

Comparing ophthalmology treatments via the integration of IPD and aggregate-level data:

A new MAIC approach

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ORIGINAL RESEARCH

Review and comparison of methodologies for indirect comparison of clinical trial results: an illustration with ranibizumab and aflibercept

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ABSTRACT

Aim: To review and compare methods for indirect comparison of aflibercept and ranibizumab in patients with diabetic macular edema.

Methods: Post-stratification, inverse probability weighting based on simulated data, weight optimization, and regression model techniques were used to compare pooled individual patient-level data from the RESTORE and RESPOND (ranibizumab 0.5 mg as needed after 3 initial monthly doses) studies with summary-level data from the VIVID and VISTA (aflibercept 2.0 mg every 8 weeks after 5 initial monthly doses, 2q8) studies. The impact of adjusting for up to two baseline characteristics was assessed.

Results: All methods provided similar results. After adjustment for baseline best-corrected visual acuity and central retinal thickness, no statistically significant difference in average gain in baseline best-corrected visual acuity from baseline at month 12 was found between ranibizumab 0.5 mg and aflibercept 2q8.

Conclusions: Weight optimization and regression methods are useful options to adjust for more than one baseline characteristic.

ARTICLE HISTORY

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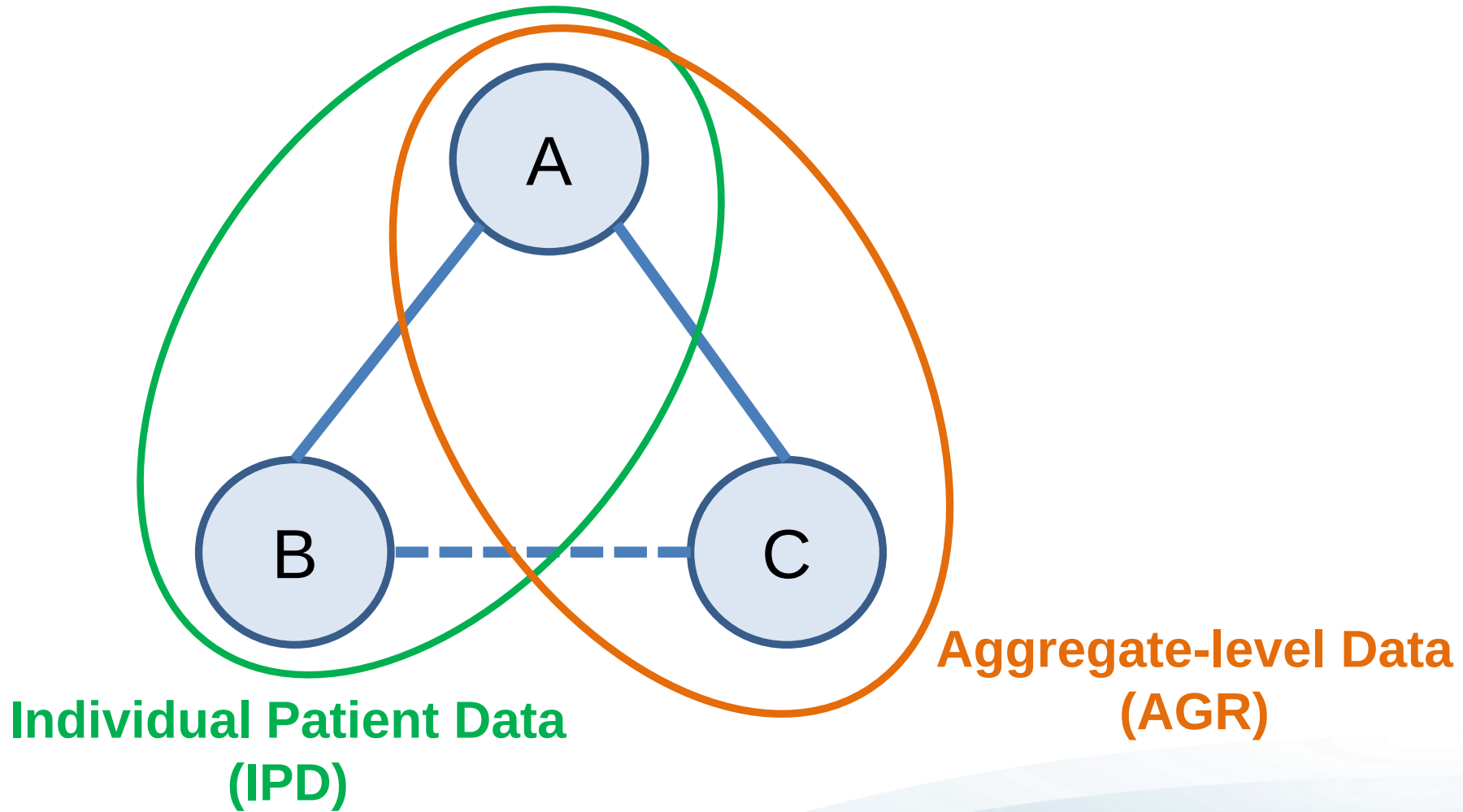
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KEYWORDS

