Appendix For Dividend Growth, Cash Flow and Discount Rate News

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1 Dividend Predictability and Small Sample Problems

It is well known that there are pitfalls in interpreting the significance of the coefficients in predictive regressions. Ang and Bekaert (2007), for example, investigate the properties of the Newey-West covariance matrix in predictive regressions. Ang and Bekaert (2007) show that there are quite severe size distortions with Newey-West t statistics. For 200 observations and a forecasting horizon of 20 quarters, for example, the empirical size of the Newey-West t statistic for a univariate regression of excess returns on the dividend yield is in excess of 30% against a nominal size of 5%. Stambaugh (1999) also documents bias in the parameter estimates in predictive regressions. We conduct Monte Carlo experiments to investigate whether size distortions and biases in the parameter estimates affect the coefficients in the dividend growth predictive regressions involving dpe. The data for the Monte Carlo experiment are generated under the null hypothesis of no predictability:

$$\Delta d_{t+k} = \nu_{t+k} \tag{1}$$

To complete the data generation process, we need to specify a generating equation for dpe_t . We assume that dpe follows an AR(1) process:¹

$$dpe_t = \rho \ dpe_{t-1} + \eta_t \tag{2}$$

 ν and η are draws from a multivariate normal distribution. The value we use for ρ is that estimated from an AR(1) regression using the actual data for dpe_t . $\rho = 0.652$; the correlation between ν and η is 0.32.

We generate 100,000 samples with 100 + T observations, where T is the sample size for the relevant regression. We then discard the first 100 observations and estimate $\Delta d_{t+k} = \delta_0 + \delta_1 dpe_t + u_{t+k}$ 100,000 times with the remaining T observations. This gives us the distribution of the t statistics testing the null hypothesis that δ_1 is zero, the distribution of δ_1 and the distribution of the \overline{R}^2 . To examine whether there are any size distortions with the Newey-West t statistics, we compare the empirical size of the Newey-West t statistics generated from the Monte Carlo experiment against a 5% nominal size. The empirical size is the percentage of times the null hypothesis of no predictability is rejected at the 5% level of significance. If the empirical size is greater than 5%, the Newey-West t statistics have a tendency to over-reject the null hypothesis, that is, they find predictability when it is not there. To examine the bias in δ_1 , we record the average values of this parameter and its respective standard error for each experiment.

Table A1 reports the results of the Monte Carlo experiments for the Newey-West t statistics. The size properties are reported in panel A. The Newey-West t statistic testing the null that dpe_t does not forecast Δd_{t+k} ($H_0: \delta_1 = 0$) has good size properties for the 1-period ahead forecasting regression. However, the size properties quickly deteriorate for the 2-period ahead regression and thereafter increases monotonically with the forecast horizon, culminating in an empirical size of approximately 16% for

¹Since we use de-meaned dpe in the empirical tests, we do not specify an intercept in the generating equation.

the 5-year forecasting horizon. This suggests that, despite the fact that ρ and corr (ν, η) are considerably lower (in absolute terms) than those for studies that examine size issues relating to predicting returns using the dividend-price ratio, predictability of dividend growth is still found more often than is actually there, at least for the data generating process used here.

To gauge how important the size distortions are, panel A also reports the Monte Carlo-generated critical values for the t statistic testing $H_0: \delta_1 = 0$ against $H_1: \delta_1 < 0.^2$ If the usual critical values were being used, they would be between -1.64 and -1.67. The true critical values for the t statistics are, with the exception of the 1-period-ahead regressions, less than -2 and are nearer to -2.6 for the five-year forecasting horizon. Panel A also reports 95% confidence intervals for the Monte Carlo-generated \overline{R}^2 . These indicate that over longer horizons an \overline{R}^2 of around 20% is not outside the realms of possibility, even under the null of no predictability.

Taken together, these results show that inference in predictive regressions and statements about predictive power based on \overline{R}^2 can be hazardous, even when the persistence in the predictor variable is reduced. In our case, however, the results in table A1 do not alter our conclusions about predictability of dividend growth: dpe is still capable of forecasting dividend growth, certainly over short and medium horizons.

Panel B of table A1 reports average values of δ_1 and respective standard errors from the Monte Carlo experiments. As δ_1 is zero under the null of no predictability, they provide a measure of the bias in the estimated δ_1 . The results show that $\hat{\delta}_1$ is downward-biased, but the magnitude of the bias is small.

