	Preprocessing Specify constants ## constants groupSize = 4 ntrials = 10 pi = 1.4 ntokens = 20 vals = list(range(21)) #possible values to contribute - from 0 to 20 tokens
	<pre>vals = list(range(21)) #possible values to contribute - from 0 to 20 tokens Gini data def get_gini(city): if city == "Melbourne": return 34.3 if city == "Minsk": return 25.3</pre>
	<pre>if city == "Chengdu": return 38.5 if city == "Copenhagen": return 28.7 if city == "Bonn": return 31.9 if city == "Athens": return 34.4</pre>
	<pre>if city == "Seoul": return 31.6 if city == "Samara": return 37.5 if city == "Zurich": return 32.7 if city == "St. Gallen":</pre>
	<pre>return 32.7 if city == "Istanbul": return 41.9 if city == "Nottingham": return 34.8 if city == "Dnipropetrovs'k": return 26.1 if city == "Boston":</pre>
	<pre>return 41.1 data["gini"] = data["city"].apply(lambda x: get_gini(x)) Only some of the data is used redDat = data.iloc[::3, :] #get only every third row, the others are other responses that we don't need</pre>
	<pre>redDat.reset_index(inplace = True, drop = True) group_names = set(redDat["groupid"]) group_names = sorted(list(group_names)) ngroups = len(group_names) ### DOES SOMETHING FUCKED HERE</pre>
V	<pre>subject_names = set(redDat["subjectid"]) nsubjects = len(subject_names) ngroups = 269 Punish & no-punish ote that the "Gc" variable is not used in the actual models (in ours or in Josh's own analysis).</pre>
si	/e think he made some error in computing it (in R) but it does not really matter here, nce we are not using it in the models ## No punish initialized c_no_punish = np.zeros(shape = (groupSize, ntrials, ngroups)) Ga_no_punish = np.zeros(shape = (ntrials, ngroups)) Gc_no_punish = np.zeros(shape = (groupSize, ntrials, ngroups))
	<pre>#punished initialized c_punish = np.zeros(shape = (groupSize, ntrials, ngroups)) Ga_punish = np.zeros(shape = (ntrials, ngroups)) Gc_punish = np.zeros(shape = (groupSize, ntrials, ngroups)) #missing vector missing = np.zeros(shape = (ngroups))</pre>
	<pre>for g in range(ngroups): ### fancy way of fixing missing data - they will just become 0, # and their position is then logged in "missing"-vector try: #no punish c_no_punish[:,:,g][0] = redDat[(redDat["groupid"] == group_names[g]) & (redDat["p"]""""""""""""""""""""""""""""""""""</pre>
	<pre>c_no_punish[:,:,g][1] = redDat[(redDat["groupid"] == group_names[g]) & (redDat["p"] "N-experiment")]["senderscontribution"][10:20].values</pre>
	<pre>c_punish[:,:,g][0] = redDat[(redDat["groupid"] == group_names[g]) & (redDat["p"] == experiment")]["senderscontribution"][0:10].values</pre>
	<pre>except: #could be more general missing[g] = 1 #make "Ga" Ga_no_punish[:,g] = c_no_punish[:,:,g].mean(axis=0) Ga_punish[:,g] = c_punish[:,:,g].mean(axis=0)</pre>
	<pre>#make "Gc" for s in range(groupSize): Gc_no_punish[:,:,g][s] = np.delete(c_no_punish[:,:,g], s, 0).sum(axis=0) #just give single number though Gc_punish[:,:,g][s] = np.delete(c_punish[:,:,g], s, 0).sum(axis=0) Concat the different conditions</pre>
	<pre>c = np.zeros(shape = (groupSize, ntrials, ngroups, 2)) Ga = np.zeros(shape = (ntrials, ngroups, 2)) c[:,:,:,0] = c_no_punish c[:,:,:,1] = c_punish Ga[:,:,0] = Ga_no_punish Ga[:,:,1] = Ga_punish</pre>
	Gini Coefficient Gini = np.zeros(shape = ngroups) for g in range(ngroups): Gini[g] = redDat[(redDat["groupid"] == group_names[g]) & (redDat["p"] == "P-experiment" ["gini"].values.mean()
	<pre>mask = np.isnan(Gini) == False Ga_punish = Ga_punish[:,mask] Ga_no_punish = Ga_no_punish[:,mask] c = c[:,:,mask,:] Ga = Ga[:,mask,:]</pre>
