Quantitative Asset Management

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Lecture 4: Time Series Momentum and Volatility

1. Time Series Momentum
   Moskowitz, Ooi, and Pedersen (2012, JFE)
2. The cross-section of volatility and expected returns
   Ang, Hodrick, Xing, and Zhang (2006, JF)
3. Volatility-managed portfolios
   Moreira and Muir (2017, JF)

Time Series Momentum

Moskowitz, Ooi, and Pedersen (2012, JFE)

Time Series Momentum

- Security's past performance forecast its own future return
  - Large abnormal returns
  - Not crash risk
- Different from cross-sectional momentum
  - Cross-sectional momentum: relative performance
  - Cross-sectional momentum: about cross-section!
- Direct test of whether returns follow a random walk
- Holds globally across different asset classes
  - Equity, currency, commodity and bonds
  - 58 liquid instruments

Data

- 24 commodity futures
- 12 cross-currency forward pairs (9 underlying currencies)
- 9 developed equity index futures
- 13 developed government bond futures

- Dates: January 1965 through December 2009

- Among the most liquid futures contracts in the world

- Source: Datastream, Bloomberg, other exchanges

Data

- Lots of heterogeneity in assets' volatility

    See Table 1

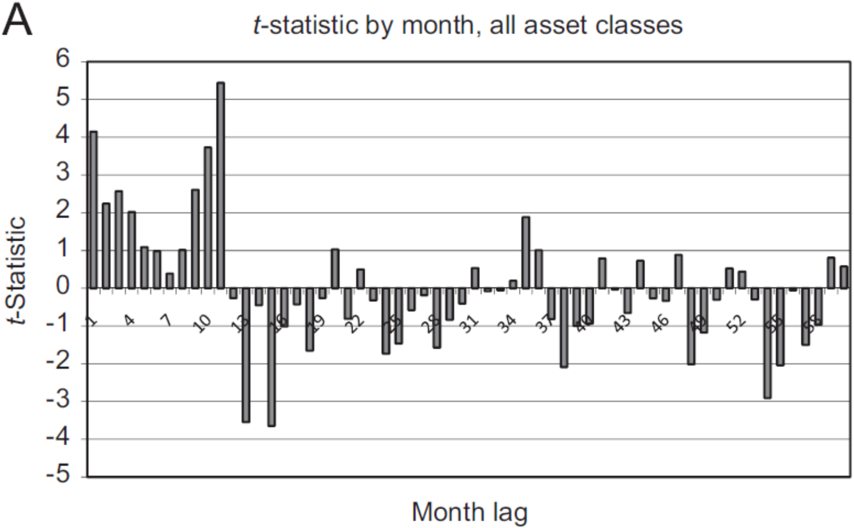
- Authors scale return by volatility

$$\sigma_t^2 = 261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \bar{r}_t)^2$$

- Change in units
- Use Sharpe ratios instead of return

Regression Evidence

$$r_t^s/\sigma_{t-1}^s = \alpha + \beta_h r_{t-h}^s/\sigma_{t-h-1}^s + \varepsilon_t^s$$

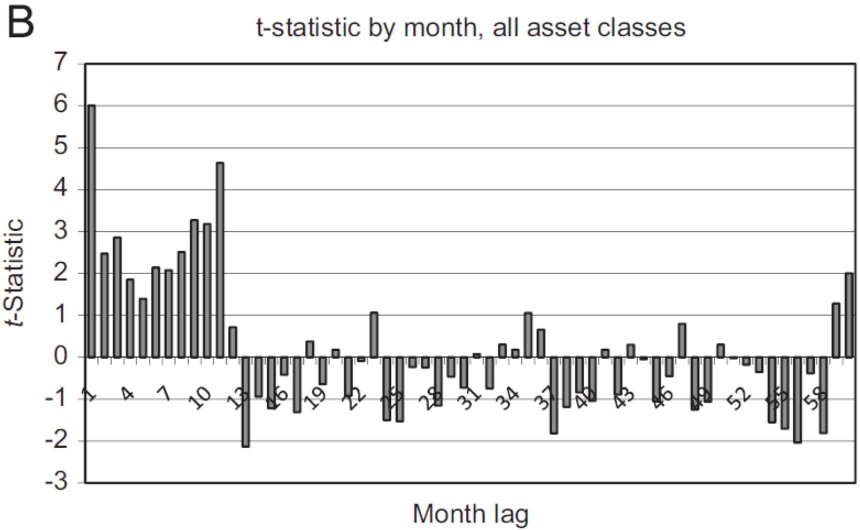


Regression Evidence

- Positive t-stats for first 12 months: suggests significant return continuation
- Negative signs suggest reversals

Regression Evidence

$$r_t^s/\sigma_{t-1}^s = \alpha + \beta_h sign(r_{t-h}^s) + \varepsilon_t^s$$



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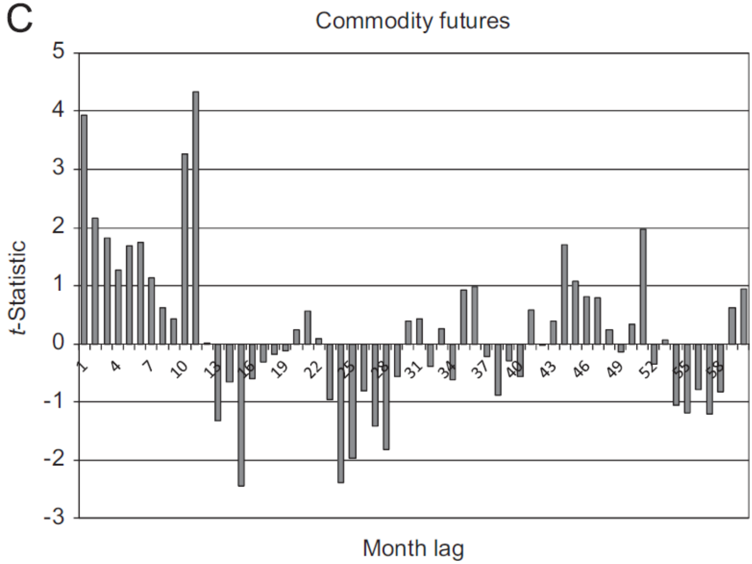

