the literature that suggests the betas are time-specific, e.g. in Ghysels (1998).

Hence, instead of estimating $\hat{\beta}_i^{(j)}$, we want to estimate $\hat{\beta}_{i,\mathbf{t}}^{(j)}$. The second stage regression then becomes

$$r_{i,t} = \omega + \sum_{j=1}^{M} \lambda_{j,t} \hat{\beta}_{i,t}^{(j)} + \eta_t,$$

for each $t \in \{1, ..., T\}$.

TVP Fama Macbeth estimation

- To attain the dynamics, we need to estimate $\hat{\beta}_{i,t}^{(j)}$.
- Rolling window regressions do not fully capture the dynamics in the evolution of betas.
- Instead of using rolling regressions, we modify the Quasi-Bayesian Local-Likelihood approach of Petrova (2019), and perform TVP regressions.
- Hence, we employ **truly TVP Fama Macbeth regressions** which provide us with much better understanding of the dynamically evolving betas.

Results

Perspectives

- Static vs. Dynamic
- Aggregate vs. Horizon-specific
- Market vs. Idiosyncratic
- Short-run vs. Long-run

Portfolio Sorts

- We sort the stocks into quintile portfolios based on exposures to corresponding variables.
  - Univariate sorts
- 3-month and 6-month length of the rolling window.
- Post-ranking average returns are recorded for the next week.

Aggregate model

- We present results from two main models, each time we compare the static, and dynamic representation.

Firstly, the Aggregate moments model

$$\begin{aligned} r_{i,t} = \alpha + \beta_{m,1} RV_{m,t} + \beta_{m,2} RS_{m,t} + \beta_{m,3} RK_{m,t} \\ + \beta_{i,1} \overline{RV}_t + \beta_{i,2} \overline{RS}_t + \beta_{i,3} \overline{RV}_t + \epsilon_t, \end{aligned} \tag{12}$$

where $RV_{m,t}$, $RS_{m,t}$, and $RK_{m,t}$ are market Realized Variance, Realized Skewness, and Realized Kurtosis, $\overline{RV}_t$, $\overline{RS}_t$, and $\overline{RK}_t$ are the cross-sectional means of Realized moments of individual assets for each t, which serve as controls for idiosyncratic risk, m indicates market, and i indicates idiosyncratic.

Horizon-specific model

$$
\begin{aligned}
r_{i,t} = \alpha &+ \beta^{(s)}_{m,1} RV^{(s)}_{m,t} + \beta^{(l)}_{m,1} RV^{(l)}_{m,t} + \beta^{(s)}_{m,2} RS^{(s)}_{m,t} \\
&+ \beta^{(l)}_{m,2} RS^{(l)}_{m,t} + \beta^{(s)}_{m,3} RK^{(s)}_{m,t} + \beta^{(l)}_{m,3} RK^{(l)}_{m,t} \\
&+ \beta^{(s)}_{i,1} \overline{RV}^{(s)}_{t} + \beta^{(l)}_{i,1} \overline{RV}^{(l)}_{t} + \beta^{(s)}_{i,2} \overline{RS}^{(s)}_{t} \\
&+ \beta^{(l)}_{i,2} \overline{RS}^{(l)}_{t} + \beta^{(s)}_{i,3} \overline{RV}^{(s)}_{t} + \beta^{(l)}_{i,3} \overline{RV}^{(l)}_{t} + \epsilon_t,
\end{aligned}
\tag{13}
$$

where $x^{(s)}_t$ corresponds to the short-run component of particular risk factor, and $x^{(l)}_t$ corresponds to the long-run component of particular risk factor. Hence, Equation (13) is a representation of Equation (10) controlling for corresponding idiosyncratic risks.

Data

- Daily data

- Exchange Traded Funds
  - 01/2010 - 11/2018
  - 101 symbols
- Individual stocks from S&P 500
  - 01/2006 - 08/2018
  - 367 stocks
  - The estimation is carried out on 100 portfolios sorted on market beta.