 $^{^{2}}$ We only consider a one-sided alternative because the coefficient on dpe should be negative.

Table A1Size Properties of the Newey-West t Statistics

The table reports the results of Monte Carlo experiments to investigate the empirical size of the Newey-West t statistics for a nominal size of 5%, the Monte Carlo-generated critical values for the Newey-West t statistics for the regression $\Delta d_{t+k} = \delta_0 + \delta_1 dpe_t + \epsilon_{t+k}$, the confidence interval for the adjusted R^2 from the regression and the bias in δ_1 . Panel A reports the percentage of times $H_0: \delta_1 = 0$ is rejected against a nominal significance level of 5%, along with Monte Carlo-generated 5% critical value testing $H_0: \delta_1 = 0$ against $H_1: \delta_1 < 0$. 95% CI \overline{R}^2 is the 95% confidence interval for the Monte Carlo-generated $\overline{\delta}_1$ from the Monte Carlo-generated \overline{R}^2 . Panel B reports the average value of δ_1 from the Monte Carlo experiments and it's standard error.

	Panel A: Size Propertie	es ($\%$ rejections, nominal siz	ze=5%)
k	Empirical Size (%), $t^{NW}(\delta_1)$	5% Left-tail Critical Value	95% CI, \overline{R}^2 (%)
1	6.30	-1.76	-1, 5
2	10.2	-2.00	-1, 8
3	11.8	-2.09	-1, 11
4	13.0	-2.15	-1, 13
5	13.7	-2.19	-1, 14

Panel B: Average Value of δ_1 Under $H_0: \delta_1 = 0$

k	$\overline{\delta}_1$	Standard Error	
1	-0.001	0.072	
2	-0.002	0.126	
3	-0.003	0.173	
4	-0.002	0.214	
5	-0.003	0.249	

2 Parameter Stability

There are two aspects of stability that are of interest. First, instability in the parameters of the forecasting regression is obviously a cause for concern and will clearly have an impact on the forecasting ability of the model. Second, another potential source of instability that is often overlooked is instability in the cointegrating vector. Since tests of stability in the cointegrating vector involve regressions where the variables are nonstationary, the tests we use for examining stability in the cointegrating vector differ slightly from those we use to analyze the stability of the forecasting regression.

2.1 Stability Of The Cointegrating Vector

To examine the stability of the cointegrating vector, we use the procedure in Hansen (1992) to test whether the parameters in the cointegrating regression that delivers dpe vary over time. The null hypothesis is that the parameters in the cointegrating vector, β , are constant, but there are several possible alternative hypotheses that we outline below. The tests of instability are based on the classic Chow test with one important difference: we follow both Hansen (1992) and Gregory, Nason and Watt (1996) and treat the timing of any structural break as unknown *a priori*. There are good reasons for doing this. Hansen (2001) argues that there are important drawbacks with the use of the standard Chow test to test for a structural break. In particular, the researcher has to pick a date for the structural break either arbitrarily or based on an analysis of the data. The problem with the former is that it may miss the actual break, rendering the test uninformative, while in the latter case the proposed date of the break is correlated with the data. The problem here is that if the date of the break is unknown *a priori*, the standard χ^2 or F critical values for the Chow test are too low. The researcher may therefore find a structural break when there isn't one.

The classic Chow test tests for a structural break at some time t by testing the null hypothesis that the coefficient vector is the same before and after the break. When the date of the break is unknown, the test statistic has to be calculated for all possible breakpoints. One test statistic that could be used to test the null that there is no break in the parameters is the maximum value of the sequence of Chow test statistics. Hansen (1992) refers to this test as SupF and this statistic tests for a single structural break. In practice it is not possible to use all available observations to construct the test statistic since the test statistic diverges to infinity if the endpoints of the sample are included (Andrews (1993)). We therefore follow Hansen (1992) and Gregory, Nason and Watt (1996) and use the fix suggested by Andrews (1993) which is to omit the first and last 15% of the observations.