Confounders; indirect treatment comparison; inverse probability weighting; regression; stratified sampling

Indirect treatment comparison



A 'baseline' problem....



$\neq$



Trial #1

Individual Patient Data

Trial #2

Aggregate Data

What is MAIC?

Matching **A**ddjusted **I**ndirect **C**omparison

Re-weighting of IPD

Weighted IPD baseline characteristics =
AGR baseline characteristics



Weighted analysis of IPD outcomes

c.f. with AGR outcome data

Optimization Challenge

Suppose i^{th} patient has a_i (baseline measure)

Primary: find weights w_i

$$\sum_i w_i a_i = \bar{a}_{(2)}$$

Target mean in AGR

$$\sum_i w_i = n_1$$

IPD study size

$$w_i \geq 0$$

Secondary:

$$w_i \leq w_{max}$$

Restrict weights (avoid possible high leverage)

$$\frac{(\sum_i w_i)^2}{\sum_i w_i^2}$$

Maximise Effective Sample Size (ESS)

Methods



- Signorovitch et al. (2010)
- Post-stratification (Di Lorenzo et al., 2011)
- Entropy balancing (Hainmueller, 2012)
- MAICn (Han, 2014)
- **Polynomial weighting (Regnier et al. 2015)**

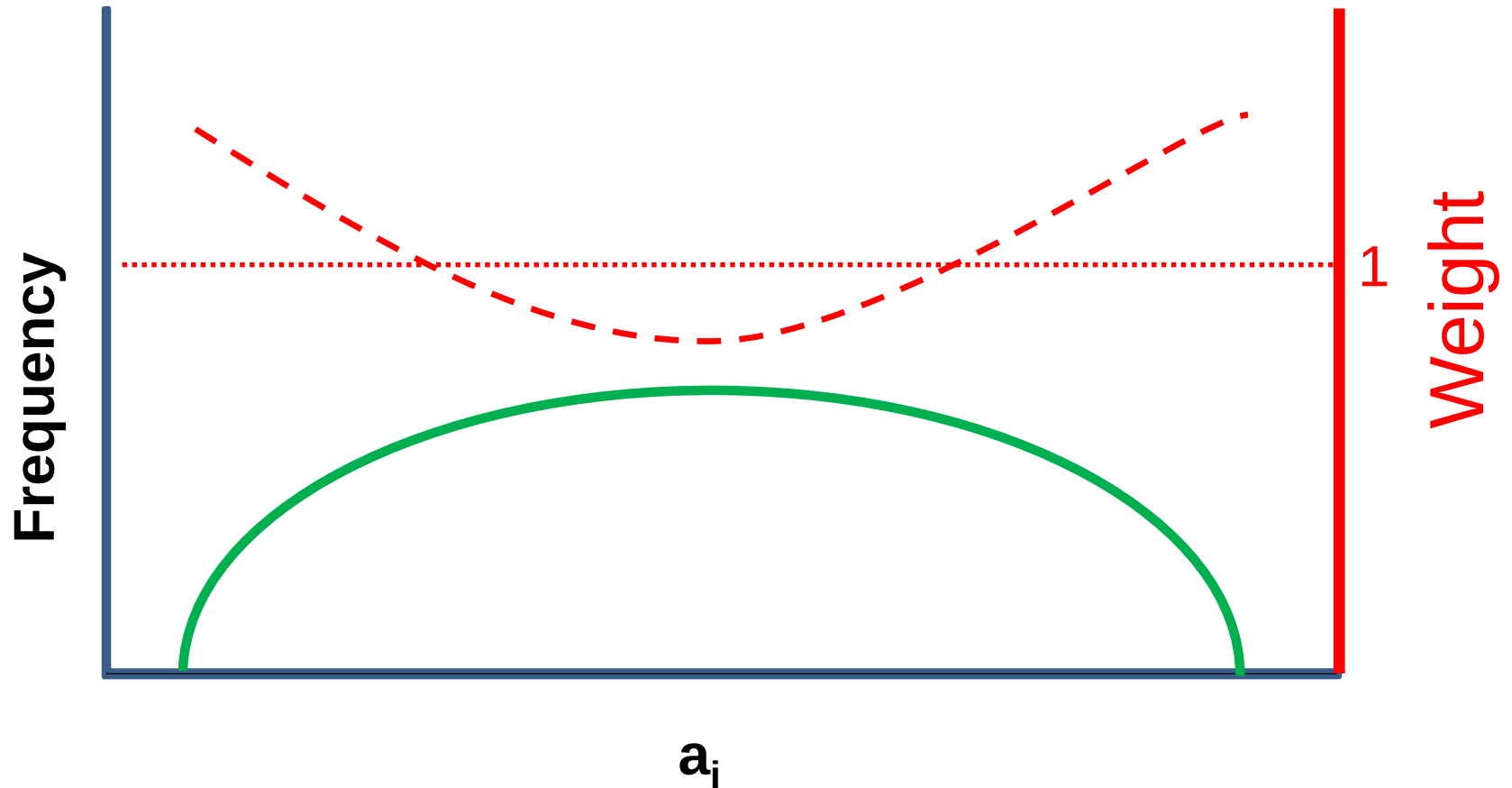
Borrowing from historic controls
Survey sampling
(e.g. cell weighting, raking)



