

Loss Uncertainty, Gain Uncertainty, and Expected Stock Returns

**Midwest Finance Association
2020 Annual Meeting at ZOOM**

Discussant: James Yae (University of Houston)

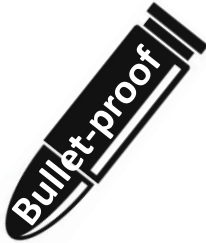
My Brain at First Sight

93
pages » 37

**Make all others
INSIGNIFICANT**

t-stat = 8 ~ 23

11 presentations



35
tables

Double sort, triple sort, ...

Heads-up

1. How to Enjoy the Paper

2. Discussion Points

- 1) How to Interpret the Main Result
- 2) The Main Innovation
- 3) A New Perspective
- 4) Other Papers
- 5) Other Comments

3. Conclusion

How to Enjoy the Paper

Wrong way to enjoy this paper

- 1) Another variance risk premium paper?
- 2) Another “... and the cross-section” paper?

How to Enjoy the Paper

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But, remember **35** tables in **93** pages!
and 3 years of revision by 4 great minds!

Discussion Point #1:

How to Interpret the Main Result

Ridiculously Simple View

$$\text{Gain QRP: } \text{QRP}_t^g \equiv \mathbb{E}_t [g_{t,t+1}^2] - \mathbb{E}_t^{\mathbb{Q}} [g_{t,t+1}^2]$$

$$\text{Loss QRP: } \text{QRP}_t^l \equiv \mathbb{E}_t^{\mathbb{Q}} [l_{t,t+1}^2] - \mathbb{E}_t [l_{t,t+1}^2]$$

$$\text{where } \mathbb{E}_t^{\mathbb{Q}} [g_{t,t+\tau}^2] = e^{r_f \tau} \int_{S_t}^{\infty} \frac{1 - \ln(K/S_t)}{K^2/2} C_t(\tau; K) dK$$

$$\mathbb{E}_t^{\mathbb{Q}} [l_{t,t+\tau}^2] = e^{r_f \tau} \int_0^{S_t} \frac{1 + \ln(S_t/K)}{K^2/2} P_t(\tau; K) dK$$

Ridiculously Simple View



$$\text{Gain QRP: } \text{QRP}_t^g \equiv \mathbb{E}_t [g_{t,t+1}^2] - \mathbb{E}_t^{\mathbb{Q}} [g_{t,t+1}^2]$$


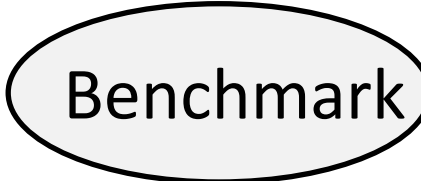
$$\text{Loss QRP: } \text{QRP}_t^l \equiv \mathbb{E}_t^{\mathbb{Q}} [l_{t,t+1}^2] - \mathbb{E}_t [l_{t,t+1}^2]$$

where $\mathbb{E}_t^{\mathbb{Q}} [g_{t,t+\tau}^2] =$  Call option bundle price

$\mathbb{E}_t [l_{t,t+\tau}^2] =$  Put option bundle price



Ridiculously Simple View


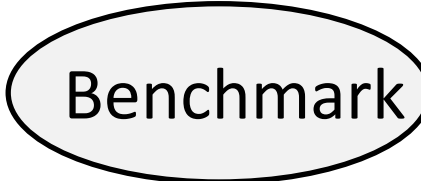
Gain QRP: $QRP_t^g \equiv$  Benchmark $-$  Call prices


Loss QRP: $QRP_t^l \equiv$  Put Prices $-$  Benchmark


Ridiculously Simple View

Academic view

Gain QRP: $QRP_t^g \equiv$  Benchmark $-$  Call prices

Loss QRP: $QRP_t^l \equiv$  Put Prices $-$  Benchmark

Gain QRP : Abnormally expensive call!
Everyone wants this stock!
Low premium! Lottery demand?

Loss QRP : Abnormally expensive put!
No one buys this stock without high premium Value stocks?

Ridiculously Simple View

Savvy traders' view: Buy Low, Sell High!