An alternative test of stability of the cointegrating vector is that the coefficient vector follows a martingale process, that is, $\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \boldsymbol{\epsilon}_t$. In this case, the null hypothesis is that the variance of the martingale difference, $\Delta \boldsymbol{\beta}_t$, is zero. This test statistic is referred to as the L_c test. Panel A of table A2 reports the results of these two tests for structural stability in the cointegrating vector dpe. The null hypothesis that the cointegrating vector does not exhibit structural shifts cannot be rejected.

2.2 Stability Of The Forecasting Regression

To assess the stability of the forecasting regression, panel B of table A2 reports the results for Andrew's (1993) SupW statistic testing the stability of the forecasting regression over all of the horizons considered. Figures A1 through A5 plot the sequence of Chow statistics testing for a structural break in the forecasting regressions, scaled by their 1% critical values. If the scaled Chow statistic crosses the critical value line, the test is significant, suggesting there may be a structural break at that point. The results are supportive of stability in the forecasting regression.

$\begin{array}{c} {\rm Table~A2}\\ {\rm Tests~of~Structural~Stability~In~The~Cointegrating~Vector~And~The}\\ {\rm Predictive~Regression~} \Delta d_{t+k} = \delta_0 + \delta_1 dp e_t + \epsilon_{t+k} \end{array}$

Panel A reports tests for structural stability in the parameters of the cointegrating regression for dpe while panel B reports results for testing parameter stability in the predictive regressions $\Delta d_{t+k} = \delta_0 + \delta_1 dpe_t + \epsilon_{t+k}$. The tests in panel A are from Hansen (1992) while the tests in panel B are from Andrews (1993). SupF is the maximum value of the sequence of Chow test statistics and tests the null that there is no break in the parameters. L_c tests whether the coefficient vector in the cointegrating vector follows a martingale process, that is, $\beta_t = \beta_{t-1} + \epsilon_t$. In this case, the null hypothesis is that the variance of the martingale difference, $\Delta \beta_t$, is zero. SupW is the same as the SupF test except that it is based on a regression involving stationary variables. ** and * denote rejection of the null hypothesis at the 1 and 5% levels respectively. Figures in panel A are p values from Hansen (1992). Figures in the p value column in Panel B are from Hansen (1997).

Panel A: Stability In the Cointegrating Vector						
	SupF	L_c				
dpe	8.214 (> 0.20)	0.476~(0.11)				
Pane	el B: Stability In	the Predictive Regression				
k	SupW	<i>p</i> -value				
1	9.572	0.11				
2	14.444^{*}	0.01				
3	11.241	0.06				
4	9.149	0.13				
5	8.259	0.19				

Figure A1





Figure A2

Sequence Of Chow Statistics Testing The Stability Of The Parameters In The Forecasting Regression $\Delta d_{t+k} = \delta_0 + \delta_1 dpe_t + \epsilon_{t+k} dpe$ For k = 2



Figure A3





Figure A4

Sequence Of Chow Statistics Testing The Stability Of The Parameters In The Forecasting Regression $\Delta d_{t+k} = \delta_0 + \delta_1 dpe_t + \epsilon_{t+k} dpe$ For k = 4



Figure A5





3 Covariances

Table A3 reports the covariance of unexpected returns with discount rate and cash flow news when cash flow news ia backed out of the return VAR rather than estimated directly. The table reports results for the different specifications of the return VAR reported in the paper.

Sensitivity of Discount Rate and Cash Flow News Variances and Covariances To Different Return Predictor Variables, VARs Estimated Using Annual Data, 1928–2001

The table reports the variance of unexpected returns $(\sigma(u_r^2))$ and covariances $(\sigma(i, j))$ of unexpected returns with discount rate news $(N_{DR,t})$ estimated from different VAR models predicting returns and cash flow news $(N_{CF,t})$ calculated as a plug such that $u_{r,t} = N_{CF,t} - N_{DR,t}$ where $u_{r,t}$ is the return shock from the relevant VAR. Panel A reports results for the VARs in Table 3 of the paper while Panel B reports results for additional VARs. R_{DR}^2 and R_{CF}^2 are the R^2 s from regressions of the return shock on discount rate news and cash flow news respectively.