	<pre>Gini = Gini[mask] #get new ngroups ngroups = len(Gini) Part 2: Decay Model</pre>
	$c_{g,s,t}^{\mu}=c_{g,s}^{0}\cdot e^{-\gamma_{s,g}\cdot t}$ $c_{g,s}^{0}=\beta_{0}^{c}+\beta_{Gini}^{c}\cdot Gini_{g}$ $\gamma_{s,g}=\beta_{0}^{\gamma}+\beta_{Gini}^{\gamma}\cdot Gini_{g}$ /ariable set-up
ווייייייייייייייייייייייייייייייייייי	ags seems to be all about for-looping which we have tried to void. However, there are many things that we have not been ble to satisfactorily do. irst we take out only the first (of two) conditions of "c". $y = c[:,:,:,0]$
	hen we create three variables: • idx_g (269 groups) • idx_s (4 subjects) • t (10 trials) idx_g = np.arange(ngroups) idx_s = np.array([0,1,2,3]) t = np.arange(ntrials)
إد	
6	<pre>ame issue with shape for Gini. Gini_stack = np.stack((Gini, Gini, Gini, Gini)) Gini_stack = Gini_stack.T Gini_stack.shape</pre>
(ame issue with shape for idx_s idx_s = idx_s[:, None] idx_s.shape (4, 1)
5	osh has shape (4, 10, 244) which corresponds to (subjects, time, groups), ut we found it easier to have (10, 4, 244) which corresponds to (time, subjects, groups). hould not make a difference. Just a different order. y = np.reshape(y, (10, 4, 244)); Decay model
	<pre>with pm.Model() as m: ## priors beta0_c0 = pm.HalfNormal("beta0_c0", sigma = 1) betaGini_c0 = pm.Normal("betaGini_c0", 0, 1) beta0_gamma = pm.HalfNormal("beta0_gamma", sigma = 1) betaGini_gamma = pm.Normal("betaGini_gamma", 0, 1)</pre>
	<pre>## group_level sigma_c = pm.Gamma("sigma_c", 1, 1, shape = (1, len(idx_s), len(idx_g))) c_0 = pm.Deterministic("c_0", beta0_c0 + betaGini_c0 * Gini_stack[idx_g, idx_s]) gamma = pm.Deterministic("gamma", beta0_gamma + betaGini_gamma * Gini_stack[idx_g, idx_s])</pre>
	<pre>## mu. mu_c = c_0 * pm.math.exp(-gamma * t_stack) ## likelihood y_pred = pm.Normal("y_pred", mu = mu_c, sigma = sigma_c, observed = y)</pre>
۸ ۱	Sample from the model //e cannot sample with "chains = 2". //e get the error: "ValueError: Mass matrix contains zeros on the diagonal." pecifically: "The derivative of RV sigma_c_logravel()[0] is zero.". owever, for some reason it works with "chains = 1".
P	with m: m_idata = pm.sample(chains = 1, # breaks with 2 chains return_inferencedata = True, random_seed = 42, tune = 2000)
	Auto-assigning NUTS sampler Enitializing NUTS using jitter+adapt_diag Sequential sampling (1 chains in 1 job) NUTS: [sigma_c, betaGini_gamma, beta0_gamma, betaGini_c0, beta0_c0] 100.00% [3000/3000 03:50<00:00 Sampling chain 0, 0 divergences] Sampling 1 chain for 2_000 tune and 1_000 draw iterations (2_000 + 1_000 draws total) took 231 seconds. Only one chain was sampled, this makes it impossible to run some convergence checks import arviz as az
	<pre>az.plot_trace(m_idata, var_names = ["betaGini_c0",</pre>
	betaGini_c0 0.025 0.000 -0.025 -0.050 -0.050 betaGini_gamma betaGini_gamma 0.0028
	0.0024 0.0025 0.0026 0.0027 0.0028 0.0029 0 200 400 600 800 beta0_c0
	9.0 9.5 10.0 10.5 11.0 11.5 12.0 0 200 400 600 800 beta0_gamma 0.010 0.005 0.002 0.004 0.006 0.008 0.010 0.012 0 200 400 600 800
F	Deterministic Deterministic
3	<pre>with m: m_post = pm.sample_posterior_predictive(m_idata,</pre>
	<pre>maxs = np.where(Gini == Gini.max()) mins = np.where(Gini == Gini.min()) ull out mean outcome predictions across samples (axis 0). y_mean = m_post["y_pred"].mean(axis = 0) # mean over samples y_mean = y_mean.mean(axis = 1) # mean over participants y_mean.shape</pre>
	<pre>graph of the state of the</pre>
	<pre>y_high_mean = y_high.mean(axis = 1) y_low_mean = y_low.mean(axis = 1) import matplotlib.pyplot as plt ull out standard deviation to get some confidence around our predictions.</pre>