Polynomial weighting

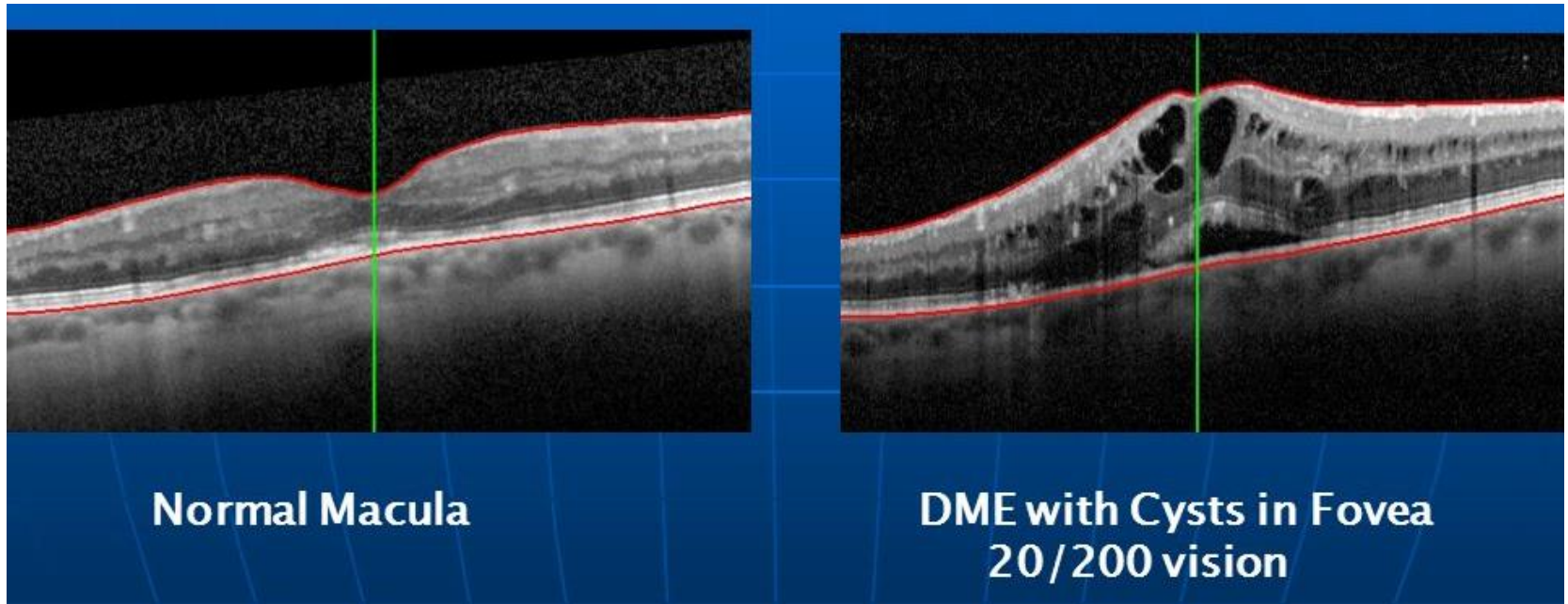


Polynomial weighting



Example

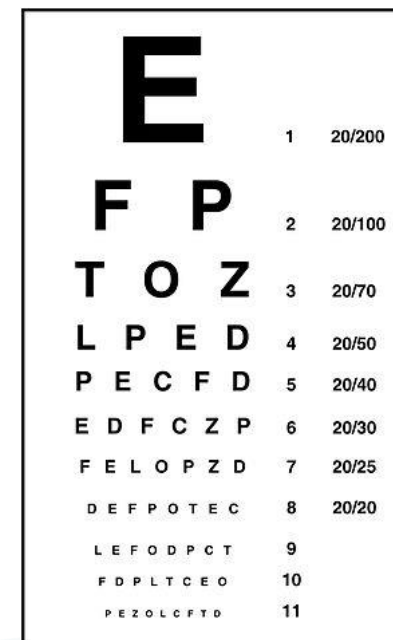
Diabetic Macular Edema (DME)



Comparison of two Anti-VEGF treatments

Studies

Characteristic	Ranibizumab	Aflibercept
Data type	IPD	AGR
Sponsor	Novartis	Regeneron
Studies	RESTORE RESPOND	VIVID VISTA
Study type	Blinded RCT	
Control arm	Laser photocoagulation therapy	
Endpoint	Δ from Baseline to M12/LOCF in visual acuity (letters)	



Treatment confounders

Baseline Characteristic	Aflibercept arm (N=286)	Ranibizumab arm (N=190)	Difference (95% CI)
BCVA (letters)	59.1 (11.0)	64.1 (10.3)	-5.0 (-7.0,-3.0)
CRT (μm)	497 (151)	435 (126)	62 (36,88)

What would have been effect of Ranibizumab in the VIVID/VISTA population?

Polynomial weighting

j=baseline parameter, i=patient

1) a_{ij} standardised to lie on $[0,1]$:
$$a_{ij}^* = \frac{a_{ij} - \min(a_{ij})}{\max(a_{ij}) - \min(a_{ij})}$$

2)
$$w_{ij}^* = \left| \beta_{2j} + \beta_{3j}(a_{ij}^* - \beta_{1j}) + \beta_{4j}(a_{ij}^* - \beta_{1j})^2 + \beta_{5j}(a_{ij}^* - \beta_{1j})^3 + \beta_{6j}(a_{ij}^* - \beta_{1j})^4 \right|$$

3)
$$w_i = \frac{\sum_j w_{ij}^*}{\sum_{ij} w_{ij}^*}$$

4) Calculate weighted mean & SD of a_{ij} using $w_i \rightarrow Mw_j$, SDw_j

5) Minimise
$$L = \sum_j \frac{[(Mw_j - Mt_j)^2 + (SDw_j - SDt_j)^2]}{SDt_j} \quad \text{w.r.t. } \beta_{ij}$$