S&P 500 - Portfolio Sorts Market

Variable	**1**	**2**	**3**	**4**	**5**	**High - Low**
			Market			
RVOL	0.57 (0.32)	1.1 (0.74)	1.63 (1.22)	1.71 (1.37)	0.49 (0.36)	-0.07 (-0.07)
RS	2.61 (2.45)	2.8 (2.34)	1.29 (0.93)	0.62 (0.39)	-1.84 (-0.91)	-4.45 (-3.07)
RK	0.9 (0.62)	1.62 (1.23)	1.57 (1.21)	1.58 (1.13)	-0.17 (-0.1)	-1.07 (-1.1)
RVOL short	0.88 (0.5)	1.26 (0.87)	1.64 (1.25)	1.69 (1.33)	0.02 (0.02)	-0.86 (-0.86)
RVOL long	0.89 (0.57)	1.04 (0.77)	1.39 (1.05)	1.5 (1.11)	0.69 (0.45)	-0.2 (-0.25)
RS short	2.78 (2.55)	2.69 (2.25)	1.26 (0.91)	0.62 (0.4)	-1.87 (-0.93)	-4.65 (-3.27)
RS long	1.12 (0.72)	1.77 (1.32)	1.18 (0.89)	0.8 (0.6)	0.64 (0.4)	-0.48 (-0.59)
RK short	0.84 (0.58)	1.99 (1.54)	1.28 (0.97)	1.49 (1.08)	-0.09 (-0.05)	-0.93 (-0.97)
RK long	1.03 (0.65)	0.68 (0.49)	1.46 (1.11)	1.66 (1.23)	0.67 (0.45)	-0.35 (-0.45)

S&P 500 - Portfolio Sorts Idiosyncratic

Variable	1	2	3	4	5	High - Low
			Idiosyncratic			
RVOL	0.78 (0.45)	1.3 (0.88)	1.64 (1.22)	1.2 (0.95)	0.58 (0.42)	-0.2 (-0.19)
RS	2.28 (1.94)	2.3 (1.9)	1.6 (1.17)	0.61 (0.39)	-1.3 (-0.67)	-3.59 (-2.63)
RK	0.94 (0.71)	1.29 (1.02)	1.57 (1.17)	1.53 (1.05)	0.16 (0.09)	-0.78 (-0.71)
RVOL short	1.07 (0.63)	1.25 (0.87)	1.99 (1.49)	1.21 (0.94)	-0.03 (-0.02)	-1.1 (-1.11)
RVOL long	1.28 (0.85)	1.38 (1.04)	1.64 (1.25)	1.3 (0.94)	-0.11 (-0.07)	-1.39 (-1.62)
RS short	2.39 (2.06)	2.26 (1.85)	1.62 (1.19)	0.58 (0.37)	-1.37 (-0.7)	-3.76 (-2.79)
RS long	0.19 (0.12)	1.19 (0.86)	1.42 (1.07)	1.9 (1.43)	0.8 (0.54)	0.61 (0.68)
RK short	1.21 (0.91)	1.07 (0.85)	1.49 (1.11)	1.12 (0.77)	0.61 (0.34)	-0.6 (-0.57)
RK long	1.18 (0.74)	1.82 (1.3)	1.76 (1.33)	1.06 (0.8)	-0.32 (-0.21)	-1.5 (-1.74)

ETF - Portfolio Sorts Market

Variable	1	2	3	4	5	High - Low
			Market			
RVOL	1.27 (0.83)	0.64 (0.47)	0.94 (0.72)	1.27 (0.97)	1.13 (0.82)	-0.14 (-0.18)
RS	1.66 (1.45)	1.24 (0.98)	1.34 (1)	1.05 (0.73)	-0.06 (-0.03)	-1.72 (-1.88)
RK	1 (0.73)	1.13 (0.87)	1.07 (0.82)	1.62 (1.16)	0.45 (0.29)	-0.55 (-0.69)
RVOL short	1.24 (0.82)	0.84 (0.61)	0.86 (0.66)	1.45 (1.1)	0.86 (0.62)	-0.38 (-0.49)
RVOL long	1.5 (1.05)	1.73 (1.33)	1.14 (0.85)	0.82 (0.61)	0.05 (0.04)	-1.45 (-2)
RS short	1.71 (1.49)	1.41 (1.11)	1.15 (0.86)	1.11 (0.77)	-0.15 (-0.09)	-1.85 (-2.04)
RS long	1.07 (0.73)	0.99 (0.75)	1.13 (0.87)	1.49 (1.13)	0.58 (0.4)	-0.49 (-0.68)
RK short	0.93 (0.67)	1.37 (1.05)	1.34 (1.03)	1.12 (0.81)	0.52 (0.34)	-0.41 (-0.5)
RK long	0.93 (0.66)	1.21 (0.9)	1.07 (0.81)	1.62 (1.2)	0.43 (0.3)	-0.5 (-0.67)