Information Set, \mathbf{z}_t'	$\sigma(u_r^2)$	$\sigma(u_r, -N_{DR})$	$\sigma(u_r, N_{CF})$	$R^2_{DR}(\%)$	$R^2_{CF}(\%)$
$ \begin{bmatrix} r_t & PE10_t & VS_t \end{bmatrix} \\ \begin{bmatrix} r_t & PE10_t & VS_t & bm_t \end{bmatrix} \\ \begin{bmatrix} r_t & PE10_t & VS_t & eqis_t \end{bmatrix} \\ \begin{bmatrix} r_t & PE10_t & VS_t & bm_t & eqis_t \end{bmatrix} \\ \begin{bmatrix} r_t & TY & PE1_t & VS_t \end{bmatrix} \\ \begin{bmatrix} r_t & TY & DP_t & VS_t \end{bmatrix} $	$\begin{array}{c} 0.0319\\ 0.0287\\ 0.0272\\ 0.0242\\ 0.0336\\ 0.0337\end{array}$	$\begin{array}{c} 0.0251 \\ 0.0219 \\ 0.0205 \\ 0.0174 \\ 0.0207 \\ 0.0194 \end{array}$	$\begin{array}{c} 0.0068\\ 0.0068\\ 0.0067\\ 0.0068\\ 0.0129\\ 0.0143 \end{array}$	82 69 78 46 85 55	25 18 27 11 68 40

4 Betas

Tables A4 through A9 report betas for the different return VARs considered in the paper.

Table A4

Cash Flow, Discount Rate and Noise Betas For The 25 Fama-French Portfolios Sorted on Market Capitalization and the Book-to-market Ratio, Returns VAR Using $\mathbf{z}'_t = [r_t \quad PE10_t \quad VS_t]$

β_{CF}	Small	2	3	4	Large	Difference
Growth	0.459	0.388	0.394	0.327	0.337	-0.122^{***}
2	0.415	0.395	0.371	0.314	0.317	-0.098^{***}
3	0.445	0.410	0.386	0.380	0.340	-0.105^{***}
4	0.459	0.408	0.369	0.386	0.387	-0.072^{***}
Value	0.458	0.420	0.441	0.450	0.383	-0.075^{***}
Difference	-0.001	0.032	0.047	0.123^{***}	0.046	
β_{DR}	Small	2	3	4	Large	Difference
Growth	1.224	1.089	1.107	0.920	0.843	-0.381^{***}
2	1.204	1.047	0.961	0.875	0.743	-0.461^{***}
3	1.145	0.986	0.886	0.860	0.756	-0.389^{***}
4	1.269	0.992	0.862	0.860	0.795	-0.474^{***}
Value	1.020	0.924	0.911	0.992	0.646	-0.374^{***}
Difference	-0.204^{***}	-0.165^{***}	-0.196^{***}	0.072^{**}	-0.197^{***}	
β_{NOISE}	Small	2	3	4	Large	
Growth	-0.353	-0.286	-0.305	-0.253	-0.186	0.167***
2	-0.223	-0.248	-0.199	-0.161	-0.164	0.059^{**}
3	-0.180	-0.152	-0.150	-0.131	-0.160	0.020
4	-0.197	-0.120	-0.096	-0.087	-0.095	0.102^{***}
Value	-0.118	-0.080	-0.078	-0.119	-0.022	0.096^{***}
Difference	0.235***	0.206***	0.227***	0.134^{***}	0.164***	

Cash Flow, Discount Rate and Noise Betas For The 25 Fama-French Portfolios Sorted on Market Capitalization and the Book-to-market Ratio, Returns VAR Using $\mathbf{z}'_t = [r_t \quad PE10_t \quad VS_t \quad bm_t]$

β_{CF}	Small	2	3	4	Large	Difference
Growth	0.510	0.432	0.438	0.363	0.374	-0.136^{***}
2	0.462	0.439	0.412	0.349	0.352	-0.110^{***}
3	0.494	0.456	0.429	0.422	0.378	-0.116^{***}
4	0.510	0.453	0.411	0.429	0.430	-0.080^{***}
Value	0.509	0.467	0.491	0.500	0.426	-0.083^{***}
Difference	-0.001	0.035	0.053	0.137^{***}	0.052	
β_{DR}	Small	2	3	4	Large	Difference
Growth	1.369	1.152	1.137	0.947	0.852	-0.517^{***}
2	1.223	1.023	0.953	0.820	0.708	-0.515^{***}
3	1.103	0.951	0.846	0.819	0.715	-0.388^{***}
4	1.182	0.935	0.837	0.834	0.738	-0.444^{***}
Value	0.981	0.896	0.842	0.950	0.562	-0.419^{***}
Difference	-0.388^{***}	-0.256^{***}	-0.295^{***}	0.003	-0.290^{***}	
β_{NOISE}	Small	2	3	4	Large	Difference
Growth	-0.392	-0.307	-0.324	-0.284	-0.227	0.165***
2	-0.165	-0.219	-0.164	-0.122	-0.173	-0.008
3	-0.101	-0.090	-0.101	-0.070	-0.142	-0.041
4	-0.077	-0.029	-0.024	-0.034	-0.036	0.041
Value	-0.003	0.022	0.033	-0.034	0.012	-0.015
Difference	0.389***	0.329***	0.357***	0.250***	0.239***	