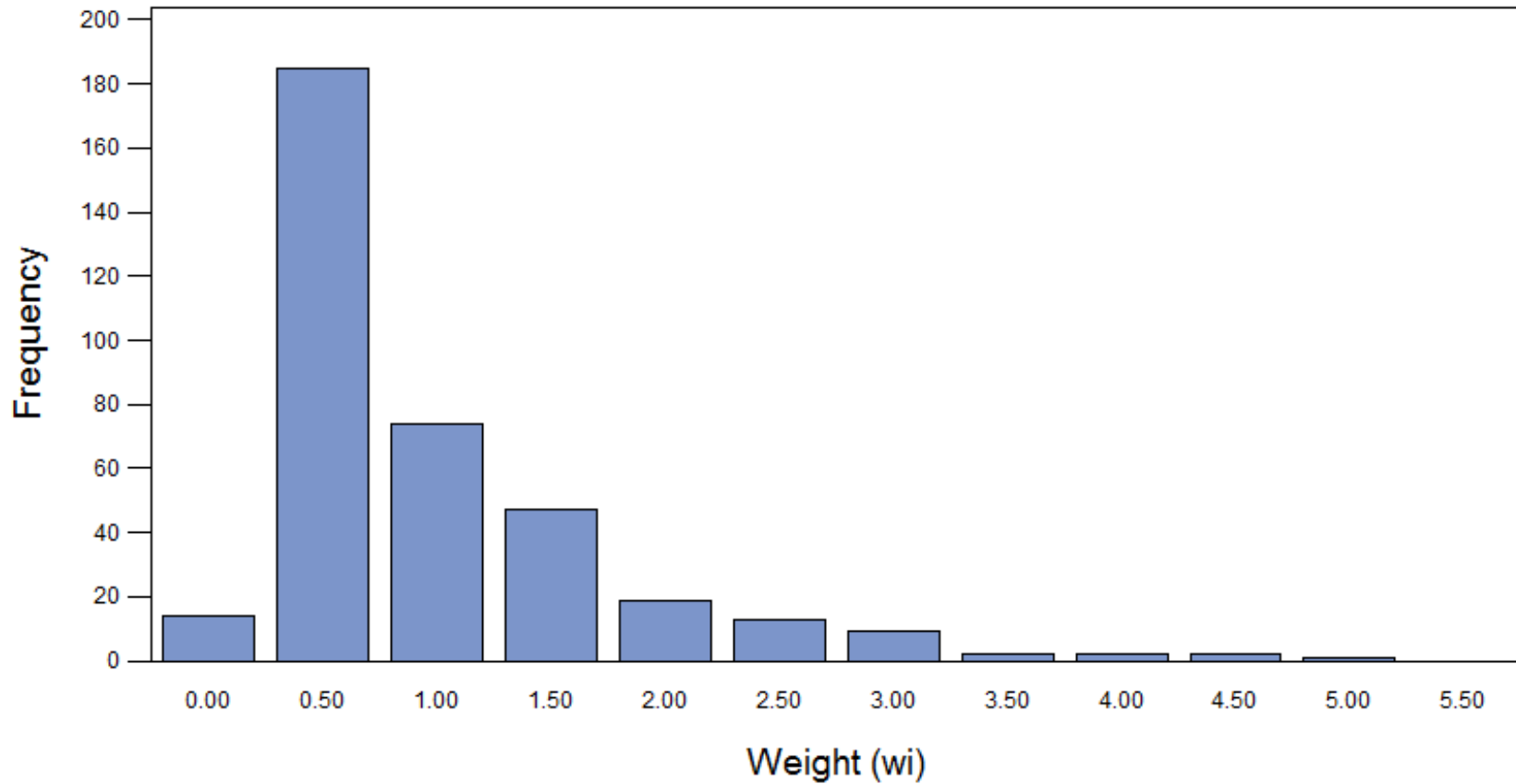
Mt_j , SDt_j = target mean & SD (AGR)

