## Negative Binomial Regression Fit Report

#### 20250610

### **Project Summary**

- We are using data from the American Society of Microbiology's (ASM) 12 published journals to investigate the relationship between the number of citations (variable 'is.referenced.by.count') a published scientific article receives and if the authors have included access to their raw sequencing data (variable 'da', data availability) in the manuscript.
- We are trying to understand if publishing raw data helps to improve citation metrics. We have data from 2000-2024, and will also adjust for time published (variable 'age.in.months'), as older papers have had the opportunity to accumulate more citations over time.

knitr::kable(rsquared, digits = 4)

journal_abrev	n	all_data_rsq	no_1percent_rsq	five_years_rsq	ten_years_rsq
aac	3237	0.3623	0.3938	0.5564	0.4759
aem	8638	0.4862	0.4964	0.6284	0.6204
genomea	6578	0.0636	0.0636	NA	0.0321
iai	1854	0.3896	0.3943	0.5975	0.6062
jb	4867	0.3152	0.3221	0.5767	0.5575
jcm	4374	0.1882	0.1878	0.5139	0.3880
jvi	4583	0.4172	0.4115	0.5264	0.5167
mbio	2498	0.6680	0.6685	0.6438	0.6633
mra	5738	0.3712	0.3712	0.3680	0.3712
msphere	1041	0.6523	0.6508	0.6510	0.6523
msystems	1436	0.7168	0.7040	0.6962	0.7168
spectrum	2957	0.5425	0.5425	0.5425	0.5425
all_journals	47808	0.6781	0.6829	0.6602	0.6801

### How well do the models fit (by Cragg-Uhler pseduo R-squared metric)

• See above table "rsquared"

- Model format for all data from all journals MASS::glm.nb(is.referenced.by.count~ da\_factor + log(age.in.months) + container.title + container.title\*da\_factor + log(age.in.months)\*da\_factor + container.title\*log(age.in.months) + log(age.in.months)\*da\_factor\*container.title, data = nsd\_yes\_metadata, link = log)
- Use model format for data from each journal MASS::glm.nb(is.referenced.by.count~da\_factor + log(age.in.months) + log(age.in.months)\*da\_factor, data = <each journal>, link = log)

#### • Overall model fit with all data from all journals:

- $R^2 \text{ value} = 0.678$
- Removal of top 1% of data:  $R^2$  value = 0.682
- Truncate data to last 5 years:  $R^2$  value = 0.660
- Truncate data to last 10 years:  $R^2$  value = 0.680
- Summary: Model fit by R^2 metric does not change by removing the top 1% of data or truncating to data from the last 5 or 10 years.

#### • Overall model fit for data from EACH journal individually:

- -4/12 journals have **overall model fit** with  $R^2 > 0.5$
- -4/12 journals have fit with  $R^2 > 0.5$  with top 1% of data removed
- -10/11 journals have model fits >0.5 when **truncated to the last 5 years**, so they are better than their fit overall (one journal has no data from this period)
- -8/12 journals have model fits >0.5 when **truncated to the last 10 years**, so they are better than their fit overall
- Summary: Data fits negative binomial model better with only more recent data considered.

#### knitr::kable(all\_journals, digits = 4)

coefficients	full_model_valuence	_1percent_valuativ	ve_years_value te	en_years_value
rsquared	0.6781	0.6829	0.6602	0.6801
(Intercept)	-0.9460	-0.6722	-3.4726	-2.6960
da_factorYes	-1.5082	-1.6296	-0.1780	-0.2667
log(age.in.months)	0.9932	0.9069	1.6141	1.3976
container.titleApplied and Environmental Microbiology	-1.0337	-0.9933	-0.1207	-0.5651
container.titleGenome Announcements	-4.5303	-4.7923	NA	-8.8809
container.titleInfection and Immunity	-0.7927	-0.8150	-1.3290	-1.1797
container.titleJournal of Bacteriology	-1.1706	-1.1146	-0.3361	-0.2502
container.titleJournal of Clinical Microbiology	0.2729	0.5180	-0.6776	1.9759
container.titleJournal of Microbiology & Biology Education	-0.2261	-0.4692	1.0220	1.5424

