# Market-Beta 

Ivo Welch

May 2019

## Notice to PhD Students

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This presentation is intended to teach how not to commit suicide on the job market.

## Because, what vou need is



## I am not saying it's right. I am saying I am impressed.

(PS: On the job market, it will be cleverness, not necessarily mathiness, that matters.)

## Why Not Job Market?

- My brownbag paper is way too simple,


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- My brownbag paper is way too simple,
...and it is not about
- new data,
- big data,
- new small data,
- and/or clever quasi-experimental identification.


## So why bother?

- It's actually very useful, and
- you will actually want to use this in your lifetime,



## So why bother?

- It's actually very useful, and
- you will actually want to use this in your lifetime,
...and it saved your Wednesday lunch.

- so no complaints, please.


## Breaks Chernov Rule

- not "serious" research


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- not "serious" research
- instead: this is a "Tinker With Data" paper


## Motivation

Why still bother with "boring" old market-beta?

- Market-beta is interesting even w/o CAPM
- Measure of risk contribution to diversified portfolios.
- Hedging against bear markets
- Down-Beta Theories (as in Ang+ or Lettau+)
- Betting against Beta (as in Frazzini-Pedersen)
- Pragmatic: used in regulation, etc.
- How should we estimate beta?
- And can it make a difference?


## Performance Metric

I will judge beta quality by prediction.

- future ols(/other) 1-mo or 1-yr market-beta estimates
- never future average returns.


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- future ols(/other) 1-mo or 1-yr market-beta estimates
- never future average returns.
- PS: If two proxies are drawn with noise from true value, the expected $R^{2}$ of each proxy with the true value is the squareroot of the $R^{2}$ of one proxy with the other proxy.


## Best Beta Estimator Known: Vasicek

- random-effects estimator = bayesian shrinkage
- Run OLS Regressions
- Calculate x-sect means and sds of betas
- For each stock,

$$
b_{\mathrm{vck}}=w \cdot b_{\mathrm{xs}}+(1-w) \cdot b_{\mathrm{ts}}
$$

where $\mathrm{w}=\sigma_{\mathrm{ts}} /\left(\sigma_{\mathrm{ts}}+\sigma_{\mathrm{xs}}\right)$.

## Other Important Choices

- Always use daily stock returns
- about 1-3 years of data.
- Never use industry beta for individual stocks.
- Indeed, less noisy;
- but just like using "1" — low predictive power.
- vasicek and its derivatives
- (random-effects and/or bayesian justification if no drift.)
- Levi-Welch linear de-bias.
more alternatives below: Dimson, Frazzini-Pedersen


## Vasicek Disadvantages

"Pseudo Optimal"

- "optimal design" was never suited to problem:
- vasicek is designed for measurement error,
- not for underlying beta drift
- (ergo 12-24 months windows)
- good $R^{2}$, but badly biased
- levi-welch (2017) suggests empirical de-biasing
- requires another stage
- spooky entangled estimates
- requires multi-step ts and xs procedure


## Better and Simpler Estimator

## Standard Bayesian Use of Prior

Data



Posterior

- Involves arguments about reasonable priors
- Often painful—days babysitting, not minutes.
- Usually primarily in dedicated papers


## (Ab-)Use of Prior

Data
Posterior
Priors

- Still involves arguments about reasonable priors
- Easy to use. minutes, not days.
- Likely novel method.



Market Return






- non-Bayesian use of prior
- with wide priors, not very costly, even if panel is true OLS w/o outliers.
- Note: Even if $\hat{b}=0.8$, the prior is still effective on individual points.
- Bayesian OLS-type prior would work on overall b estimate.
- If final is near 1.0, Bayesian method says "just fine."
- Here, a prior( $-1,3$ ) still influences points, and thus even estimates close to 1.0. $\rightarrow$ can move a $\hat{b}$ away from 1.0.
- PS: could use Bayesian with priors on mixed distributions, plain + outliers. Would work, too, but far more painful.