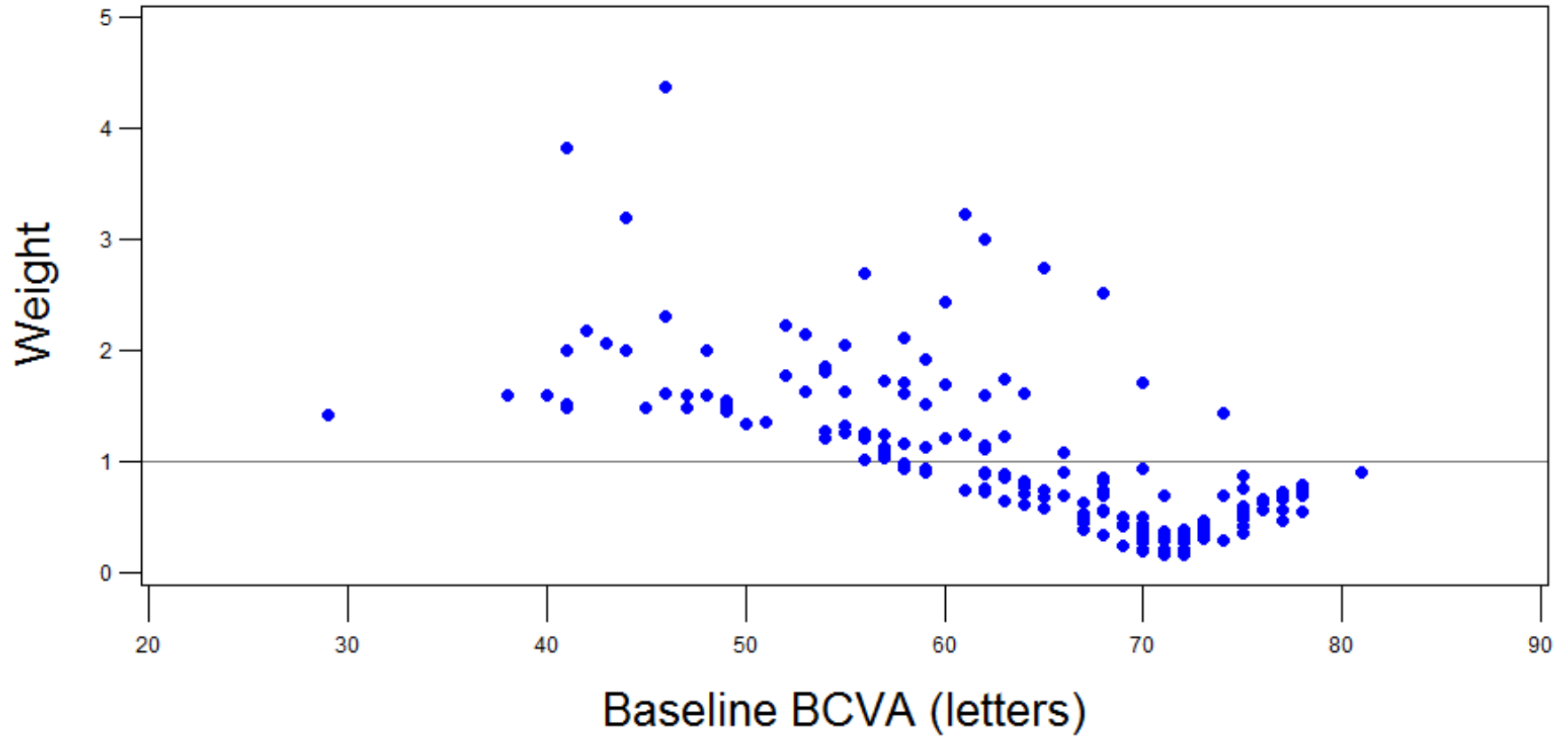
Baseline Matching

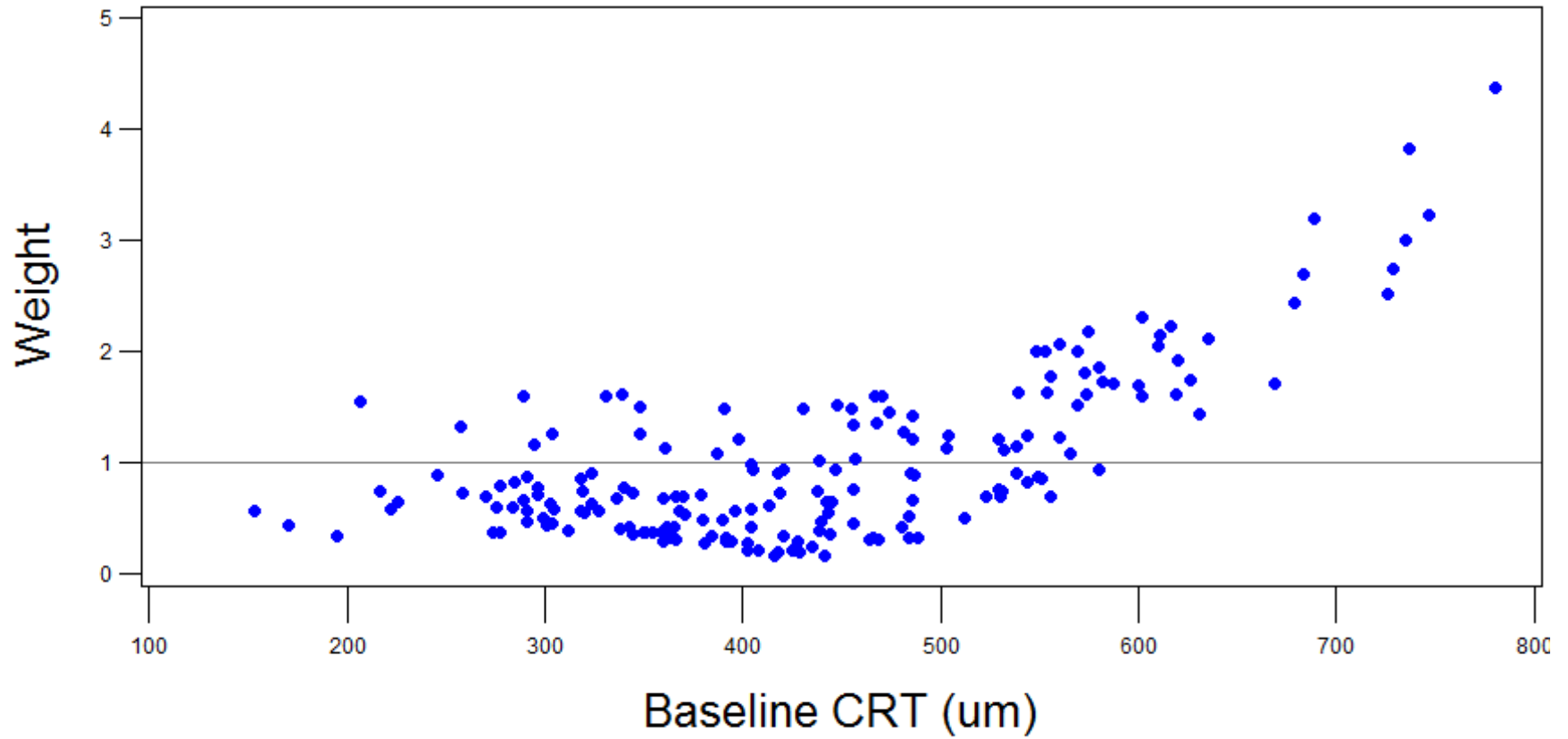
Source	Baseline BCVA (letters)		Baseline CRT (μm)	
	Laser Mean (SD)	Anti-VEGF Mean (SD)	Laser Mean (SD)	Anti-VEGF Mean (SD)
VIVID/ VISTA (target AGR)	60.2 (10.8)	59.1 (11.0)	509 (153)	497 (151)
RESTORE/ RESPOND*	59.8 (9.8)	61.5 (9.5)	442 (133)	449 (126)
RESTORE/ RESPOND (weighted IPD)	60.2 (10.8)	59.1 (11.0)	509 (153)	497 (151)