ETF - Portfolio Sorts Idiosyncratic

Variable	1	2	3	4	5	High - Low
			Idiosyncratic			
RVOL	1.38 (0.89)	0.57 (0.41)	0.97 (0.75)	1.19 (0.92)	1.14 (0.83)	-0.23 (-0.3)
RS	1.98 (1.86)	1.4 (1.12)	0.87 (0.64)	0.94 (0.63)	0.02 (0.01)	-1.96 (-2.03)
RK	1.59 (1.13)	1.22 (0.96)	1.14 (0.86)	0.98 (0.72)	0.3 (0.19)	-1.29 (-1.68)
RVOL short	1.4 (0.92)	0.72 (0.53)	1.09 (0.83)	1.23 (0.94)	0.8 (0.58)	-0.6 (-0.75)
RVOL long	0.74 (0.52)	1.18 (0.91)	0.98 (0.74)	1.43 (1.07)	0.94 (0.63)	0.2 (0.3)
RS short	1.96 (1.82)	1.44 (1.16)	0.89 (0.65)	0.84 (0.57)	0.09 (0.05)	-1.87 (-1.93)
RS long	1.7 (1.19)	1.41 (1.09)	1.03 (0.79)	1.4 (1.03)	-0.31 (-0.21)	-2.02 (-2.9)
RK short	1.49 (1.04)	1.94 (1.49)	1.19 (0.91)	0.76 (0.56)	-0.13 (-0.08)	-1.62 (-2.04)
RK long	0.18 (0.13)	0.92 (0.7)	1.57 (1.18)	1.87 (1.4)	0.77 (0.5)	0.58 (0.83)

S&P 500 - Aggregate moments

	Panel A: Full Sample			Panel B: Dynamic		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
const	0.0004	0.0005	0.0005	0.0008	0.0014	0.0012
	(2.0543)	(2.6684)	(2.4852)	(6.4051)	(7.8673)	(8.282)
RVm	-0.0005		-0.0005	0.0001		0.0
	(-1.4266)		(-1.5496)	(0.4066)		(0.144)
RSm	-0.0837		-0.0922	-0.1566		-0.1192
	(-1.4611)		(-1.5224)	(-4.7665)		(-3.6271)
RKm	-0.7431		-0.5971	2.3795		2.8932
	(-1.915)		(-1.6488)	(17.4188)		(25.8071)
RV		-0.0001	-0.0002		0.002	0.0016
		(-0.6228)	(-0.7965)		(8.9237)	(7.8826)
RS		-0.052	-0.0266		-0.2387	-0.1205
		(-2.0946)	(-1.0287)		(-10.2195)	(-4.8286)
RK		0.3286	0.3952		5.2587	4.8313
		(1.4903)	(1.721)		(33.7716)	(35.5618)
R^2	0.1031	0.1057	0.1466			

S&P 500 - Decomposed moments

	Panel A: Full Sample			Panel B: Dynamic		
	(4)	**(5)**	**(6)**	**(4)**	**(5)**	**(6)**
const	0.0006	0.0006	0.0006	0.0009	0.0002	0.0005
	(2.7736)	(2.7658)	(3.1908)	(7.4304)	(1.1737)	(3.5693)
RVms	-0.0002		-0.0003	0.0007		-0.0002
	(-1.0527)		(-1.4256)	(3.2642)		(-1.0061)
RVml	-0.0002		-0.0002	-0.0017		-0.0001
	(-1.016)		(-1.2073)	(-9.6661)		(-0.8431)
RSms	-0.091		-0.1026	-0.064		-0.0731
	(-1.6543)		(-1.7191)	(-1.9767)		(-2.3009)
RSml	-0.028		-0.026	-0.0281		0.0077
	(-3.2446)		(-3.0115)	(-3.4361)		(0.983)
RKms	-0.7292		-0.5959	-0.1131		-0.1024
	(-1.8871)		(-1.6358)	(-1.2859)		(-1.2093)
RKml	0.0622		0.0524	0.5947		0.2842
	(1.4279)		(1.2308)	(15.016)		(8.101)
RVs		-0.0001	-0.0001		-0.0002	-0.0002
		(-0.3492)	(-0.3984)		(-1.4391)	(-1.1676)
RVl		0.0	-0.0		0.0008	0.0003
		(0.0391)	(-0.1759)		(5.8946)	(2.6649)
RSs		-0.0446	-0.0253		0.008	0.0112
		(-1.8125)	(-0.9916)		(0.3521)	(0.4591)
RSl		-0.0077	-0.0087		-0.0096	-0.0076
		(-3.3511)	(-3.7843)		(-4.2514)	(-3.5378)
RKs		0.2246	0.3963		0.0221	0.0473
		(1.1092)	(1.8265)		(0.3775)	(0.8275)
RKl		0.1005	0.0995		0.7708	0.6281
		(1.858)	(1.7215)		(15.6545)	(12.8836)
R^2	0.2199	0.2298	0.3152			