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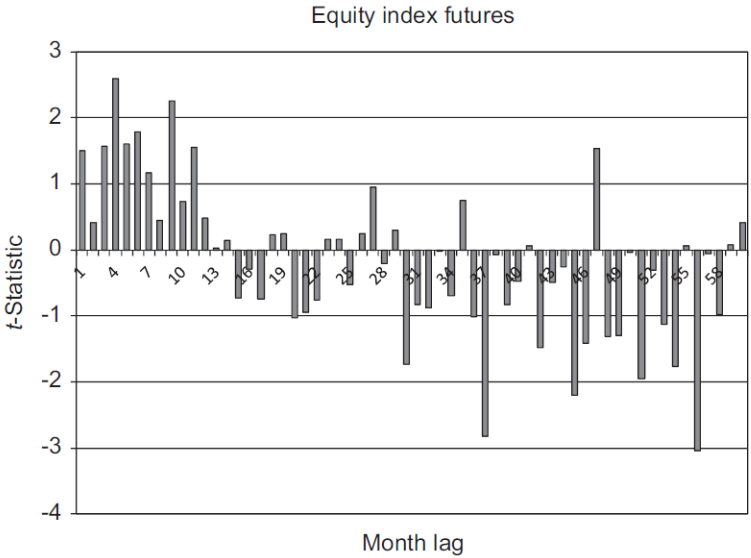

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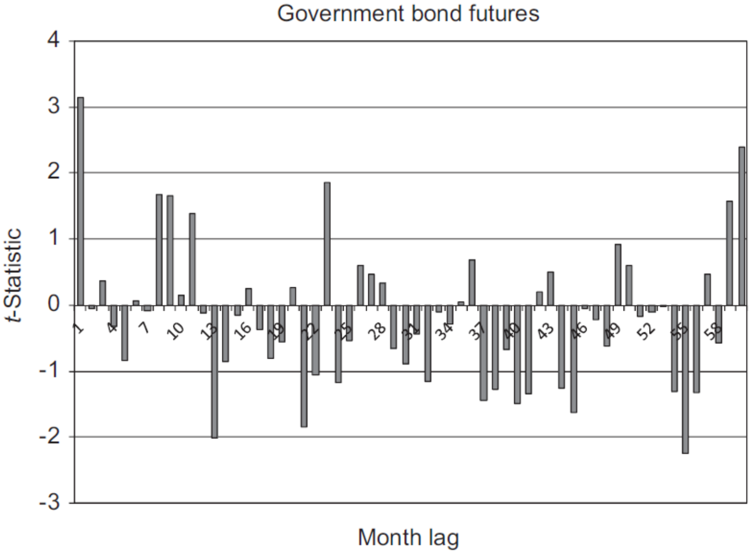

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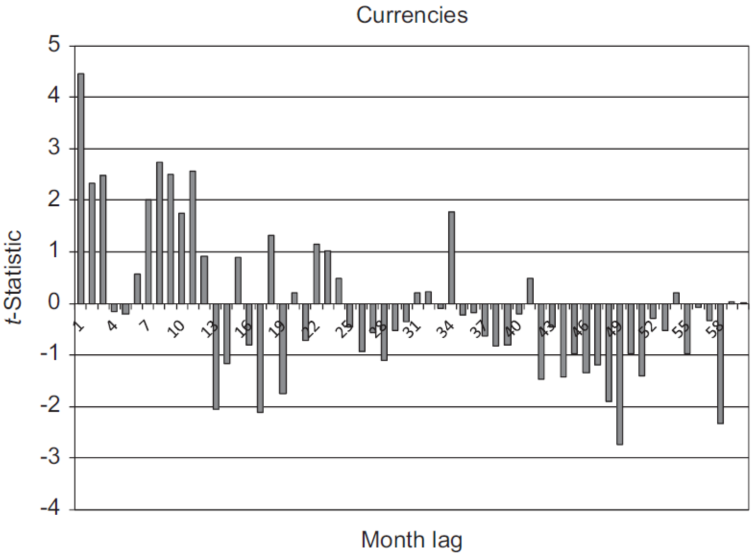


Time Series Momentum Strategy

For each instrument s and month t

- Compute the excess return over the past k months
  - past returns from $t-k-1$ to $t-1$
  - Check whether it is positive or negative
- Long contract with positive excess returns: past k months
- Short contract with negative excess returns: past k months
- Position size: inversely proportional to ex-ante volatility:

$$\frac{1}{\sigma^s_{t-1}}$$

Time Series Momentum Strategy

- How to deal with holding periods longer than 1 month?
  - They follow Jegadeesh and Titman (1993)
  - Overlapping holding periods (remember?)
  - "The return at time t represents the average return across all portfolios at that time, namely the return on the portfolio that was constructed last month, the month before that (and still held if the holding period h is greater than two), and so on for all currently 'active' portfolios."

- Does the strategy works?
- Compute alphas relative to the following factor model

$$r_t^{TSMOM(k,h)} = \alpha + \beta_1 MKT_t + \beta_2 BOND_t + \beta_3 GSCI_t + sSMB_t + hHML_t + mUMD_t + \varepsilon_t,$$

Table 2: alphas

		Holding period (months)							
		1	3	6	9	12	24	36	48
Panel A: All assets									
Lookback period (months)	1	4.34	4.68	3.83	4.29	5.12	3.02	2.74	1.90
	3	5.35	4.42	3.54	4.73	4.50	2.60	1.97	1.52
	6	5.03	4.54	4.93	5.32	4.43	2.79	1.89	1.42
	9	6.06	6.13	5.78	5.07	4.10	2.57	1.45	1.19
	12	6.61	5.60	4.44	3.69	2.85	1.68	0.66	0.46
	24	3.95	3.19	2.44	1.95	1.50	0.20	−0.09	−0.33
	36	2.70	2.20	1.44	0.96	0.62	0.28	0.07	0.20
	48	1.84	1.55	1.16	1.00	0.86	0.38	0.46	0.74

- What is the difference between time series and cross-sectional momentum?