*VIVID/VISTA inclusion/exclusion criteria applied.

Weights







Effect on BCVA Change to M12

Source	Anti-VEGF vs. Laser Mean (95% CI)
VIVID/VISTA	10.0 (8.3, 11.7)
RESTORE/RESPOND (raw IPD)	7.6 (5.3, 9.8)
RESTORE/RESPOND (weighted IPD)	10.3 (7.9, 12.7)

SAS Code (brute force approach)

*** Make multiple copies of original dataset;**

```
proc surveyselect data=d1 out=d2 method=srs samsize = 368 reps=50000 seed=1;  
run;
```

*** Simulate beta weighting parameters for each baseline variable;**

```
data d3;  
do Replicate=1 to 50000;  
  a1=ranuni(0); b11=ranuni(0); b12=ranuni(0);b13=ranuni(0);b14=ranuni(0);*BCVA;  
  a2=ranuni(0); b21=ranuni(0); b22=ranuni(0);b23=ranuni(0);b24=ranuni(0); *CRT;  
  output;end;  
run;
```

*** Calculate weight;**

```
data d4;  
merge d2 d3;  
by Replicate;  
t1=(BCVA-min1)/(max1-min1);  
t2=(CRT -min2)/(max2-min2);  
w1=abs(b11*(t1-a1)+b12*(t1-a1)**2+b13*(t1-a1)**3+b14*(t1-a1)**4);  
w2=abs(b21*(t2-a2)+b22*(t2-a2)**2+b23*(t2-a2)**3+b24*(t2-a2)**4);  
wo=w1+w2;* Overall weight;  
run;
```