Gain QRP: $QRP_t^g \equiv$ Benchmark — Call prices

Loss QRP: $QRP_t^l \equiv$ Put Prices — Benchmark

Gain QRP ↓: Abnormally expensive call!
The stock is also overheated!

Yes, they are right.

Loss QRP ↑: Abnormally expensive put!
Then the stock is on sale!

Yes, they are right.

Discussion Point #2:

The Main Innovation

Why Did We Miss This?

Squared monthly return


$$\left(\sum_{j=1}^{1/\delta} r_{t-1+j\delta} \right)^2 = \underbrace{RV_{t-1,t}}_{\text{quadratic variation}} + \underbrace{2RA_{t-1,t}}_{\text{Realized Autocovariance!!!}}$$

where

$$RV_{t-1,t} = \sum_{j=1}^{1/\delta} r_{t-1+j\delta}^2$$

$$RA_{t-1,t} = \sum_{i=1}^{1/\delta-1} \sum_{j=1}^{1/\delta-i} r_{t-1+j\delta} r_{t-1+j\delta+i\delta}$$

Why Did We Miss This?


$$r_{t-1,t}^2 = \underbrace{\text{RV}_{t-1,t}}_{\text{quadratic variation}} + \underbrace{2\text{RA}_{t-1,t}}_{\text{Realized Autocovariance!!!}}$$


Continuous time modeling with serial-correlation?

We know how strong short-term reversal is. ☹

$$\frac{dS_t}{S_{t-}} = \mu_S dt + \sigma_t dB_t + (e^{Z_{g,t}} - 1) d + (e^{-Z_{b,t}} - 1) dN_{b,t},$$

Kilic and Shaliastovich (2019) used both LHS and RV but did not point out how they are mathematically different.

Why Did We Miss This?

$$r_{t-1,t}^2 = \underbrace{\text{RV}_{t-1,t}}_{\text{quadratic variation}} + \underbrace{2\text{RA}_{t-1,t}}_{\text{Realized Autocovariance???$$


Q1. BTW, what is inside the autocovariance-looking term?

Q2. Is it just serial-correlation or something else?

Q3. Stronger results with $E[r_{t-1,t}^2]$ than $E[\text{RV}]$. Why?

Really, why?

Discussion Point #3:

A New Perspective

Create a Derivative for Myself?

(My return) = $g^2 - l^2$ contingent on stock returns

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$$\begin{aligned}\text{Risk premium of my asset} &= E^P[g^2 - l^2] - E^Q[g^2 - l^2] \\ &= \text{Gain QRP} + \text{Loss QRP}\end{aligned}$$

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This measure will also explain CS.

Of course, the following works better.

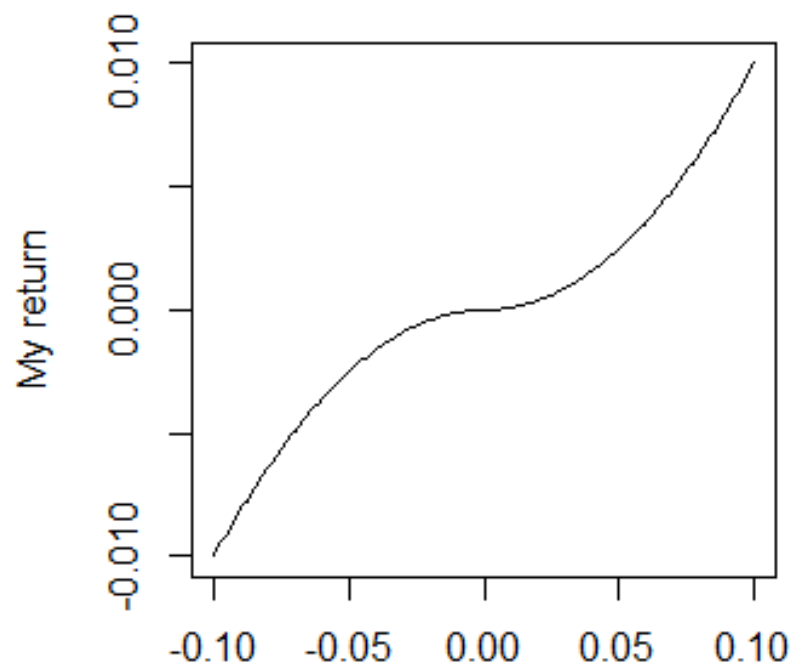
$$(\text{My return}) = 1.3g^2 - 0.7l^2$$

$$\text{RP}(\text{My return}) = 1.3\text{Gain QRP} + 0.7\text{Loss QRP}$$

Create a Derivative for Myself?