Cross-sectional Momentum

Based on Daniel and Moskowitz (2016, JFE)

Standard Sample Selection

- CRSP share codes 10 and 11
- NYSE, AMAX, Nasdaq
- Valid share price and number of shares on the formation date
- At least 8 months of return data between $t-12$ and $t-2$ (skip one month)

Momentum Strategy

- Rank stock based on their cumulative returns from $t-12$ to $t-2$ (11 months)
- Skip one month as formation period
- Sort stocks into deciles (cross-section)
- Form long-short portfolio

Time Series Momentum Factor

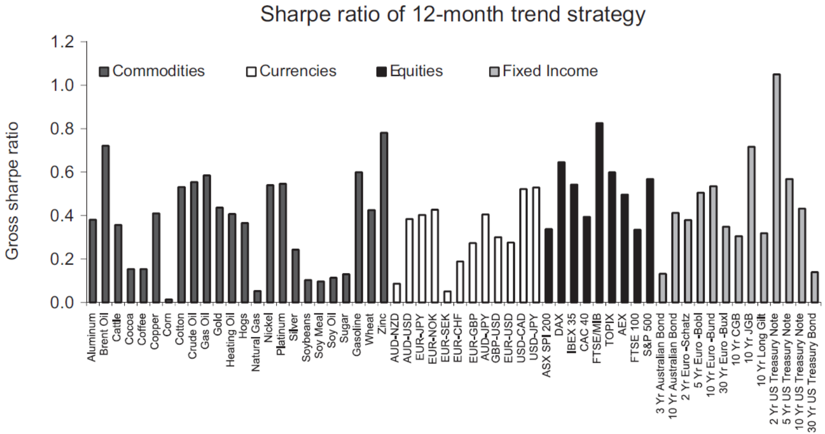
- $k = 12$
- $h = 1$
- TSMOM return for any instrument s at time t:

$$r_{t,t+1}^{TSMOM,s} = sign(r_{t-12,t}^{s}) \frac{40\%}{\sigma_t^s} r_{t,t+1}^{s}$$

- TSMOM return across all securities:

$$r_{t,t+1}^{TSMOM} = \frac{1}{S_t} \sum_{s=1}^{S_t} sign(r_{t-12,t}^{s}) \frac{40\%}{\sigma_t^s} r_{t,t+1}^{s}$$

Time Series Momentum Factor



Time Series Momentum Factor

Performance of the diversified time series momentum strategy.

Panel A reports results from time series regressions of monthly and non-overlapping quarterly returns on the diversified time series momentum strategy that takes an equal-weighted average of the time series momentum strategies across all futures contracts in all asset classes, on the returns of the MSCI World Index and the Fama and French factors SMB, HML, and UMD, representing the size, value, and cross-sectional momentum premiums in US stocks. Panel B reports results using the Asness, Moskowitz, and Pedersen (2010) value and momentum "everywhere" factors instead of the Fama and French factors, which capture the premiums to value and cross-sectional momentum globally across asset classes. Panel C reports results from regressions of the time series momentum returns on the market (MSCI World Index), volatility (VIX), funding liquidity (TED spread), and sentiment variables from Baker and Wurgler (2006, 2007), as well as their extremes.

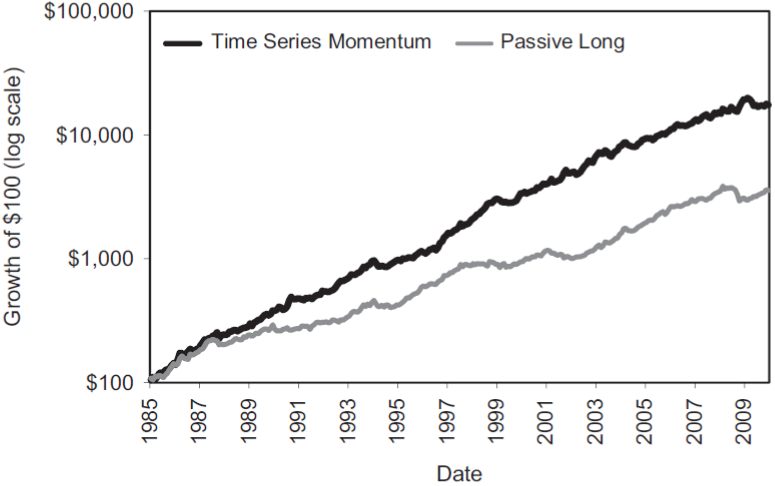
Panel A: Fama and French factors

		MSCI World	SMB	HML	UMD	Intercept	R^2
Monthly	Coefficient	0.09	−0.05	−0.01	0.28	1.58%	14%
	(t-Stat)	(1.89)	(−0.84)	(−0.21)	(6.78)	(7.99)	
Quarterly	Coefficient	0.07	−0.18	0.01	0.32	4.75%	23%
	(t-Stat)	(1.00)	(−1.44)	(0.11)	(4.44)	(7.73)	

Panel B: Asness, Moskowitz, and Pedersen (2010) factors

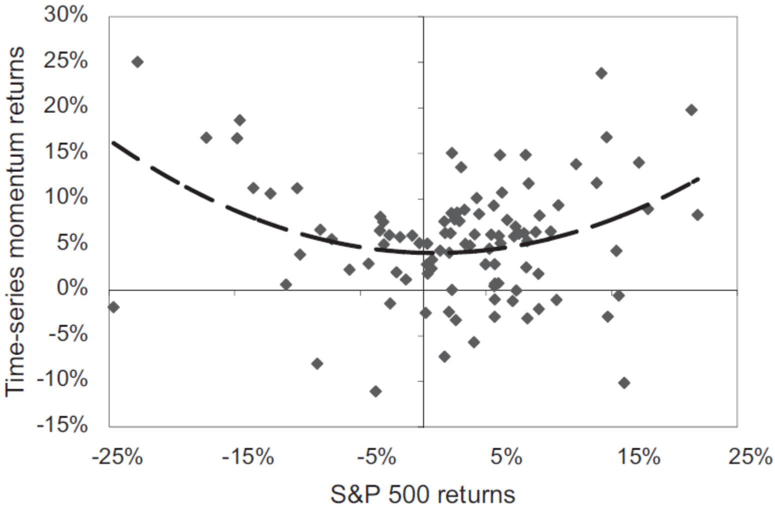
		MSCI World		VAL Everywhere	MOM Everywhere	Intercept	R^2
Monthly	Coefficient	0.11		0.14	0.66	1.09%	30%
	(t-Stat)	(2.67)		(2.02)	(9.74)	(5.40)	
Quarterly	Coefficient	0.12		0.26	0.71	2.93%	34%
	(t-Stat)	(1.81)		(2.45)	(6.47)	(4.12)	

Crash risk?



Cumulative excess return of time series momentum and diversified passive long strategy, January 1985 to December 2009. Plotted are the cumulative excess returns of the diversified TSMOM portfolio and a diversified portfolio of the possible long position in every futures contract we study. The TSMOM portfolio is defined in Eq. (5) and across all futures contracts summed. Sample period is January 1985 to December 2009.

Crash risk?



The time series momentum smile. The non-overlapping quarterly returns on the diversified (equally weighted across all contracts) 12-month time series momentum or trend strategy are plotted against the contemporaneous returns on the S&P 500

Time Series vs. Cross-Sectional Momentum

- Regress TSMOM on XSMOM (Table 5, Panel A)

Time Series vs. Cross-Sectional Momentum

Time series momentum vs. cross-sectional momentum.