## beta slope winsorized (bsw)

1. 12-24 mos of daily stock returns
2. winsorize all returns $\left(\Delta_{s}=2\right)$ :

$$
\mathrm{rsw}_{\mathrm{i}, \mathrm{t}} \in 1.0+\left[-\Delta_{\mathrm{s}}, \Delta_{\mathrm{s}}\right] \cdot r_{\mathrm{m}, \mathrm{t}}
$$

3. estimate ols market-model

$$
r s w_{i, t}=a_{i}+b_{s w} \cdot r_{m, t}
$$

(just a reuse of the model with a reasonable prior. note: model-specific.)

## why $\Delta_{\mathrm{s}}=2 ?$

- fewer than 1\% of betas exceed -1 and +3
- fewer than $0.03 \%$ repeat in consecutive years - (greater than $1 \% \cdot 1 \%$, but not by much.
- beyond, no monotonicity between $b_{t}$ and $E\left(b_{t+1}\right)$
- not philosophical, but also not highly searched:
- you could also use [-0.5, 2.5] or [-3, 5].
- lower $\Delta_{\mathrm{s}}$ forces too much towards 1.
- higher $\Delta_{\mathrm{s}}$ forces nada.


## does it matter?

are betas even different?
rmsd $\left(\right.$ bols $\left._{\mathrm{D}}, \mathrm{bsw}\right) \approx 0.37$
rmsd ( bvck $_{\mathrm{D}}$, bsw $) \approx 0.20$
rmsd $\left(\right.$ bols $\left._{\mathrm{M}}, \mathrm{bsw}\right) \approx 0.60$

## "gamma" panel reg for bolst+1

Dependent: future 1-year ols beta from daily returns, same set.

|  | $\gamma_{0}$ | $\operatorname{se}\left(\gamma_{0}\right)$ | $\gamma_{1}$ | $\operatorname{se}\left(\gamma_{1}\right)$ | $\mathrm{R}^{2}$ |
| :--- | ---: | ---: | ---: | ---: | :---: |
| (bols) | 0.34 | .004 | 0.54 | .005 | $25.5 \%$ |
| (bvck) | 0.19 | .002 | 0.74 | .002 | $30.8 \%$ |
| $\ldots$ (blw) | -0.01 | .003 | 0.98 | .003 | same |
| level (blw) | 0.27 | .002 | 0.70 | .003 | $29.7 \%$ |
| band (bbw) | 0.04 | .002 | 0.93 | .003 | $30.9 \%$ |
| slope (bsw) | 0.01 | .002 | 0.96 | .003 | $31.4 \%$ |
| slope + v | -0.01 | .003 | 1.00 | .003 | $31.5 \%$ |

True $\mathrm{R}^{2}$ is squareroot. $\sqrt{.3} \approx 0.55$.


## Nothing Sensitive or Edgy

- very stable by year.
- very stable by ols beta.
- no meaningful improvement by varying $\Delta_{s}$.
- even by own lagged beta, beta-sd, marketcap, trading volume, volatility, etc.


## RMSE by ols se(b) Percentile




## $\Delta^{*}$ by ols se(b) Percentile


possible improvements: obtain ols b se rank, then

- more winsorization ( $\Delta_{s}=1.5$ ) for $>85 \%$ and 1 for $>95 \%$.
- but stable from 5 to 80 and look at absolute improvement,
- only the 95\%+ do.
- $\quad \Rightarrow$ 1st-stage firm-specific deltas won't help much, on avg.


## RMSE by Market Cap Percentile



## $\Delta^{*}$ by market cap percentile


possible improvements: obtain mcap rank, then

- more winsorization ( $\Delta_{\mathrm{S}}=1.5$ ) for small-caps (rank $<40 \%$ ),
- less winsorization $\left(\Delta_{s}=3\right)$ for big-caps (rank $>80 \%$ ).