coefficients	full_model_valueno	_1percent_valuativ	ve_years_value te	en_years_valu
container.titleJournal of Virology	-0.4370	-0.4275	-0.1728	0.2013
container.titlemBio	-1.8817	-1.7910	0.0115	-0.2660
container.titleMicrobiology Resource Announcements	-3.0840	-3.3426	-0.0170	-1.3247
container.titleMicrobiology Spectrum	-3.5550	-3.8058	-1.0015	-1.7913
container.titlemSphere	-2.5767	-2.7184	-0.2216	-0.8267
container.titlemSystems	-2.6293	-2.6203	-0.0287	-0.8701
da_factorYes:container.titleApplied and Environmental Microbiology	0.8693	0.9714	-0.1907	0.1001
da_factorYes:container.titleGenome Announcements	1.6881	1.7938	NA	7.2193
da_factorYes:container.titleInfection and Immunity	1.0848	0.9853	0.9639	0.8601
da_factorYes:container.titleJournal of Bacteriology	1.5260	1.5178	0.8850	0.2051
da_factorYes:container.titleJournal of Clinical Microbiology	0.7994	0.6000	1.1103	-1.6342
da_factorYes:container.titleJournal of Microbiology & Biology Education	NA	NA	NA	NA
da_factorYes:container.titleJournal of Virology	0.8019	0.7830	-0.0860	-0.3469
da_factorYes:container.titlemBio	1.1512	1.1542	-0.2339	-0.1494
da_factorYes:container.titleMicrobiology Resource Announcements	0.6208	0.7466	-1.7384	-0.6183
da_factorYes:container.titleMicrobiology Spectrum	1.0273	1.1494	-0.3022	-0.2138
da_factorYes:container.titlemSphere	1.3657	1.3770	-0.1163	0.1374
da_factorYes:container.titlemSystems	0.8815	0.9763	-0.6710	-0.3577
da_factorYes:log(age.in.months)	0.3675	0.3986	0.0661	0.0957
log(age.in.months):container.titleApplied and Environmental Microbiology	0.2058	0.2073	-0.0156	0.1092
log(age.in.months):container.titleGenome Announcements	0.5778	0.6617	NA	1.5084
log(age.in.months):container.titleInfection and Immunity	0.0813	0.1089	0.2478	0.1951
log(age.in.months):container.titleJournal of Bacteriology	0.1570	0.1612	-0.0098	-0.0566
log(age.in.months):container.titleJournal of Clinical Microbiology	-0.0931	-0.1295	0.3100	-0.4809
log(age.in.months):container.titleJournal of Microbiology & Biology Education	-0.5427	-0.4649	-0.7173	-0.9522
log(age.in.months):container.titleJournal of Virology	0.0693	0.0849	0.0714	-0.0526
log(age.in.months):container.titlemBio	0.5267	0.4983	0.0984	0.1610
log(age.in.months):container.titleMicrobiology Resource Announcements	0.3927	0.4751	-0.4083	-0.0141
log(age.in.months):container.titleMicrobiology Spectrum	0.9389	1.0180	0.3094	0.5302
log(age.in.months):container.titlemSphere	0.6216	0.6690	0.0632	0.2172
$\log(\text{age.in.months})$ :container.titlemSystems	0.7187	0.7154	0.0735	0.3119
da_factorYes:log(age.in.months):container.titleApplied and Environmental	-0.1698	-0.1948	0.1092	0.0088
Microbiology				
${\tt da\_factorYes:log(age.in.months):container.title Genome\ Announcements}$	-0.3920	-0.4198	NA	-1.6043
da_factorYes:log(age.in.months):container.titleInfection and Immunity	-0.2392	-0.2182	-0.2194	-0.1933
da_factorYes:log(age.in.months):container.titleJournal of Bacteriology	-0.4067	-0.4056	-0.2304	-0.0223
da_factorYes:log(age.in.months):container.titleJournal of Clinical Microbiology	-0.1115	-0.0999	-0.3246	0.4618