(My return) = $g^2 - l^2$ contingent on stock returns

Risk premium of my asset = $E^P[g^2 - l^2] - E^Q[g^2 - l^2]$
= Gain QRP + Loss QRP



This measure will also explain CS.
Of course, the following works better.

(My return) = $1.3g^2 - 0.7l^2$
RP(My return) = 1.3Gain QRP + 0.7Loss QRP

Maybe

RP(my asset) \approx RP(the stock) ?

A Toy Example


Suppose stock i 's monthly log return r_i follows iid $N(\mu_i, \sigma_i^2)$
Constant volatilities. No true VRP. No serial correlation.

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$$\begin{aligned}\text{Wrong VRP: } E^P[RV_i] - E^Q[r_i^2] &= \sigma_i^2 - (\sigma_i^2 + r_f^2) \\ &= -r_f^2\end{aligned}$$

$$\begin{aligned}\text{Net QRP: } E^P[r_i^2] - E^Q[r_i^2] &= (\mu_i^2 + \sigma_i^2) - (\sigma_i^2 + r_f^2) \\ &= \mu_i^2 - r_f^2\end{aligned}$$

- 
- The autocovariance-looking term RA has this term even with zero autocorrelation!
 - Remember autocovariance notations in the text book are about demeaned series.

A Toy Example

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QRP has information about the expected return of the stock.

What about Gain QRP and Loss QRP?

A Toy Example

Assumptions

500 stocks

Expected returns: from 3% to 30% (annualized)

The riskfree rate: 2% (annualized)

Volatility: 30% (annualized)