Panel A reports results from regressions of the 12-month time series momentum strategies by asset class (TSMOM) on 12-month cross-sectional momentum strategies (XSMOM) of Asness, Moskowitz, and Pedersen (2010). Panel B reports results from the decomposition of cross-sectional momentum and time series momentum strategies according to Section 4.2, where Auto is the component of profits coming from the auto-covariance of returns, Cross is the component coming from cross-serial correlations or lead-lag effects across the asset returns, Mean is the component coming from cross-sectional variation in unconditional mean returns, and Mean squared is the component coming from squared mean returns. Panel C reports results from regressions of several XSMOM strategies in different asset classes, the Fama-French momentum, value, and size factors, and two hedge fund indexes obtained from Dow Jones/Credit Suisse on our benchmark TSMOM factor.

Panel A: Regression of TSMOM on XSMOM

		Independent variables							
		XSMOM ALL	XSMOM COM	XSMOM EQ	XSMOM FI	XSMOM FX	XSMOM US stocks	Intercept	R^2
Dependent variable	TSMOM ALL	0.66 (15.17)						0.76% (5.90)	44%
	TSMOM ALL		0.31 (7.09)	0.20 (4.25)	0.17 (3.84)	0.37 (8.11)	0.12 (2.66)	0.73% (5.74)	46%
	TSMOM COM		0.65 (14.61)					0.57% (4.43)	42%
	TSMOM COM		0.62 (13.84)	0.05 (1.01)	0.02 (0.50)	0.14 (3.08)	0.05 (1.06)	0.51% (3.96)	45%
	TSMOM EQ			0.39 (7.32)				0.47% (3.00)	15%
	TSMOM EQ		0.07 (1.29)	0.28 (5.07)	0.04 (0.67)	0.06 (1.11)	0.24 (4.26)	0.43% (2.79)	22%
	TSMOM FI				0.37 (6.83)			0.59% (3.77)	14%
	TSMOM FI		−0.03 (−0.62)	0.18 (3.05)	0.34 (6.19)	0.01 (0.20)	0.03 (0.48)	0.50% (3.15)	17%
	TSMOM FX					0.75 (19.52)		0.42% (3.75)	56%
	TSMOM FX		0.04 (1.07)	0.00 (−0.04)	−0.01 (−0.17)	0.75 (18.89)	−0.01 (−0.24)	0.40% (3.49)	56%

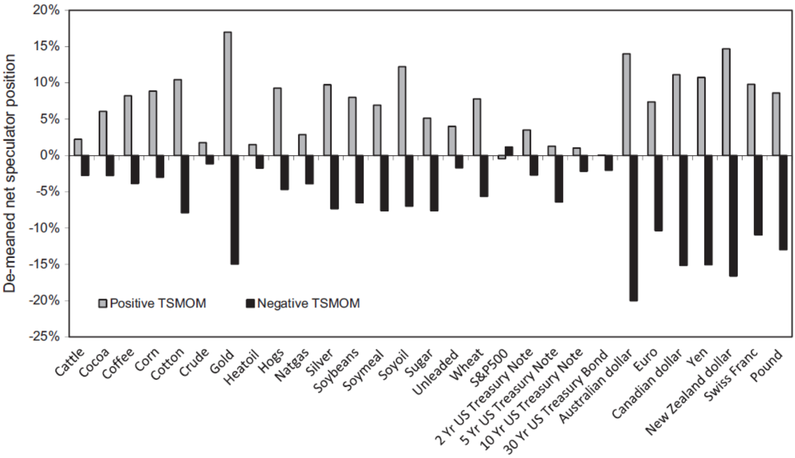
- Is time-series momentum inconsistent with Lewellen's (2002) findings?

Who trades on time series momentum?

Data

- Positions of traders from Commodity Futures Trading Commission
- Data covers mostly commodity and currency positions, as well as US equity and bond
- No information about foreign equity/bonds positions
- Large trades: commercial (hedges) vs. non-commercial (speculators)
- Focus on net position of speculators (why?)

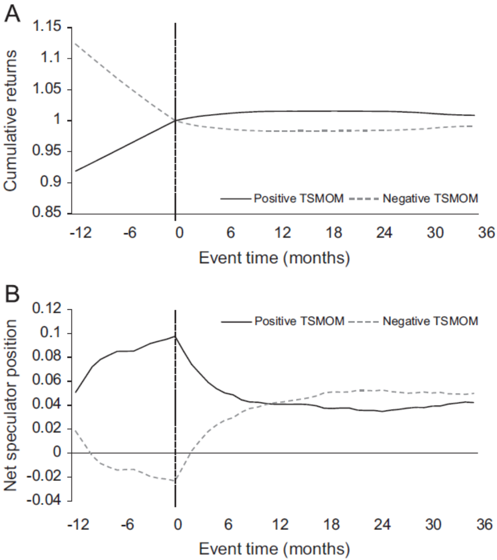
Who trades on time series momentum?



Net speculator positions. For each futures contract, the figure plots the average de-meaned Net speculator position in, respectively, the subsample where the past 12-month returns on the contract are positive ("Positive TSMOM") and negative ("Negative TSMOM"). The figure illustrates that speculators are on average positioned to benefit from trends, whereas hedgers, by definition, have the opposite positions.

Who trades on time series momentum?

Figure 6



Takeaway

- Time series momentum in equity indexes, commodity, bonds, and currency
- Persistence in returns in liquid contracts
- Time series momentum is different from cross-sectional momentum
- It seems that speculators profit from time series momentum
- Time series momentum not driven by:
  - transaction costs (liquidity)
  - Crash risk
  - Standard risk factors (3FF+MOM, bond, commodity, etc)