coefficients	full_model_valueno	_1percent_valufiv	e_years_value te	en_years_value
da_factorYes:log(age.in.months):container.titleJournal of Microbiology & Biology	NA	NA	NA	NA
Education				
da_factorYes:log(age.in.months):container.titleJournal of Virology	-0.1740	-0.1730	0.0329	0.0975
da_factorYes:log(age.in.months):container.titlemBio	-0.2141	-0.2046	0.1095	0.0758
da_factorYes:log(age.in.months):container.titleMicrobiology Resource	-0.2456	-0.2778	0.3859	0.0256
Announcements				
da_factorYes:log(age.in.months):container.titleMicrobiology Spectrum	-0.1533	-0.1846	0.1478	0.1183
da_factorYes:log(age.in.months):container.titlemSphere	-0.2926	-0.2903	0.0498	-0.0242
da_factorYes:log(age.in.months):container.titlemSystems	-0.1622	-0.1815	0.2131	0.1090

# All journal model is resistant to changes from removing top 1% of data, but less resistant to changes from truncating at 5 and 10 years.

- When working across the columns in the second table, we have coefficients on the left, followed by their values under the following conditions
  - full model value = all data included in the model
  - no 1percent value = top 1% of data removed
  - five\_years\_value = data truncated at 5 years in age of paper
  - -ten\_years\_value = data truncated at 10 years in age of paper
  - **Note:** Journal of Microbiology and Biology Education(jmbe) has N=7 papers with new sequence data and has been excluded for these analyses, but is a part of the model, and appears as NAs in the table above.
- Would graphing be helpful here to look at the ways the values change over these transformations? What kind of graphing?

#### knitr::kable(each\_journal, digits = 4)

name	coefficients	all_journal_value	no_1p_value	five_years_value	ten_years_value
aac	(Intercept)	-0.9609	-0.6665	-3.4423	-2.6960
aac	$da_factorYes$	-1.5204	-1.6244	-0.1890	-0.2667
aac	log(age.in.months)	0.9961	0.9057	1.6058	1.3976
aac	da_factorYes:log(age.in.months)	0.3708	0.3972	0.0691	0.0957
aem	(Intercept)	-1.9654	-1.6400	-3.5278	-3.2253
aem	da_factorYes	-0.6343	-0.6462	-0.4172	-0.1718
aem	log(age.in.months)	1.1963	1.1092	1.5802	1.4985