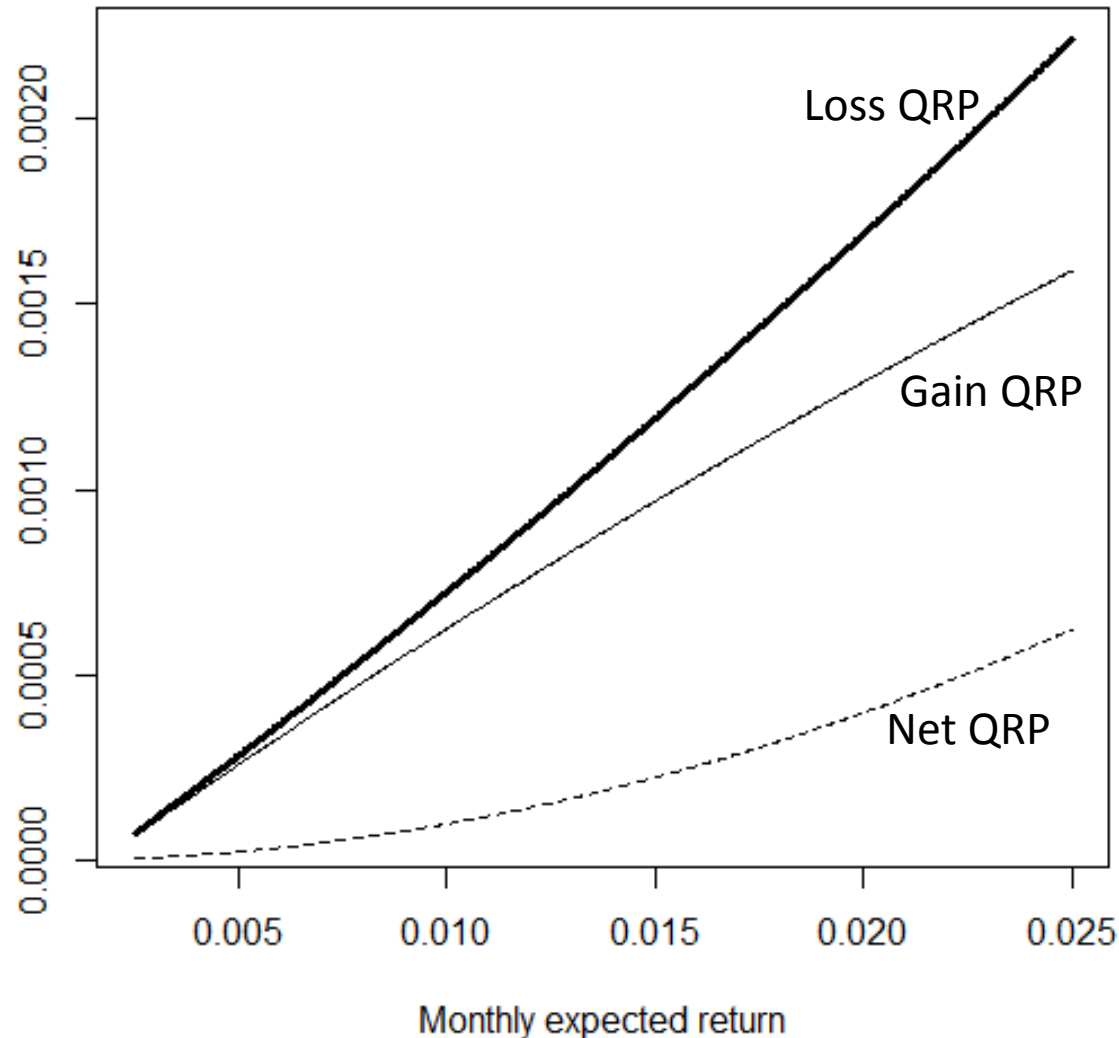
Calculate Gain QRP & Loss QRP using

$$\begin{aligned}\mathbb{E}_t [l_{t,t+1}^2] &= (\mu_t^2 + \sigma_t^2) \Phi \left(-\frac{\mu_t}{\sigma_t} \right) - \mu_t \sigma_t \phi \left(\frac{\mu_t}{\sigma_t} \right) \\ \mathbb{E}_t [g_{t,t+1}^2] &= (\mu_t^2 + \sigma_t^2) \Phi \left(\frac{\mu_t}{\sigma_t} \right) + \mu_t \sigma_t \phi \left(\frac{\mu_t}{\sigma_t} \right),\end{aligned}$$

QRPs Should Explain the Expected Returns!

even without VRP and Serial-Correlation

Quadratic Risk Premium (QRP)