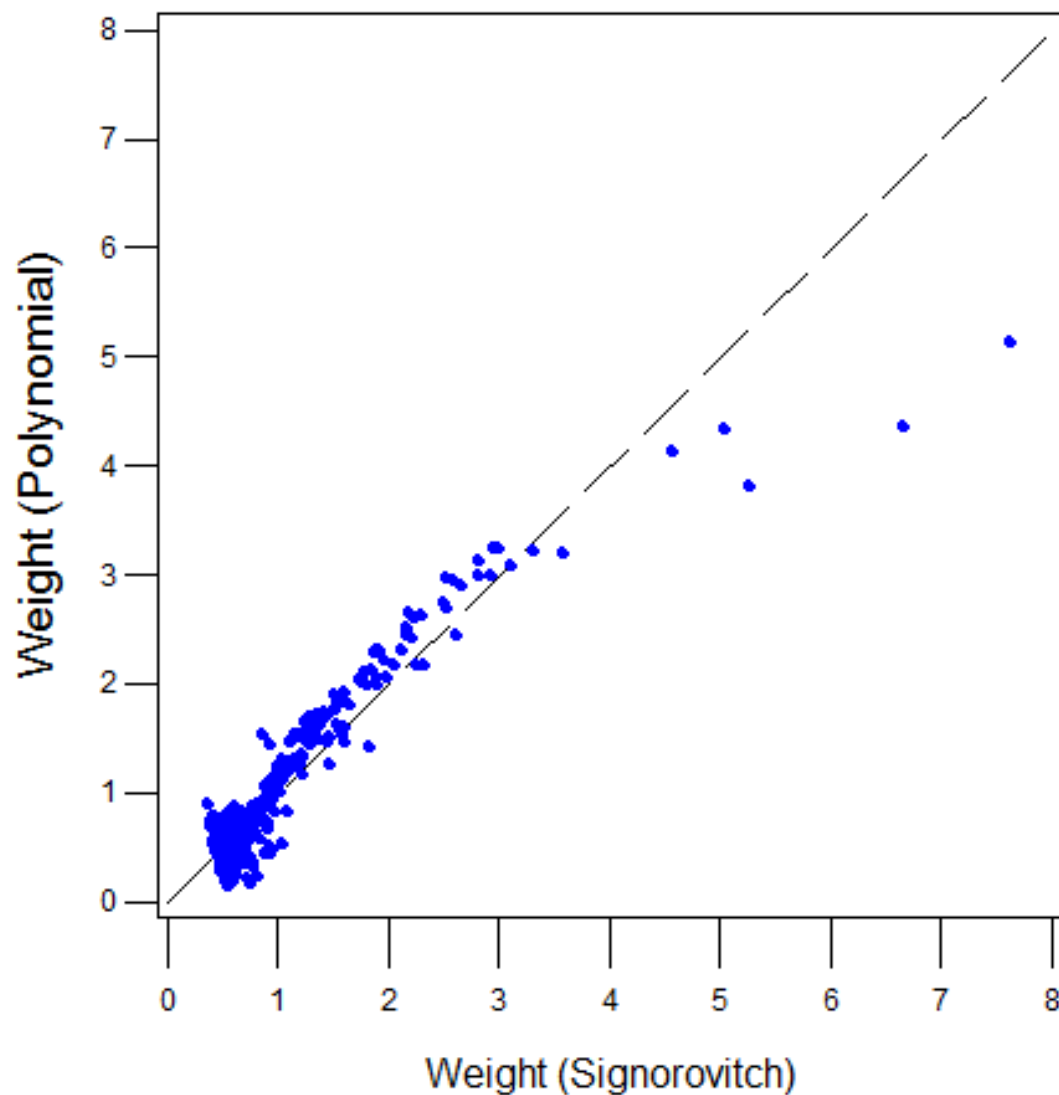
*** Calculate weighted means and SDs;**

```
proc means data=d5 noprint;
  var BCVA CRT;
  weight wo
  by Replicate trt;
  output out=ss2 mean=m1 m2 std=s1 s2;
run;
```

*** Compare vs. AGR: target means / SDs , loss function;**

```
data ss3;
  set ss2;
  if trt='Ranibizumab' then do;mean1=59.1;std1=11.0;mean2=497;std2=151; end;
  if trt='Laser'          then do;mean1=60.2;std1=10.8;mean2=509;std2=153; end;
  dm1=(m1-mean1)**2;
  dm2=(m2-mean2)**2;
  sm1=(s1-std1)**2;
  sm2=(s2-std2)**2;
  r1=sqrt(dm1)/std1; r2=sqrt(sm1)/std1;
  r3=sqrt(dm2)/std2; r4=sqrt(sm2)/std2;
  loss=r1+r2+r3+r4; * Loss function;
run;
```

Polynomial weighting vs. Signorovitch



Effective Sample Size:

$N = 368$

Signorovitch = 221

Polynomial = 229

Polynomial Weighting: Weaknesses

- Cannot match against what is not reported
- Lack of distribution overlap between IPD and AGR
- Weights are estimates (bootstrap CIs?)
- How to choose maximum weight?
- How to maximise ESS?
- Best trade off between matching AGR & max ESS?

Matching vs. Effective Sample Size

IPD: 1, 2, 6, 7

AGR target: mean=4, SD=2.94

How to weight data, i.e. choose w_1, w_2, w_3, w_4 ?

**Simple(!) solution: $w_1=w_2=w_3=w_4=1$
(ESS=4.0)**

**Suboptimal solution: $w_1=0.57, w_2=1.64, w_3=0.37, w_4=1.42$
(ESS=3.1)**

Polynomial Weighting: Benefits

- 'Convergence' appears to be good
- Allows maximum weights to be specified
- Flexible (user-defined) loss function:
 - weight some baseline characteristics more heavily than others
 - weight some summary stats more others (e.g. mean > SD)
 - match against multiple summary stats (e.g. mean, median, SD, proportions, IQR, other percentiles)
 - could incorporate ESS maximisation



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Signorovitch

- SAS: NLPNRA subroutine and GRD option in PROC IML
- R: Optim function

Malangone and Sherman

- SAS

Polynomial weighting

- SAS: Brute force, Proc IML?
- R : Optim function