	y_high_std = y_high.std(axis = 1) y_low_std = y_high.std(axis = 1) Reproducing Josh plot the plot below closely matches the plot from the Josh paper. The proups from high-gini countries show faster declining coopeartion (red line)
	# reproducing Josh w. uncertainty. std = 3 # 3 standard deviations. plt.plot(y_high_mean, color = "r", label = "high Gini") plt.plot(y_low_mean, color = "b", label = "low Gini") plt.fill_between(t, y_high_mean - std*y_high_std, y_high_mean + std*y_high_std, alpha = 0.2, color = "r")
	<pre>plt.fill_between(t, y_low_mean - std*y_low_std, y_low_mean + std*y_low_std,</pre>
	9 - low Gini 7 - 6 - 5 - 4 - 2
	Hierarchical model (attempt) Preferences: $pvec = p_0 + \beta_p \cdot tokenvalues$ $p_t = pvec[Gb_t]$
	$p_t = pvec[Gb_t]$ here Gb_t is the belief of what the other person will do at time T
F	$Gb_t=\gamma(Gb_{t-1})+(1-\gamma)(G_{a_{t-1}})$ $c_t=\omega_t(Gb_t)+(1-\omega_t)(p_t)$ $\omega_t=\omega_{t-1}(1-\lambda)$
F	$c_t = \omega_t(Gb_t) + (1-\omega_t)(p_t)$
	Setting the hierachical model $B_{g,s}^P \sim Beta(Shape_{g,s,1}, Shape_{g,s,2})$ $Shape_1 = \mu B_{g,s}^P + \sigma_{g,s}$ $Shape_2 = (1 - \mu B_{g,s}^P) + \sigma_{g,s}$ $Shape_2 = (1 - \mu B_{g,s}^P) + \sigma_{g,s}$ $Probit(\mu B_{g,s}^P) = \beta_0^P + \beta_{Gini}^P \cdot Gini$ is we did for the first model we attempted to make this model without looping. However, this proved difficult for several reasons. Fixere are a lot of loops in Josh's code. More importantly, we have variables that depend on previous time-steps. E.g. $Gb_t = \gamma(Gb_{t-1}) + (1 - \gamma)(G_{a_{t-1}})$ this proved tricky, because we attempted to solve it using theano.scan which is the theano-way of doing for-loops. We tried a lot of
F Arr	Setting the hierachical model $B_{g,s}^P \sim Beta(Shape_{g,s,1}, Shape_{g,s,2})$ $Shape_1 = \mu B_{g,s}^P + \sigma_{g,s}$ $Shape_2 = (1 - \mu B_{g,s}^P) + \sigma_{g,s}$ $Shape_2 = (1 - \mu B_{g,s}^P) + \sigma_{g,s}$ $Probit(\mu B_{g,s}^P) = \beta_0^P + \beta_{Gini}^P \cdot Gini$ So we did for the first model we attempted to make this model without looping. However, this proved difficult for several reasons. Fivere are a lot of loops in Josh's code. More importantly, we have variables that depend on previous time-steps. E.g. $Gb_t = \gamma(Gb_{t-1}) + (1 - \gamma)(Ga_{t-1})$ this proved tricky, because we attempted to solve it using theano.scan which is the theano-way of doing for-loops. We tried a lot out eventually gave up because the integration between pymc3-objects and theano scan is really tricky. The issue is that theano.scan
A th	Setting the hierachical model $B_{g,s}^P \sim Beta(Shape_{g,s,1}, Shape_{g,s,2})$ $Shape_1 = \mu B_{g,s}^P + \sigma_{g,s}$ $Shape_2 = (1 - \mu B_{g,s}^P) + \sigma_{g,s}$ $Shape_2 = (1 - \mu B_{g,s}^P) + \sigma_{g,s}$ $Probit(\mu B_{g,s}^P) = \beta_0^P + \beta_{Gini}^P \cdot Gini$ is we did for the first model we attempted to make this model without looping. However, this proved difficult for several reasons. Five are a lot of loops in Josh's code. More importantly, we have variables that depend on previous time-steps. E.g. $Gb_1 = \gamma(Gb_{i-1}) + (1 - \gamma)(G_{a_{i-1}})$ his proved tricky, because we attempted to solve it using theano-scan which is the theano-way of doing for-loops. We tried a lot of atteventually gave up because the integration between pymc3-objects and theano scan is really tricky. The issue is that theano-scapects array-like structures, but we need to use "gamma" which is a parameter we want to infer. **et up parameters** ### hard-coded parameters* #### hard-coded parameters* ##### pi = 1.4 ###################################