# Another 2\% R ${ }^{2}$ Improvement 

- retain 1-pass simplicity of use
- WLS market-model, w=f(age)
steep exponential decline:

|  | Now | 3 mo | 6 mo | 1 yr | 2 yr |
| :---: | :---: | :---: | :---: | :---: | :---: |
| WLS w | $100 \%$ | $80 \%$ | $50 \%$ | $10 \%$ | $2 \%$ |

- PS: this WLS decay allowed for a kink
- want approx formula? $\approx \exp [-2(\Delta$ days $) / 252]$
- trivially easy in time
- no marginal loss of observations


## PS: Mean Reversion on Monthly BSW

- not fixing outliers suggests faster mean reversion of beta
- need to estimate mean reversion of betas after fixing outliers


## PS: Mean Reversion on Monthly BSW



Note: weighting is not the same as tilting.
Months
Note: dependent ne OLS, but BSW. Indep is WLS.BSW. Daily Stock Returns.

## another $1 \% R^{2}$ improvement

- no longer simple, 1-pass, no-obs-loss
- add one extra variable reflecting firm-size or dollar trading volume.
- big firms have bigger market-betas (yes!),
- but use requires first-stage regression,
- and marketcap requires merging, data loss, etc.
- I could find no other useful accounting compustat or crsp derived variable or ratio.


## Dimson + Frazzini-Pedersen

| care for |  | $\mathrm{R}^{2}$ with $\mathrm{x}_{\mathrm{t}}$ being only |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{y}_{\mathrm{t}+1} \downarrow$ | ols | bsw | vck | dim | fp |
| ols | 38\% | 44\% | 43\% | 28\% | 27\% |

(Monthly-overlaps)

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| $\mathrm{y}_{\mathrm{t}+1} \downarrow$ | ols | bsw | vck | dim | fp |
| ols | 38\% | 44\% | 43\% | 28\% | 27\% |
| vck |  | 51\% | 50\% |  |  |
| bsw |  | 57\% | $\Rightarrow R^{2}$ | $\beta_{\text {rue }}$ should | be $\approx 75 \%$ |
| dim |  | 30\% |  | 22\% |  |
| fp |  | 30\% |  |  | 21\% |

$\rightarrow$ what should you use if you care (but why?) about future dimson or fp estimates? (Monthly-overlaps)
if you are interested in future Dimson beta, $\rightarrow$ use current bsw never use current Dimson beta as estimator
if you are interested in future Frazzini-Pedersen beta. $\rightarrow$ use current bsw never use current FP beta as estimator
did they ever try to validate their measures?

## Monthly-Frequency Return Data?

- even long-window monthly betas are miserable predictors of anything (like $R^{2}$ of $<15 \%$, not $40 \%$ ).
- daily predicts monthly better than monthly itself.
$-\rightarrow$ use daily frequency even if interested in future monthly market betas.


## Future

Can some of this be generalized?

- To what extent can we use our prior information to manipulate the incoming data first,
- and then run plain classical procedures,
- because Bayesian methods are so painful that only dedicated B papers are using them.
- (e.g., stick fitted values w/ se [as weights?] from 1st-stage OLS into 2nd-stage OLS?)


## Conclusion

- novel slope winsorization method afaik, with use of prior in different way,
- novel application of winsorization method in important context of market-beta estimation.
- only simple use of prior. no 1st stage needed.
- superb ease of use. pto.


## So Why Not?

```
wins.rel <- function( r, rmin, rmax ) {
    rl <- ifelse( (rmin<rmax), rmin, rmax )
    ru <- ifelse( (rmin<rmax), rmax, rmin )
    ifelse( r<rl, rl, ifelse(r>ru, ru, r) )
}
delta <- 2
wri <- wins.rel( ri, (1-delta)*rm, (1+delta)*rm )
beta <- function(...) coef(lm(...))[2]
bsw <- beta( wri ~ rm )
wbsw <- beta( wri ~ rm, w=exp(-2*(length(ri):1)/256) )
    ## note age = reverse-time weights
```