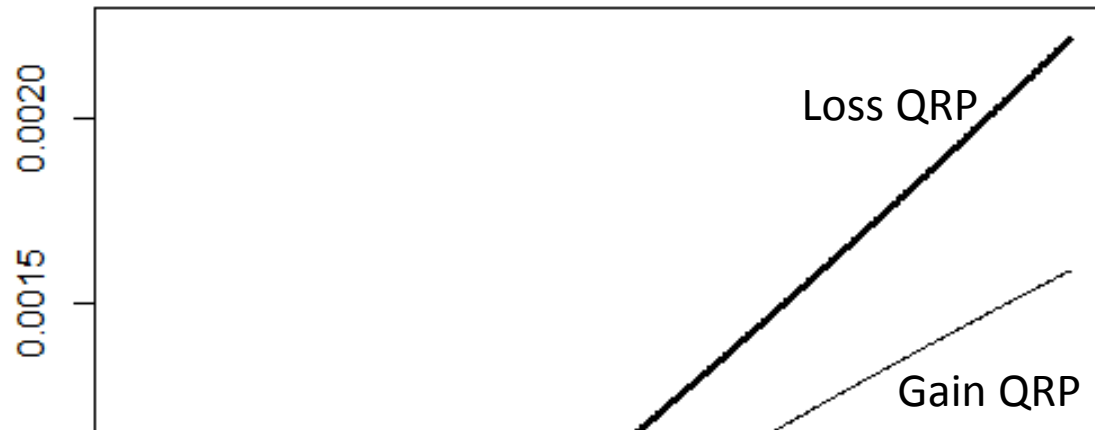


Don't be fooled
by slopes

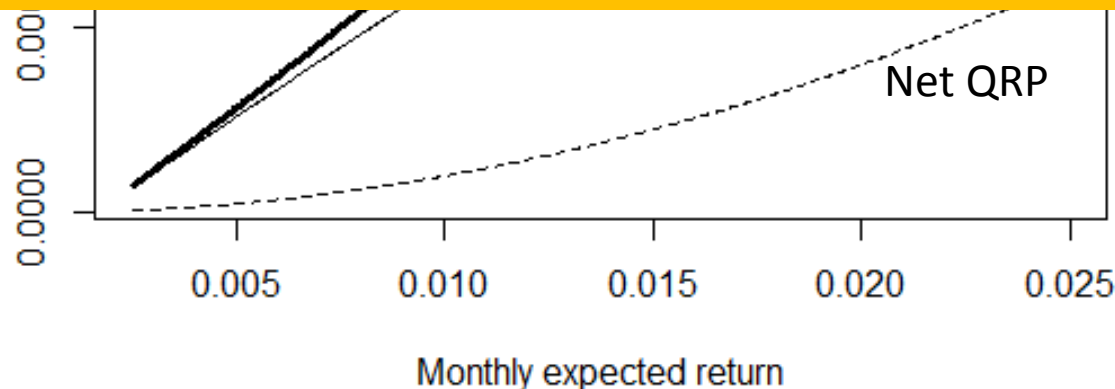
QRPs Should Explain the Expected Returns!

even without VRP and Serial-Correlation

Quadratic Risk Premium (QRP)



- Q1. Which QRP should be the strongest predictor?
- Q2. Which QRP should have the largest coefficient?



Make QRPs More Realistic!

1. Add measurement errors. (alternatively, assign different volatilities)
 - Follow the variance & correlation estimates in the paper
2. Generate 20 years of the monthly returns of 500 stocks.
3. Run Fama-Macbeth regressions.

Easy to replicate the table in the paper. Question: But why is net QRP not working?

Measurement errors!

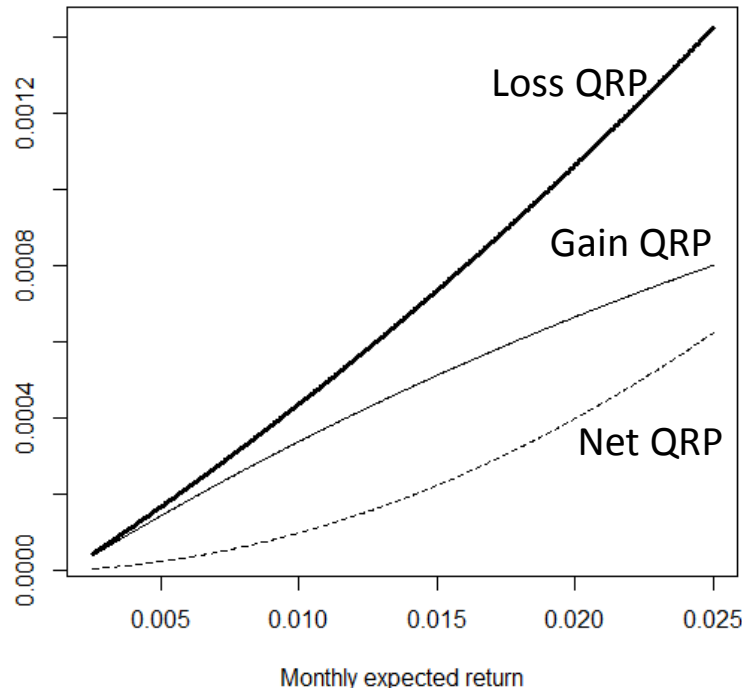
	I	II
QRP	0.10 (1.19)	
Gain QRP		1.31*** (7.06)
Loss QRP		0.71*** (6.39)

Measurement Errors Matter w/ High Vol

Individual stocks have higher total volatility than the market.
Therefore, net QRP or VRP might not work on individual stocks.