	Setting the hierachical model $B_{g,s}^{F} \sim Beta(Shape_{g,s,1}, Shape_{g,s,2})$ $Shape_{1} = \mu B_{g,s}^{F} + \sigma_{g,s}$ $Shape_{2} = (1 - \mu B_{g,s}^{F}) + \sigma_{g,s}$ $Shape_{2} = (1 - \mu B_{g,s}^{F}) + \sigma_{g,s}$ $Shape_{2} = (1 - \mu B_{g,s}^{F}) + \sigma_{g,s}$ $Probit(\mu B_{g,s}^{F}) = \beta_{0}^{F} + \beta_{Gmi}^{F} \cdot Gini$ since we did for the first model we attempted to make this model without looping. However, this proved difficult for several reasons. Five are a lot of loops in Josh's code. More importantly, we have variables that depend on previous time-steps. E.g. $Gb_{t} = \gamma(Gb_{t-1}) + (1 - \gamma)(G_{\alpha_{t-1}})$ his proved tricky, because we attempted to solve it using theano.scan which is the theano-way of doing for-loops. We tried a lot of atteventually gave up because the integration between pymc3-objects and theano scan is really tricky. The issue is that theano-sex (spects array-like structures, but we need to use "gamma" which is a parameter we want to infer. Let up parameters # hard-coded parameters # hard-coded parameters # in 1.4 # https://books.google.dk/books? # id-ys8oDwAAQBAJ&pg=PA114&lpg=PA114&dq=probit+transformation+theano&source=bl&ots=uK3a2NXdV # def probit_phi(x): # mu = 0 # sd = 1
	Setting the hierachical model $B_{\eta,s}^{\prime\prime}\sim Beta(Shape_{g,s,1},Shape_{g,s,2})$ $Shape_1=\mu B_{g,s}^{\prime\prime}\rightarrow \sigma_{g,s}$ $Shape_2=(1-\mu B_{g,s}^{\prime\prime})+\sigma_{g,s}$ $Shape_2=(1-\mu B_{g,s}^{\prime\prime})+\sigma_{g,s}$ $Shape_2=(1-\mu B_{g,s}^{\prime\prime})+\sigma_{g,s}$ $Probit(\mu B_{g,s}^{\prime\prime})=\beta_0^{\prime\prime\prime}+\beta_{Gin}^{\prime\prime\prime}$ Similar with the first model we attempted to make this model without looping. However, this proved difficult for several reasons. Fiver are a lot of loops in Josh's code. More importantly, we have variables that depend on previous time-steps. E.g. $Gb_t=\gamma(Gb_{t-1})-(1-\gamma)(G_{h_{t-1}})$ this proved tricky, because we attempted to solve it using theano-scan which is the theano-way of doing for-loops. We tried a lot of the trentually gave up because the integration between pymc3-objects and theano scan is really tricky. The issue is that theano-scan septime is the structures, but we need to use "gamma" which is a parameter we want to infer. The parameters $\frac{1}{2} + \frac{1}{2} +$
	Setting the hierachical model $R_{gs}^{\mu} \sim Beta(Shape_{g,s,*}), Shape_{g,g,s})$ $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{gs}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{g,s}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{g,s}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{g,s}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{g,s}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{g,s}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{g,s}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{g,s}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{g,s}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{g,s}^{\mu}) + \sigma_{g,s}$ Shape_{g,s} $Shape_{g,s} = (1 - \mu R_{g,s}^{\mu}) + \sigma_{g,s}$ Shape_{g,s