aem   da_factorYes:log(age.in.months)   0.1963   0.2004   0.1888   0.10     genomea   (Intercept)   -5.4902   -5.4902   -3.5278   -11.52     genomea   da_factorYes   0.1984   0.1984   -0.4172   6.92     genomea   log(age.in.months)   1.5740   1.5740   1.5802   2.89     genomea   da_factorYes:log(age.in.months)   -0.0284   -0.0284   0.1888   -1.49     iai   (Intercept)   -1.7012   -1.4506   -4.7673   -3.85     iai   da_factorYes   -0.4050   -0.6297   0.7774   0.60     iai   log(age.in.months)   1.0675   1.0090   1.8523   1.56     iai   da_factorYes:log(age.in.months)   0.1231   0.1761   -0.1510   -0.10     jb   (Intercept)   -2.1151   -1.7806   -3.7023   -2.86     jb   da_factorYes   0.0163   -0.1174   0.6339   -0.11     jb   da_factorYes:log(age.in.months)   1.1499   1.0669 <td< th=""></td<>
genomea   da_factorYes   0.1984   0.1984   -0.4172   6.99     genomea   log(age.in.months)   1.5740   1.5740   1.5802   2.86     genomea   da_factorYes:log(age.in.months)   -0.0284   -0.0284   0.1888   -1.49     iai   (Intercept)   -1.7012   -1.4506   -4.7673   -3.85     iai   da_factorYes   -0.4050   -0.6297   0.7774   0.60     iai   log(age.in.months)   1.0675   1.0090   1.8523   1.56     iai   da_factorYes:log(age.in.months)   0.1231   0.1761   -0.1510   -0.10     jb   (Intercept)   -2.1151   -1.7806   -3.7023   -2.86     jb   da_factorYes   0.0163   -0.1174   0.6339   -0.11     jb   log(age.in.months)   1.1499   1.0669   1.5749   1.33     jb   da_factorYes:log(age.in.months)   -0.0389   -0.0060   -0.1444   0.08
genomea   log(age.in.months)   1.5740   1.5740   1.5802   2.88     genomea   da_factorYes:log(age.in.months)   -0.0284   -0.0284   0.1888   -1.49     iai   (Intercept)   -1.7012   -1.4506   -4.7673   -3.85     iai   da_factorYes   -0.4050   -0.6297   0.7774   0.66     iai   log(age.in.months)   1.0675   1.0090   1.8523   1.56     iai   da_factorYes:log(age.in.months)   0.1231   0.1761   -0.1510   -0.10     jb   (Intercept)   -2.1151   -1.7806   -3.7023   -2.86     jb   da_factorYes   0.0163   -0.1174   0.6339   -0.11     jb   log(age.in.months)   1.1499   1.0669   1.5749   1.35     jb   da_factorYes:log(age.in.months)   -0.0389   -0.0060   -0.1444   0.08
genomea da_factorYes:log(age.in.months) -0.0284 -0.0284 0.1888 -1.49   iai (Intercept) -1.7012 -1.4506 -4.7673 -3.82   iai da_factorYes -0.4050 -0.6297 0.7774 0.60   iai log(age.in.months) 1.0675 1.0090 1.8523 1.58   iai da_factorYes:log(age.in.months) 0.1231 0.1761 -0.1510 -0.10   jb (Intercept) -2.1151 -1.7806 -3.7023 -2.86   jb da_factorYes 0.0163 -0.1174 0.6339 -0.11   jb log(age.in.months) 1.1499 1.0669 1.5749 1.32   jb da_factorYes:log(age.in.months) -0.0389 -0.0060 -0.1444 0.08
iai (Intercept) -1.7012 -1.4506 -4.7673 -3.85   iai da_factorYes -0.4050 -0.6297 0.7774 0.60   iai log(age.in.months) 1.0675 1.0090 1.8523 1.58   iai da_factorYes:log(age.in.months) 0.1231 0.1761 -0.1510 -0.10   jb (Intercept) -2.1151 -1.7806 -3.7023 -2.80   jb da_factorYes 0.0163 -0.1174 0.6339 -0.11   jb log(age.in.months) 1.1499 1.0669 1.5749 1.32   jb da_factorYes:log(age.in.months) -0.0389 -0.0060 -0.1444 0.08
iai da_factorYes -0.4050 -0.6297 0.7774 0.60   iai log(age.in.months) 1.0675 1.0090 1.8523 1.58   iai da_factorYes:log(age.in.months) 0.1231 0.1761 -0.1510 -0.16   jb (Intercept) -2.1151 -1.7806 -3.7023 -2.86   jb da_factorYes 0.0163 -0.1174 0.6339 -0.11   jb log(age.in.months) 1.1499 1.0669 1.5749 1.35   jb da_factorYes:log(age.in.months) -0.0389 -0.0060 -0.1444 0.08