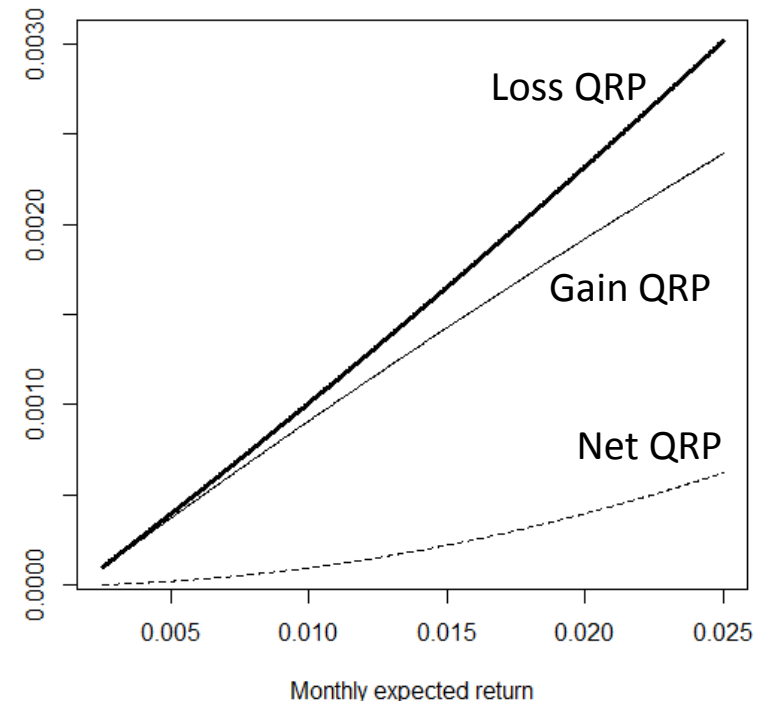
Return Vol=20%

Quadratic Risk Premium (QRP)