	Setting the hierachical model $ R_{g,s}^{p} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t}) $ Shape $ R_{g,s} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t}) $ Shape $ R_{g,s} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t}) $ Shape $ R_{g,s} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t}) $ Shape $ R_{g,s} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t}) $ Shape $ R_{g,s,t} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t}) $ Shape $ R_{g,s,t} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t}) $ Shape $ R_{g,s,t} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t} \sim Beta(Shap_{g,s,t}), Shape R_{g,s,t} \sim Beta(Shap_{g,s,t}), Shap_{g,s,t} \sim Beta(Sh$
	Setting the hierachical model $B_{p,n}^{p} \sim Beta(Shape_{p,n}1,Shape_{p,n}2)$ $Shape_1 = \mu B_{p,n}^{p} + \sigma_{p,n}$ $Shape_2 = (1 - \mu D_{p,n}^{p}) + \sigma_{p,n}$ $Shape_2 = (1 - \mu D_{p,n}^{p}) + \sigma_{p,n}$ $Shape_3 = (1 - \mu D_{p,n}^{p}) + \sigma_{p,n}$ $Shape_3 = (1 - \mu D_{p,n}^{p}) + \sigma_{p,n}$ $Shape_3 = (1 - \mu D_{p,n}^{p}) + \sigma_{p,n}$ $Probit(\mu D_{p,n}^{p}) = S_n^{p} + S_{p,n}^{p} + S_{p,n$
	Setting the hierachical model $B_{p_n}^{C} \sim \omega_n(\Omega_n) - (1-\omega_n)(p_n)$ $\omega_n - \omega_n(\Omega_n)$ $Shape_1 = \mu B_{p_n}^{C} - \sigma_{p_n}$ $Shape_2 - (1-\mu D_{p_n}^{C}) - \sigma_{p_n}$ $Shape_3 = \mu B_{p_n}^{C} - \sigma_{p_n}$ $Problem(nB_{p_n}^{C}) = \mu^{C}_0 + \mu^{C}_0$ $G_0 = \eta(Gh_{p_n}) + (1-\eta)(G_{p_n})$ Is a use off for the first model we alterpret to make this model without looping. However, this proved difficult for several reasons. For each of loops in Joshis code. More importantly, we have variables that depend on previous time steps. Fig. of the proved trick, because we alterpreted to solve it using them according to the province of the solve it uses the treath of the province of the policy of the province of the pr
	Setting the hierarchical model $E_{s,s}^{*} \sim Beta(Shaps_{s,s,s}, Shaps_{s,p,d})$ Setting the hierarchical model $E_{s,s}^{*} \sim Beta(Shaps_{s,s,s}, Shaps_{s,p,d})$ Shaps_ $s_{s,p,d}$ Shaps_ $s_$
	Setting the hierachical model $B_{0,1}^{(1)} = Beta(Shop_{n_1, k_1} Shop_{n_2, k_2})$ $Shop_{n_2} = H_{n_1}^{(1)} = H_{n_2}^{(1)} = H_{n_2}^{(1)}$ $Shop_{n_2} = H_{n_2}^{(1)} = H_{n_2}^{(1)} = H_{n_2}^{(1)} = H_{n_2}^{(1)}$ $Shop_{n_2} = H_{n_2}^{(1)} = H_{n_2}^$
	Setting the hierarchical model $D_{ijj}^{ij} = D_{ij}^{ij}(1-C_i) = D_{ijj}^{ij}(1-C_i)$ Setting the hierarchical model $D_{ijj}^{ij} = D_{ij}^{ij}(1-C_i)$ $Shope_i = D_{ijj}^{ij}(1-C_i)$ $C(i) = C(i) + (i) + $
	Setting the hierarchical model $R_{p_1}^{(i)} \sim Red (Steps_{p_1, i}) \cdot Steps_{p_1, i}$ Setting the hierarchical model $R_{p_1}^{(i)} \sim Red (Steps_{p_1, i}) \cdot Steps_{p_1, i}$ $Steps_{p_1, i} \sim R_{p_1, i}^{(i)} \sim R_{p_1, i}$
	exting the hierarchical model $\frac{\partial f_{n}}{\partial x_{n}} = \frac{\partial f_{n}}{\partial$
Att The S	$\begin{aligned} & = -m/N(c) \left(\left(- m/N_p \right) \right) \\ & = -m/N(c) \left(\left(- m/N_p \right) \right) \\ & = -m/N(c) \left(\left(- m/N_p \right) \right) \\ & = -m/N(c) \left(\left(- m/N_p \right) \right) \\ & = -m/N(c) \left(\left(- m/N_p \right) \right) \\ & = -m/N(c) \left(\left(- m/N_p \right) \right) \\ & = -m/N(c) \left(\left(- m/N_p \right) \right) \\ & = -m/N(c) \left(\left(- m/N_p \right) \right) \\ & = -m/N(c) \left(\left(- m/N_p \right) \right) \\ & = -m/N(c) \left(- m/N_p \right) \\ $
	$c = abC(k) = (1 - ab(k))$ $c = abC(k) = (2 - ab(k))$ $c = abC(k) = (3 - ab(k))$ $c = abC(k) = (3 - ab(k))$ $d(x_k) = abC(k)$
	$c = abC(k) = (1 - ab(k))$ $c = abC(k) = (2 - ab(k))$ $c = abC(k) = (3 - ab(k))$ $c = abC(k) = (3 - ab(k))$ $d(x_k) = abC(k)$
	compared to the interactional model setting the hierarchical model stage — model (1-1) analysis stage — model (1-1) stage — model (