The cross-section of volatility and expected returns

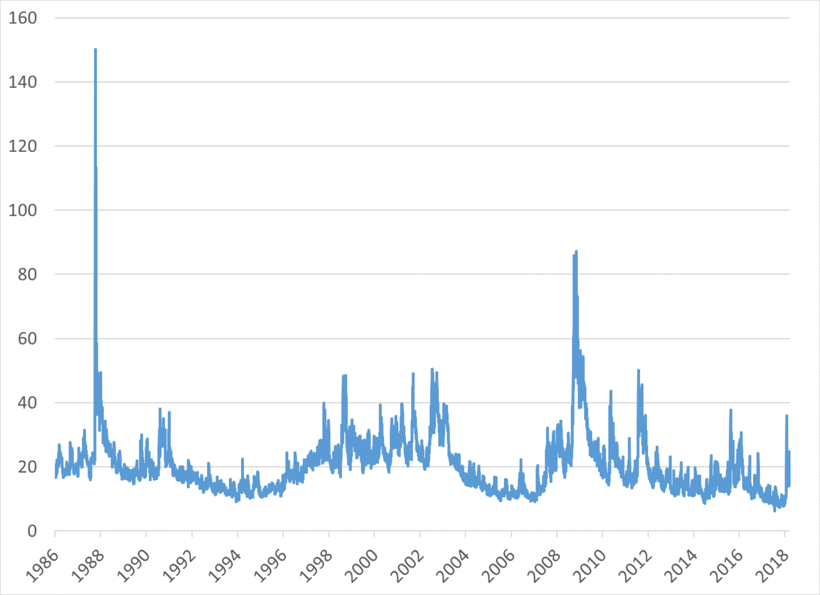
Ang, Hodrick, Xing, and Zhang (2006, JF)

Is volatility priced in cross-section of stocks returns?

The cross-section of volatility and expected returns

- Verify whether volatility is priced
- *exposure* to vol $\Rightarrow$ lower average returns
- Puzzle: stocks with *high* idiosyncratic volatility have low returns

Daily VIX



160
140
120
100
80
60
40
20
0
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018

The cross-section of volatility and expected returns

Portfolio Sorting

- Pre-formation betas

$$r_t^i = \beta_0 + \beta^i_{MKT} MKT_t + \beta^i_{\Delta VIX} \Delta VIX_t + \varepsilon_t^i$$

- Use daily data
- Get monthly beta estimates
- Sort stocks into Vol-beta ($\beta^i_{\Delta VIX}$) quintiles

The cross-section of volatility and expected returns

Factor Mimicking Portfolio

- Use volatility-beta sorted portfolios as test assets: X_t
- Regress changes in VIX on test assets:

$$\Delta VIX_t = c + b'X_t + u_t$$

- Regression at daily frequency every month
- $FVIX_t \equiv b'X_t$
- $FVIX_t$ is traded and it is a zero-cost portfolio

Portfolios Sorted by Exposure to Changes in VIX

We form value-weighted quintile portfolios every month by regressing excess individual stock returns on ΔVIX, controlling for the MKT factor as in equation (3), using daily data over the previous month. Stocks are sorted into quintiles based on the coefficient $\beta_{\Delta VIX}$ from lowest (quintile 1) to highest (quintile 5). The statistics in the columns labeled Mean and Std. Dev. are measured in monthly percentage terms and apply to total, not excess, simple returns. Size reports the average log market capitalization for firms within the portfolio and B/M reports the average book-to-market ratio. The row "5-1" refers to the difference in monthly returns between portfolio 5 and portfolio 1. The Alpha columns report Jensen's alpha with respect to the CAPM or the Fama–French (1993) three-factor model. The pre-formation betas refer to the value-weighted $\beta_{\Delta VIX}$ or β_{FVIX} within each quintile portfolio at the start of the month. We report the pre-formation $\beta_{\Delta VIX}$ and β_{FVIX} averaged across the whole sample. The second to last column reports the $\beta_{\Delta VIX}$ loading computed over the next month with daily data. The column reports the next month $\beta_{\Delta VIX}$ loadings averaged across months. The last column reports ex post β_{FVIX} factor loadings over the whole sample, where $FVIX$ is the factor mimicking aggregate volatility risk. To correspond with the Fama–French alphas, we compute the ex post betas by running a four-factor regression with the three Fama–French factors together with the $FVIX$ factor that mimics aggregate volatility risk, following the regression in equation (6). The row labeled "Joint test p-value" reports a Gibbons, Ross and Shanken (1989) test for the alphas equal to zero, and a robust joint test that the factor loadings are equal to zero. Robust Newey–West (1987) t-statistics are reported in square brackets. The sample period is from January 1986 to December 2000.

								Factor Loadings			
Rank	Mean	Std. Dev.	% Mkt Share	Size	B/M	CAPM Alpha	FF-3 Alpha	Pre-Formation $\beta_{\Delta VIX}$	Pre-Formation β_{FVIX}	Next Month Post-Formation $\beta_{\Delta VIX}$	Full Sample Post-Formation β_{FVIX}
1	1.64	5.53	9.4%	3.70	0.89	0.27	0.30	−2.09	−2.00	−0.033	−5.06
						[1.66]	[1.77]				[−4.06]
2	1.39	4.43	28.7%	4.77	0.73	0.18	0.09	−0.46	−0.42	−0.014	−2.72
						[1.82]	[1.18]				[−2.64]
3	1.36	4.40	30.4%	4.77	0.76	0.13	0.08	0.03	0.08	0.005	−1.55
						[1.32]	[1.00]				[−2.86]
4	1.21	4.79	24.0%	4.76	0.73	−0.08	−0.06	0.54	0.62	0.015	3.62
						[−0.87]	[−0.65]				[4.53]
5	0.60	6.55	7.4%	3.73	0.89	−0.88	−0.53	2.18	2.31	0.018	8.07
						[−3.42]	[−2.88]				[5.32]
5-1	−1.04					−1.15	−0.83				
	[−3.90]					[−3.54]	[−2.93]				
Joint test p-value						0.01	0.03				0.00

Factor Correlation

The table reports correlations of first differences in *VIX, FVIX*, and *STR* with various factors. The variable ΔVIX ($\Delta_m VIX$) represents the daily (monthly) change in the *VIX* index, and *FVIX* is the mimicking aggregate volatility risk factor. The factor *STR* is constructed by Coval and Shumway (2001) from the returns of zero-beta straddle positions. The factors *MKT, SMB, HML* are the Fama and French (1993) factors, the momentum factor *UMD* is constructed by Kenneth French, and *LIQ* is the Pástor and Stambaugh (2003) liquidity factor. The sample period is January 1986 to December 2000, except for correlations involving *STR*, which are computed over the sample period January 1986 to December 1995.