iai log(age.in.months) 1.0675 1.0090 1.8523 1.56   iai da_factorYes:log(age.in.months) 0.1231 0.1761 -0.1510 -0.16   jb (Intercept) -2.1151 -1.7806 -3.7023 -2.86   jb da_factorYes 0.0163 -0.1174 0.6339 -0.11   jb log(age.in.months) 1.1499 1.0669 1.5749 1.32   jb da_factorYes:log(age.in.months) -0.0389 -0.0060 -0.1444 0.08
iai da_factorYes:log(age.in.months) 0.1231 0.1761 -0.1510 -0.16   jb (Intercept) -2.1151 -1.7806 -3.7023 -2.86   jb da_factorYes 0.0163 -0.1174 0.6339 -0.15   jb log(age.in.months) 1.1499 1.0669 1.5749 1.35   jb da_factorYes:log(age.in.months) -0.0389 -0.0060 -0.1444 0.08
jb   (Intercept)   -2.1151   -1.7806   -3.7023   -2.86     jb   da_factorYes   0.0163   -0.1174   0.6339   -0.15     jb   log(age.in.months)   1.1499   1.0669   1.5749   1.32     jb   da_factorYes:log(age.in.months)   -0.0389   -0.0060   -0.1444   0.08
jb   da_factorYes   0.0163   -0.1174   0.6339   -0.11     jb   log(age.in.months)   1.1499   1.0669   1.5749   1.32     jb   da_factorYes:log(age.in.months)   -0.0389   -0.0060   -0.1444   0.08
jb log(age.in.months) 1.1499 1.0669 1.5749 1.35 jb da_factorYes:log(age.in.months) -0.0389 -0.0060 -0.1444 0.08
jb log(age.in.months) 1.1499 1.0669 1.5749 1.35 jb da_factorYes:log(age.in.months) -0.0389 -0.0060 -0.1444 0.08
jb $da_{a.s}(age.in.months)$ $-0.0389$ $-0.0060$ $-0.1444$ 0.08
jcm (Intercept) $-0.6815$ $-0.1575$ $-4.3089$ $-0.78$
jcm da_factorYes -0.7281 -1.0364 1.1310 -1.84
jcm log(age.in.months) 0.9018 0.7780 1.9686 0.95
jcm da_factorYes:log(age.in.months) 0.2605 0.3003 -0.3140 0.54
jvi (Intercept) -1.3855 -1.1081 -3.6656 -2.49
jvi da_factorYes -0.7088 -0.8540 -0.2909 -0.65
jvi log(age.in.months) 1.0630 0.9935 1.6911 1.34
jvi da_factorYes:log(age.in.months) 0.1941 0.2275 0.1068 0.19
mbio (Intercept) -2.8112 -2.4410 -3.4651 -2.99
mbio da_factorYes -0.3597 -0.4783 -0.4089 -0.47
mbio log(age.in.months) 1.5161 1.4000 1.7137 1.55
mbio $da_factorYes:log(age.in.months)$ 0.1539 0.1944 0.1747 0.17
mra (Intercept) $-4.0497$ $-4.0497$ $-3.5995$ $-4.0497$
mra da_factorYes -0.8906 -0.8906 -1.8301 -0.89
mra log(age.in.months) 1.3911 1.3911 1.2378 1.39
mra da_factorYes:log(age.in.months) 0.1228 0.1228 0.4267 0.12
msphere (Intercept) -3.5233 -3.3874 -3.7000 -3.55
msphere da_factorYes -0.1065 -0.2401 -0.2685 -0.10
msphere log(age.in.months) 1.6149 1.5751 1.6790 1.66
msphere $da_factorYes:log(age.in.months)$ 0.0657 0.1050 0.1088 0.06
msystems (Intercept) $-3.5575$ $-3.2742$ $-3.4729$ $-3.558$
msystems da_factorYes -0.6220 -0.6507 -0.8537 -0.62
msystems $\log(\text{age.in.months})$ 1.7072 1.6174 1.6794 1.70
msystems $da_factorYes:log(age.in.months)$ 0.2040 0.2163 0.2807 0.20

name	coefficients	all_journal_value	no_1p_value	five_years_value	ten_years_value
spectrum	(Intercept)	-4.4608	-4.4608	-4.4608	-4.4608
spectrum	$da_factorYes$	-0.4802	-0.4802	-0.4802	-0.4802
spectrum	$\log(\text{age.in.months})$	1.9194	1.9194	1.9194	1.9194
spectrum	$da\_factorYes:log(age.in.months)$	0.2139	0.2139	0.2139	0.2139

# Each journal model are semi-resistant to changes from removing top 1% of data, and even less resistant to changes from truncating at 5 and 10 years.

- See above for mutations on these columns, but these models look less resistant to the transformation of removing the top 1% of data, and even less resistant to changes in coefficients from truncating at 5 and 10 years of data.
- Would graphing be helpful here to look at the ways the values change over these transformations? What kind of graphing?