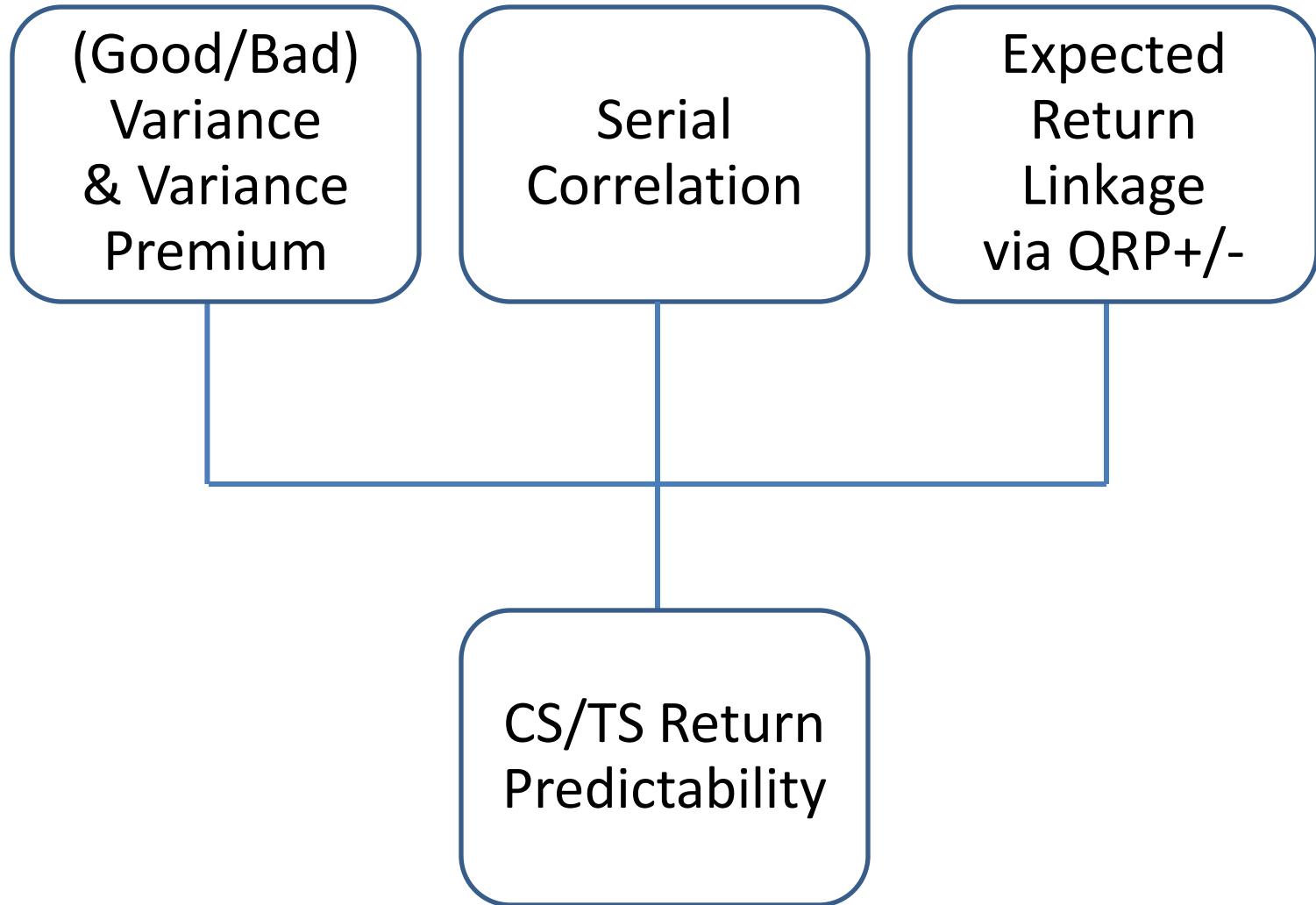


Return Vol=50%

Quadratic Risk Premium (QRP)



Three Sources of Predictability



Discussion Point #4:

Other Papers

Related Papers

Among the papers that predict equity returns by variance premium, ...

Year	Journal	Authors	Asset to predict	Predictor	Physical E[.]
2009	RFS	Bollerslev et al.	Market	VRP	R-QV-P
2018	JFEt	Feunou et al.	Market	VRP+ / VRP-	E-QV-P
2019	JFE	Pyun	Market	VRP	E-QV-P
2019	MS	Kilic and Shaliastovich	Market / Portfolios	VRP+ / VRP-	R-QV-P, E-QP-P
?	?	This paper	Individual stocks	VRP+ / VRP-	E-QP-P

Working papers are NOT included

QV: quadratic variation

R- : realized

QP: quadratic payoff

E- : expected (predicted)

-P : premium

**If the innovation is in the physical term,
these are the most relevant competitors.**

Final Chapter

Other Comments

1. $E^P[r^2]$, $E^P[g^2]$ and $E^P[l^2]$ prediction needs $E^P[r]$ estimates. What?

$$\mathbb{E}_t[r_{t,t+1}^2] = \mu_t^2 + \sigma_t^2 \quad \mathbb{E}_t[g_{t,t+1}^2] = (\mu_t^2 + \sigma_t^2) \Phi\left(\frac{\mu_t}{\sigma_t}\right) + \mu_t \sigma_t \phi\left(\frac{\mu_t}{\sigma_t}\right), \quad \mathbb{E}_t[l_{t,t+1}^2] = (\mu_t^2 + \dots$$

Isn't it what we are eventually looking for? Coherency? Recursive estimation? Too little predictors? ML?

2. $E^P[r^2]$, $E^P[g^2]$ and $E^P[l^2]$ assume “monthly returns $\sim N(\mu_t, \sigma_t^2)$ ”.

3. If QRP+/- results are associated with information asymmetry, why is it different from RN-Skewness prediction? Any long-term prediction effect?

Predictor		Holding Period (month)			
		1	3	6	12
VOLSKEW	β	-0.39	-0.34	1.26	4.98
	t-stat.	-7.39	-2.98	6.50	15.30

from “A Comprehensive Look at the Option-Implied Predictors of Stock Returns”
by Hitesh Doshi, Yang Luo, and James Yae

Conclusion

1. An important observation on the carelessly used proxy
2. Cross-sectional results are so strong and robust
 - Important to both academia and industry.
 - They can be even better.
3. Worth reading it. Learned a lot. A great paper with rich contents!

Thank you!