Panel A: Daily Correlation							
	ΔVIX						
FVIX	0.91						
Panel B: Monthly Correlations							
	FVIX	$\Delta_m VIX$	*MKT*	*SMB*	*HML*	*UMD*	*LIQ*
$\Delta_m VIX$	0.70	1.00	−0.58	−0.18	0.22	−0.11	−0.33
FVIX	1.00	0.70	−0.66	−0.14	0.26	−0.25	−0.40
STR	0.75	0.83	−0.39	−0.39	0.08	−0.26	−0.59

Volatility-beta sorted portfolios

Robustness

- VIX innovations calculations
- Portfolio formation window
- Characteristics controls: BM and size

  "Every month, each stock is matched with one of the FamaFrench 25 size and book-to-market portfolios according to its size and book-to-market characteristics. The table reports value-weighted simple returns in excess of the characteristic-matched returns."
- Liquidity effect
  - One-way sort controlling for liquidity: first sort on liquidity, then sort each quintile bucket by $\beta_{\Delta VIX}$ (sequential double sort). Finally, for each volatility group (low to high), we average across all liquidity buckets.
- Also control for volume and momentum

Prices of Risk

Fama and MacBeth

$$r_t^i = c + \beta_{MKT}^i \lambda_{MKT} + \beta_{FVIX}^i \lambda_{FVIX} + \beta_{SMB}^i \lambda_{SMB} + \beta_{HML}^i \lambda_{HML} + \beta_{UMD}^i \lambda_{UMD} + \beta_{LIQ}^i \lambda_{LIQ} + \varepsilon_t^i$$

- Test assets: 25 portfolio double sorted on market- and volatility-betas

Panel A reports the Fama–MacBeth (1973) factor premiums on 25 portfolios sorted first on β_{MKT} and then on $\beta_{\Delta VIX}$. *MKT* is the excess return on the market portfolio, *FVIX* is the mimicking factor for aggregate volatility innovations, *STR* is Coval and Shumway's (2001) zero-beta straddle return, *SMB* and *HML* are the Fama–French (1993) size and value factors, *UMD* is the momentum factor constructed by Kenneth French, and *LIQ* is the aggregate liquidity measure from Pástor and Stambaugh (2003). In Panel B, we report ex post factor loadings on *FVIX*, from the regression specification I (Fama–French model plus *FVIX*). Robust t-statistics that account for the errors-in-variables for the first-stage estimation in the factor loadings are reported in square brackets. The sample period is from January 1986 to December 2000, except for the Fama–MacBeth regressions with *STR*, which are from January 1986 to December 1995.

Panel A: Fama–MacBeth (1973) Factor Premiums

	I	II	III	IV
Constant	−0.145	−0.527	−0.202	−0.247
	[−0.23]	[−0.88]	[−0.31]	[−0.36]
MKT	0.977	1.276	1.034	1.042
	[1.11]	[1.47]	[1.13]	[1.13]
FVIX	−0.080		−0.082	−0.071
	[−2.49]		[−2.39]	[−2.02]
STR		−0.194		
		[−2.32]		
SMB	−0.638	−0.246	−0.608	−0.699
	[−1.24]	[−0.59]	[−1.13]	[−1.25]
HML	−0.590	−0.247	−0.533	−0.232
	[−0.95]	[−0.40]	[−0.82]	[−0.34]
UMD			0.827	0.612
			[0.83]	[0.59]
LIQ				−0.021
				[−1.00]
Adj R^2	0.67	0.56	0.65	0.79

Idiosyncratic Volatility

- Idiosyncratic Volatility: vol of factor model residuals
$$r_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i$$
- Asset-specific volatility measure

- Strategy: construct idiosyncratic volatility sorted portfolios
- Estimate vol using 1 month of data
- Hold portfolio for 1 month

Idiosyncratic volatility sorted portfolios

2017 Final Exam

Rank	Mean	Std. Dev.	% Mkt Share	Size	B/M	CAPM Alpha	FF-3 Alpha
Panel A: Portfolios Sorted by Total Volatility							
1	1.06	3.71	41.7%	4.66	0.88	0.14	0.03
						[1.84]	[0.53]
2	1.15	4.48	33.7%	4.70	0.81	0.13	0.08
						[2.14]	[1.41]
3	1.22	5.63	15.5%	4.10	0.82	0.07	0.12
						[0.72]	[1.55]
4	0.99	7.15	6.7%	3.47	0.86	−0.28	−0.17
						[−1.73]	[−1.42]
5	0.09	8.30	2.4%	2.57	1.08	−1.21	−1.16
						[−5.07]	[−6.85]
5-1	−0.97					−1.35	−1.19
	[−2.86]					[−4.62]	[−5.92]
Panel B: Portfolios Sorted by Idiosyncratic Volatility Relative to FF-3							
1	1.04	3.83	53.5%	4.86	0.85	0.11	0.04
						[1.57]	[0.99]
2	1.16	4.74	27.4%	4.72	0.80	0.11	0.09
						[1.98]	[1.51]
3	1.20	5.85	11.9%	4.07	0.82	0.04	0.08
						[0.37]	[1.04]
4	0.87	7.13	5.2%	3.42	0.87	−0.38	−0.32
						[−2.32]	[−3.15]
5	−0.02	8.16	1.9%	2.52	1.10	−1.27	−1.27
						[−5.09]	[−7.68]
5-1	−1.06					−1.38	−1.31
	[−3.10]					[−4.56]	[−7.00]

Takeaways

- Volatility is priced in the cross-section
- *exposure* to vol $\Rightarrow$ lower average returns
- Puzzle: stocks with *high* idiosyncratic volatility have low returns
  - Relationship is flat, except for the 5th quintile
- From my research: Idiosyncratic volatility obeys a strong factor structure and the common factor in idiosyncratic volatility carries a negative price of risk (Herskovic, Kelly, Lustig, and Van Nieuwerburgh, 2016 JFE).

Volatility-managed portfolios

Moreira and Muir (2017, JF)

Should Investors Time Volatility?

How to respond to volatility

Volatility often spikes suddenly, typically around market downturn. Response?

1. Don't panic, ride out turbulence
2. Buy: prices are low (more potential return)
3. Sell: volatility is high (more risk). Buy back when volatility subsides

Volatility-managed portfolios

1. Volatility managed portfolios: scale aggregate priced factor by $1/\sigma_t^2$

2. Motivation: risky asset demand (e.g. mean-variance)

$$w_t = \frac{1}{\gamma} \frac{E_t(R_{t+1})}{Var_t(R_{t+1})}$$

3. Volatility doesn't forecast returns $\Rightarrow$ volatility timing beneficial

Volatility-managed portfolios

Data:

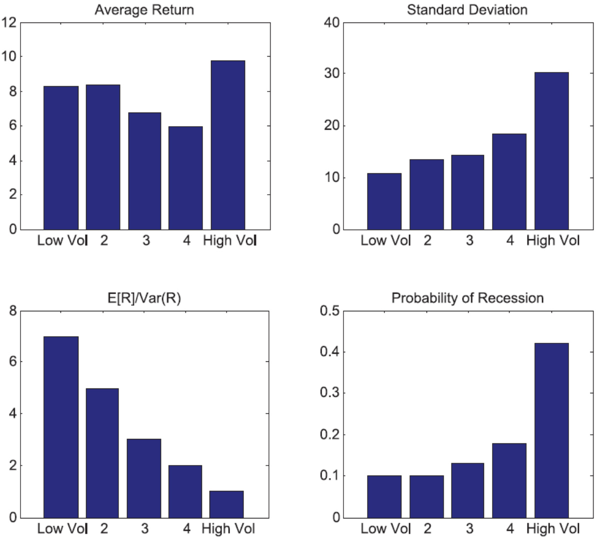
- Usual factors: SMB, HML, MOM, etc
- Sample from 1925 to 2015 (CRSP), post 1960 (Accounting)

Findings:

- Increase Sharpe ratios, generate large alpha on original factors
- Timing exposure: take *less* risk in recessions when σ high
- Timing exposure: *Sell* after market crashes

Do you find those findings intuitive?

Risk-return trade-off



High volatility periods: *more risk* but *same* return on average

Portfolio formation

- Managed portfolio:

$$f_{t+1}^{\sigma} = \frac{c}{\hat{\sigma}_t^2(f)} f_{t+1}$$

- Constant c sets the average exposure
- Realized variance of previous month:

$$\hat{\sigma}_t^2(f) = RV_t^2(f) = \sum_{d=1/22}^{1} \left(f_{t+d} - \frac{\sum_{d=1/22}^{1} f_{t+d}}{22} \right)^2$$

- Run time-series regressions:

$$f_{t+1}^{\sigma} = \alpha + \beta f_{t+1} + \epsilon_{t+1}.$$

- Test whether α is positive

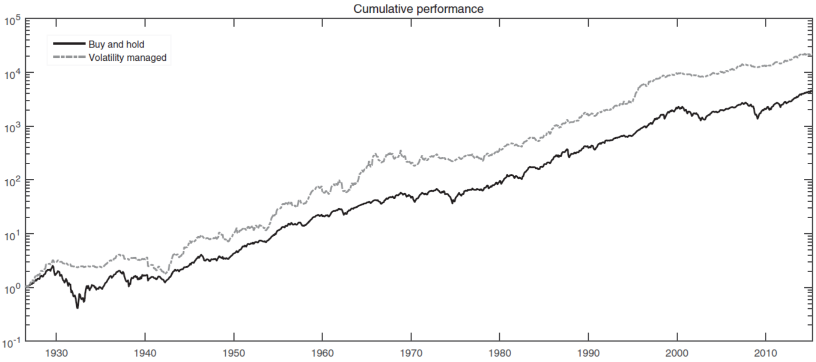
Panel A: Univariate Regressions

	(1) Mkt^{σ}	(2) SMB^{σ}	(3) HML^{σ}	(4) Mom^{σ}	(5) RMW^{σ}	(6) CMA^{σ}	(7) FX^{σ}	(8) ROE^{σ}	(9) IA^{σ}	(10) BAB^{σ}
MktRF	0.61									
	(0.05)									
SMB		0.62								
		(0.08)								
HML			0.57							
			(0.07)							
Mom				0.47						
				(0.07)						
RMW					0.62					
					(0.08)					
CMA						0.68				
						(0.05)				
Carry							0.71			
							(0.08)			
ROE								0.63		
								(0.07)		
IA									0.68	
									(0.05)	
BAB										0.57
										(0.05)
Alpha (α)	4.86	−0.58	1.97	12.51	2.44	0.38	2.78	5.48	1.55	5.67
	(1.56)	(0.91)	(1.02)	(1.71)	(0.83)	(0.67)	(1.49)	(0.97)	(0.67)	(0.98)
N	1,065	1,065	1,065	1,060	621	621	360	575	575	996
R^2	0.37	0.38	0.32	0.22	0.38	0.46	0.33	0.40	0.47	0.33
RMSE	51.39	30.44	34.92	50.37	20.16	17.55	25.34	23.69	16.58	29.73

Panel B: Alphas Controlling for Fama-French Three Factors

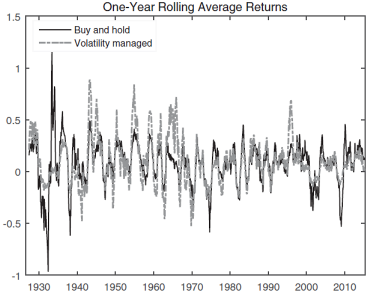
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Alpha (α)	5.45	−0.33	2.66	10.52	3.18	−0.01	2.54	5.76	1.14	5.63
	(1.56)	(0.89)	(1.02)	(1.60)	(0.83)	(0.68)	(1.65)	(0.97)	(0.69)	(0.97)

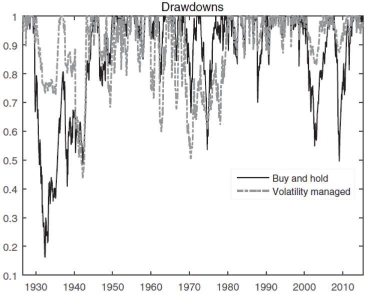
Volatility-managed market return



Cumulative returns to a buy-and-hold strategy versus a volatility-managed strategy for the market portfolio from 1926 to 2015. The y-axis is on a log scale and both strategies have the same unconditional monthly standard deviation.

Volatility-managed market return





Rolling one-year returns from each strategy and the lower right panel shows the drawdown of each strategy.

Combining factors: MVE portfolios

Not tradable:

1. For given set of factors construct in sample MVE
2. Volatility time the MVE portfolio as before

Panel A: Mean-Variance Efficient Portfolios (Full Sample)

	(1) Mkt	(2) FF3	(3) FF3 Mom	(4) FF5	(5) FF5 Mom	(6) HXZ	(7) HXZ Mom
Alpha (α)	4.86	4.99	4.04	1.34	2.01	2.32	2.51
	(1.56)	(1.00)	(0.57)	(0.32)	(0.39)	(0.38)	(0.44)
Observations	1,065	1,065	1,060	621	621	575	575
R^2	0.37	0.22	0.25	0.42	0.40	0.46	0.43
RMSE	51.39	34.50	20.27	8.28	9.11	8.80	9.55
Original Sharpe	0.42	0.52	0.98	1.19	1.34	1.57	1.57
Vol-Managed Sharpe	0.51	0.69	1.09	1.20	1.42	1.69	1.73
Appraisal Ratio	0.33	0.50	0.69	0.56	0.77	0.91	0.91

Robustness of result

Appears very strong

1. Look across 20 countries, similar results
2. Survives transactions costs
3. “Tail risk” lower
4. Stronger results with VIX or expected vol
5. Different from standard risk-parity
6. Subsamples since 1926
7. Leverage?