ETF - Aggregate moments

	Panel A: Full Sample			Panel B: Dynamic		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
const	0.0008	0.0006	0.0008	0.0006	0.0009	0.0006
	(4.2851)	(2.7386)	(4.7001)	(4.9902)	(4.8434)	(3.89)
RVm	0.0005		0.0002	0.0004		-0.0008
	(1.5771)		(0.5023)	(2.2747)		(-4.2688)
RSm	-0.1519		-0.2753	-0.1341		-0.079
	(-2.3598)		(-3.7039)	(-3.1633)		(-1.821)
RKm	0.8864		0.1222	1.4944		1.7962
	(1.3568)		(0.1669)	(7.1682)		(10.8138)
RV		0.0008	0.0004		0.0004	0.0002
		(1.1812)	(0.6159)		(0.8677)	(0.2962)
RS		-0.0369	-0.0538		-0.0788	-0.0624
		(-1.4233)	(-2.0409)		(-3.3432)	(-2.8767)
RK		0.5738	0.3998		2.1047	1.8239
		(2.4414)	(1.8646)		(13.6624)	(14.852)
R^2	0.3298	0.2871	0.392			

ETF - Decomposed moments

	Panel A: Full Sample			Panel B: Dynamic		
	(4)	**(5)**	**(6)**	**(4)**	**(5)**	**(6)**
const	0.0006	0.0004	0.0002	0.0005	0.0002	0.0002
	(3.4259)	(2.2648)	(1.3075)	(4.1364)	(1.5136)	(1.3154)
RVms	0.0003		-0.0	0.0007		0.0005
	(1.2024)		(-0.0541)	(3.3162)		(3.1961)
RVml	0.0014		0.0013	0.0001		0.0004
	(4.5459)		(4.5781)	(0.4434)		(1.5283)
RSms	-0.1107		-0.1846	-0.0593		-0.0731
	(-1.7693)		(-2.3295)	(-1.4901)		(-1.8988)
RSml	-0.0045		-0.0007	-0.0004		-0.0123
	(-0.3256)		(-0.0573)	(-0.0302)		(-0.9728)
RKms	-0.208		-0.7413	0.0787		0.0673
	(-0.3728)		(-1.1996)	(0.6116)		(0.6668)
RKml	-0.21		-0.2195	0.2943		0.1798
	(-2.9096)		(-3.1045)	(3.8256)		(2.8121)
RVs		-0.0001	-0.001		0.0004	0.0002
		(-0.1713)	(-1.6535)		(0.7509)	(0.4432)
RVl		0.0017	0.0016		0.001	0.0011
		(5.0002)	(5.3814)		(3.2607)	(3.867)
RSs		-0.0392	-0.0296		-0.0046	-0.0299
		(-1.6174)	(-1.0033)		(-0.2049)	(-1.4348)
RSl		0.0047	0.001		-0.0044	0.0047
		(0.6922)	(0.1608)		(-0.7211)	(0.8706)
RKs		0.0948	0.0691		0.0451	0.0856
		(0.5495)	(0.4448)		(0.8253)	(1.7868)
RKl		-0.0761	-0.0524		0.1036	0.1175
		(-1.4522)	(-1.2876)		(2.4064)	(3.2872)
R^2	0.6242	0.6525	0.7906			

Conclusions

- We build model containing horizon-specific volatility, skewness, and kurtosis risk.
- Dynamic estimation using truly TVP Fama Macbeth regression shows that it is essential to capture the dynamics in the coefficients in order to understand the risk-return relationships on the financial markets.
- Market and idiosyncratic are both important drivers of asset returns.
- Decomposing to the horizon-specific components of risk allows us to uncover the discrepancies in relevance of individual moments in different horizons.

THANK YOU!

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