Cash Flow, Discount Rate and Noise Betas For The 25 Fama-French Portfolios Sorted on Market Capitalization and the Book-to-market Ratio, Returns VAR Using $\mathbf{z}'_t = [r_t \quad PE10_t \quad VS_t \quad eqis_t]$

β_{CF}	Small	2	3	4	Large	Difference
Growth	0.538	0.455	0.462	0.383	0.394	-0.144^{***}
2	0.487	0.463	0.434	0.368	0.371	-0.116^{***}
3	0.521	0.480	0.452	0.445	0.398	-0.123^{***}
4	0.538	0.478	0.433	0.453	0.454	-0.084^{***}
Value	0.536	0.493	0.517	0.528	0.449	-0.087^{***}
Difference	-0.002	0.038	0.055	0.145^{***}	0.055	
β_{DR}	Small	2	3	4	Large	Difference
Growth	1.082	0.933	1.003	0.835	0.781	-0.301^{***}
2	1.063	0.947	0.878	0.803	0.695	-0.368^{***}
3	0.978	0.870	0.808	0.790	0.691	-0.287^{***}
4	1.112	0.860	0.759	0.736	0.721	-0.391^{***}
Value	0.836	0.789	0.765	0.879	0.554	-0.282^{***}
Difference	-0.246^{***}	-0.144^{***}	-0.238^{***}	0.044	-0.227^{***}	
β_{NOISE}	Small	2	3	4	Large	Difference
Growth	-0.410	-0.350	-0.380	-0.314	-0.225	0.185***
2	-0.296	-0.307	-0.258	-0.209	-0.201	0.095^{***}
3	-0.221	-0.210	-0.196	-0.185	-0.216	0.005
4	-0.302	-0.179	-0.140	-0.133	-0.153	0.149^{***}
Value	-0.179	-0.119	-0.135	-0.201	-0.044	0.135^{***}
Difference	0.231***	0.231***	0.245^{***}	0.113***	0.181***	

Cash Flow, Discount Rate and Noise Betas For The 25 Fama-French Portfolios Sorted on Market Capitalization and the Book-to-market Ratio, Returns VAR Using $\mathbf{z}'_t = [r_t \quad PE10_t \quad VS_t \quad bm_t \quad eqis_t]$

β_{CF}	Small	2	3	4	Large	Difference
Growth	0.606	0.513	0.521	0.432	0.445	-0.161^{***}
2	0.549	0.522	0.490	0.415	0.418	-0.131^{***}
3	0.588	0.542	0.509	0.502	0.449	-0.139^{***}
4	0.606	0.538	0.488	0.510	0.512	-0.094^{***}
Value	0.605	0.555	0.583	0.595	0.506	-0.099^{***}
Difference	-0.001	0.042	0.062^{**}	0.163^{***}	0.061^{**}	
β_{DR}	Small	2	3	4	Large	
Growth	1.231	0.992	1.029	0.883	0.821	-0.410^{***}
2	0.987	0.844	0.805	0.673	0.647	-0.340^{***}
3	0.779	0.738	0.680	0.660	0.619	-0.160^{***}
4	0.872	0.671	0.629	0.635	0.594	-0.278^{***}
Value	0.629	0.608	0.544	0.747	0.412	-0.217^{***}
Difference	-0.602^{***}	-0.384^{***}	-0.485^{***}	-0.136^{***}	-0.409^{***}	
β_{NOISE}	Small	2	3	4	Large	
Growth	-0.458	-0.385	-0.413	-0.384	-0.312	0.146***
2	-0.156	-0.215	-0.168	-0.111	-0.214	-0.058
3	-0.004	-0.067	-0.070	-0.045	-0.184	-0.180^{***}
4	-0.052	0.029	0.027	-0.018	-0.039	0.013
Value	0.090	0.130	0.115	-0.039	0.027	-0.063^{**}
Difference	0.548^{***}	0.515^{***}	0.528^{***}	0.345^{***}	0.339***	