Subsamples

	(1) Mkt	(2) FF3	(3) FF3 Mom	(4) FF5	(5) FF5 Mom	(6) HXZ	(7) HXZ Mom
α: 1926-1955	8.11	1.94	2.45				
	(3.09)	(0.92)	(0.74)				
α: 1956-1985	2.06	0.99	2.54	0.13	0.71	0.77	1.00
	(2.82)	(1.43)	(1.16)	(0.43)	(0.67)	(0.39)	(0.51)
α: 1986-2015	4.22	5.66	4.98	1.88	2.65	3.03	3.24
	(1.66)	(1.74)	(0.95)	(0.41)	(0.47)	(0.50)	(0.57)

Vol managed portfolios take less risk in recessions

	(1) Mkt^{σ}	(2) HML^{σ}	(3) Mom^{σ}	(4) RMW^{σ}	(5) CMA^{σ}	(6) FX^{σ}	(7) ROE^{σ}	(8) IA^{σ}
MktRF	0.83							
	(0.08)							
MktRF $\times 1_{rec}$	−0.51							
	(0.10)							
HML		0.73						
		(0.06)						
HML $\times 1_{rec}$		−0.43						
		(0.11)						
Mom			0.74					
			(0.06)					
Mom $\times 1_{rec}$			−0.53					
			(0.08)					
RMW				0.63				
				(0.10)				
RMW $\times 1_{rec}$				−0.08				
				(0.13)				
CMA					0.77			
					(0.06)			
CMA $\times 1_{rec}$					−0.41			
					(0.07)			
Carry						0.73		
						(0.09)		
Carry $\times 1_{rec}$						−0.26		
						(0.15)		
ROE							0.74	
							(0.08)	
ROE $\times 1_{rec}$							−0.42	
							(0.11)	
IA								0.77
								(0.07)
IA $\times 1_{rec}$								−0.39
								(0.08)
Observations	1,065	1,065	1,060	621	621	362	575	575
R^2	0.43	0.37	0.29	0.38	0.49	0.51	0.43	0.49

Transaction costs

1. Results for the market portfolio
2. Transaction cost from Frazzini, Israel, and Moskowitz (2015)

					α After Trading Costs			
w	Description	$\mid \Delta w \mid$	$E[R]$	α	1bps	10bps	14bps	Break Even
$\frac{1}{RV_t^2}$	Realized variance	0.73	9.47%	4.86%	4.77%	3.98%	3.63%	56bps
$\frac{1}{RV_t}$	Realized vol	0.38	9.84%	3.85%	3.80%	3.39%	3.21%	84bps
$\frac{1}{E_t[RV_{t+1}^2]}$	Expected variance	0.37	9.47%	3.30%	3.26%	2.86%	2.68%	74bps
$min(\frac{c}{RV_t^2}, 1)$	No leverage	0.16	5.61%	2.12%	2.10%	1.93%	1.85%	110bps
$min(\frac{c}{RV_t^2}, 1.5)$	50% leverage	0.16	7.18%	3.10%	3.08%	2.91%	2.83%	161bps

Leverage constraints

Panel A: Weights and Performance for Alternative Volatility-Managed Portfolios

					Distribution of Weights w			
w_t	Description	α	Sharpe	Appraisal	P50	P75	P90	P99
$\frac{1}{RV_t^2}$	Realized variance	4.86 (1.56)	0.52	0.34	0.93	1.59	2.64	6.39
$\frac{1}{RV_t}$	Realized volatility	3.30 (1.02)	0.53	0.33	1.23	1.61	2.08	3.36
$\frac{1}{E_t[RV_{t+1}^2]}$	Expected variance	3.85 (1.36)	0.51	0.30	1.11	1.71	2.38	4.58
$min(\frac{c}{RV_t^2}, 1)$	No leverage	2.12 (0.71)	0.52	0.30	0.93	1	1	1
$min(\frac{c}{RV_t^2}, 1.5)$	50% leverage	3.10 (0.98)	0.53	0.33	0.93	1.5	1.5	1.5

Different from risk parity and other low risk anomalies

Risk parity:

$$RP_{t+1} = b_t' f_{t+1} \tag{1}$$

where

$$b_{i,t}' = \frac{1/\sigma_{i,t}}{\sum 1/\sigma_{i,t}} \tag{2}$$

MVE: control for this factor in the regressions, alphas don't change

Cross-section vs. time series

Conventional wisdom: don't panic

The New York Times

Stocks and Bonds August 21, 2015 SUBSCRIBE | LOG IN

Advice After Stock Market Drop: Take Some Deep Breaths, and Don't Do a Thing

> "If you decide to put a bunch of money in cash...how will you know when to get back in?"

Vanguard (8/15): *What to do during market volatility? Perhaps nothing*

- Vol was at 30-40% in August

Oct/Nov 2008 op-eds Buffett (NYT), Cochrane (WSJ): buying opportunity

- Vol was 60-80%

This paper

Data: panic driven selling can be beneficial

- NYT: "If you decide to put a bunch of money in cash...how will you know when to get back in?"

  This paper: get back in gradually as volatility returns to normal (on *average* 18 months)

- E.g., October 2008: reduce exposure by 90%

- Performance holds up in 1930, 1987, and 2008

Out of Sample

Data in original paper was through 2015

Looking at data since then 2016-present

- Buy-hold mkt Sharpe was 1.5, vol managed was 2
- Mkt down 2.7% in March 2018, vol managed down 1.5%
    - Increased VIX in Feb → reduce exposure (still true now)

Should a long horizon investor also time volatility?

1. Common argument: long-term investors should not care about short-term gyrations in the stock market
   - Correct: long-term investor should take more risk if there is some mean-reversion
   - Not Correct: long-term investor should not care about volatility
2. In fact a long-term investor should volatility time exactly as a short-term investor (see math in the paper)

Takeaways

Risk-return tradeoff is *weak* in the data

- Vol managed portfolios across many factors / strategies
  - large α's
  - Sharpe ratios increase $\approx 75\%$
  - Take less risk in recessions and after market crashes
  - Evidence strong: this paper + Moreira and Muir (JFE, Forthcoming)
- Better to avoid high volatility episodes
  - Future returns are not higher during these times
  - Enter again as volatility subsides
  - Large benefits for long and short horizon investors