Cash Flow, Discount Rate and Noise Betas For The 25 Fama-French Portfolios Sorted on Market Capitalization and the Book-to-market Ratio, Returns VAR Using $\mathbf{z}'_t = [r_t \ TY_t \ PE1 \ VS_t]$

β_{CF}	Small	2	3	4	Large	Difference
Growth	0.436	0.369	0.375	0.310	0.320	-0.116^{***}
2	0.395	0.376	0.352	0.298	0.301	-0.094^{***}
3	0.423	0.390	0.366	0.361	0.323	-0.100^{***}
4	0.436	0.387	0.351	0.367	0.368	-0.068^{**}
Value	0.435	0.399	0.419	0.428	0.364	-0.071^{**}
Difference	-0.001	0.030	0.044	0.118^{***}	0.044	
β_{DR}	Small	2	3	4	Large	
Growth	0.882	0.821	0.866	0.695	0.650	-0.232***
2	0.918	0.805	0.741	0.693	0.559	-0.359^{***}
3	0.882	0.786	0.698	0.684	0.584	-0.298^{***}
4	1.050	0.798	0.682	0.690	0.643	-0.407^{***}
Value	0.822	0.743	0.735	0.817	0.584	-0.238^{***}
Difference	-0.060^{**}	-0.078^{**}	-0.131^{***}	0.122^{***}	-0.066^{**}	
β_{NOISE}	Small	2	3	4	Large	
Growth	0.047	0.061	0.032	0.024	0.029	-0.018
2	0.135	0.078	0.088	0.085	0.055	-0.080^{***}
3	0.160	0.120	0.094	0.100	0.050	-0.110^{***}
4	0.159	0.157	0.137	0.134	0.091	-0.068^{**}
Value	0.165	0.168	0.146	0.118	0.088	-0.077^{***}
Difference	0.118^{***}	0.107^{***}	0.114^{***}	0.094^{***}	0.058	

Cash Flow, Discount Rate and Noise Betas For The 25 Fama-French Portfolios Sorted on Market Capitalization and the Book-to-market Ratio, Returns VAR Using $\mathbf{z}'_t = \begin{bmatrix} r_t & TY_t & VS_t & dp_t \end{bmatrix}$

β_{CF}	Small	2	3	4	Large	Difference
Growth	0.435	0.368	0.374	0.309	0.319	-0.116^{***}
2	0.393	0.374	0.351	0.297	0.300	-0.093^{***}
3	0.421	0.388	0.365	0.360	0.322	-0.099^{***}
4	0.434	0.386	0.350	0.366	0.367	-0.067^{***}
Value	0.434	0.398	0.418	0.426	0.363	-0.071^{***}
Difference	-0.001	0.030	0.044	0.117^{***}	0.044	
β_{DR}	Small	2	3	4	Large	
Growth	0.808	0.746	0.826	0.673	0.608	-0.200***
2	0.885	0.713	0.730	0.718	0.526	-0.359^{***}
3	0.822	0.723	0.619	0.635	0.510	-0.312^{***}
4	0.999	0.753	0.636	0.639	0.568	-0.431^{***}
Value	0.722	0.657	0.620	0.764	0.614	-0.108^{***}
Difference	-0.086^{***}	-0.089^{***}	-0.206^{***}	0.091^{***}	0.006	
β_{NOISE}	Small	2	3	4	Large	
Growth	0.128	0.140	0.072	0.043	0.071	-0.057
2	0.171	0.178	0.099	0.061	0.090	-0.081^{***}
3	0.227	0.184	0.178	0.154	0.130	-0.097^{***}
4	0.215	0.202	0.186	0.186	0.170	-0.045
Value	0.274	0.262	0.265	0.176	0.055	-0.219^{***}
Difference	0.146^{***}	0.122^{***}	0.193^{***}	0.133^{***}	-0.016	

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