Enhancing Epidemiological Models with Activity-Travel Behavior and Risk Perception: A Simulation Framework for Policy Management

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Transport and Mobility Laboratory

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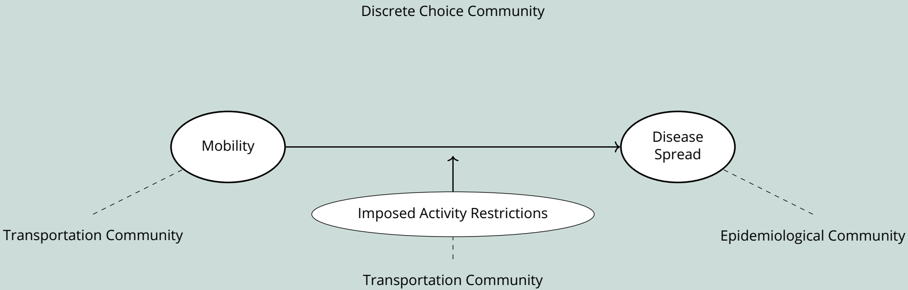

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2. Imposed activity restrictions change how people schedule their day.

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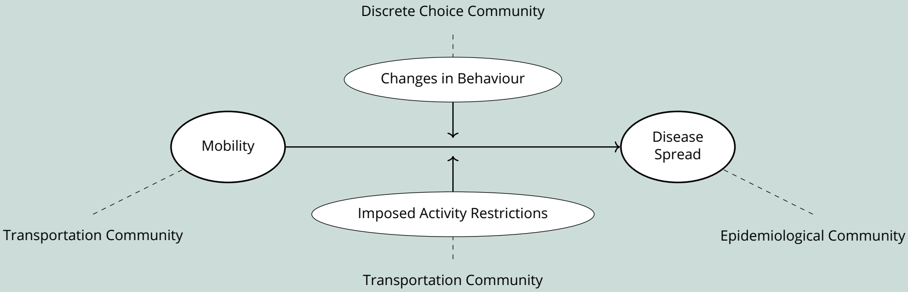


1. Activity-travel behaviour impacts disease spread.
2. Imposed activity restrictions change how people schedule their day.
3. Risk perception in performing activities changes how people schedule their day.

Research Gaps

- Existing models fail to account for how individuals **adjust their behaviors** in response to health **risk perception and restrictions** (Hancean, Slavinec, and Perc 2021, Mazzoli et al. 2020, and Palguta, Levinsky, and Skoda 2022).
- **Overlooking** the potential for **activity swapping** alters the **dynamics** of public space usage and **disease transmission**.
- The **computational complexity** of solving these models increases dramatically with the number of facilities and individuals involved (Pougala, Hillel, and Bierlaire 2022).

Description of the Data

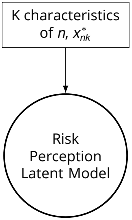
COVID Future Wave 1 Survey Data (see Salon et al. 2021)

- Attitudinal variables of the individuals Y_{in} reflecting individuals' risk perceptions and concerns regarding the pandemic.
- Demographic information k of the individual n is represented as x_{kn}. With $k =$ age, gender, education level, region, race.

A synthetic population provided by He et al. 2020:

- Information on individuals' age, gender, employment status, and education level.
- Information on geographic network that assigns coordinates to nodes, each tagged with specific activity types such as leisure, education, shop, work, and home.

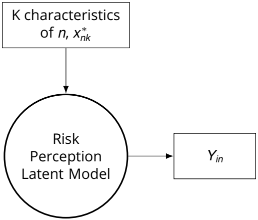
Methodology: Overall framework



Structural Equation:[1] $X^*_n = \beta^*_0 + \sum_{k=1}^{K} \beta^*_k x^*_{kn} + \sigma\epsilon^*$

[1] β^*_0 is the intercept, β^*_k are the coefficients for the K explanatory variables x^*_{kn} for each individual n, σ is the standard deviation of the error term, ϵ^* represents the error term associated with the latent variable.

Methodology: Overall framework

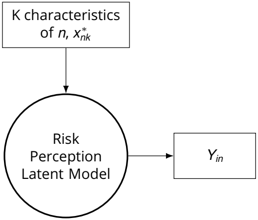


Measurement Equations:[1] $Y^*_{in} = \alpha^*_{0i} + \alpha^*_i X^*_n + \sigma^*_i \xi^*_i$

$$Y_{in} = \begin{cases} 1 & \text{if } Y^*_{in} < \tau_1, \\ 2 & \text{if } \tau_1 \leq Y^*_{in} < \tau_2, \\ 3 & \text{if } \tau_2 \leq Y^*_{in} < \tau_3, \\ 4 & \text{if } \tau_3 \leq Y^*_{in} < \tau_4, \\ 5 & \text{if } \tau_4 \leq Y^*_{in}. \end{cases}$$

[1] α^*_{0i} is the intercept for the i-th indicator,α^*_i is the coefficient relating the latent variable to the i-th indicator,σ^*_i is the standard deviation of the error term for the i-th indicator,ξ^*_i is the error term for the i-th indicator,τ_j are the thresholds that define the categories of the Likert scale.

Methodology: Overall framework



Contribution to the likelihood for the ordered probit model: [1]

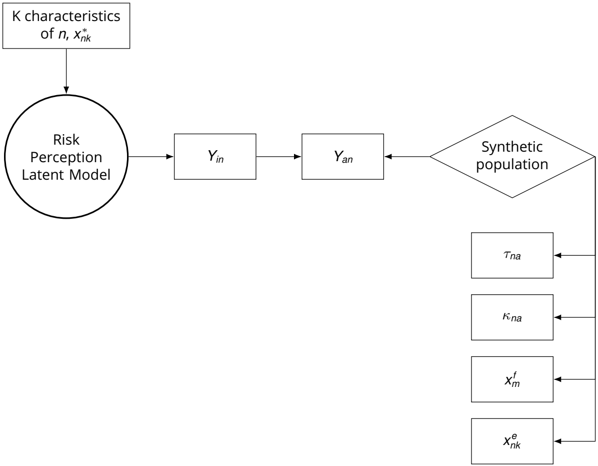
$$\Pr(Y_{jn} = j_i) = \Pr(\tau_{j-1} \leq Y^*_n \leq \tau_j) = \Pr\left(\frac{\tau_{j-1} - \alpha^*_{0i} - \alpha^*_i X^*_n}{\sigma^*_i} < \xi_i \leq \frac{\tau_j - \alpha^*_{0i} - \alpha^*_i X^*_n}{\sigma^*_i}\right)$$

$$= \Phi\left(\frac{\tau_j - \alpha^*_{0i} - \alpha^*_i X^*_n}{\sigma^*_i}\right) - \Phi\left(\frac{\tau_{j-1} - \alpha^*_{0i} - \alpha^*_i X^*_n}{\sigma^*_i}\right).$$

[1] We define two positive parameters δ^*_1 and δ^*_2 as:

$$\tau_1 = -\delta^*_1 - \delta^*_2, \tau_2 = -\delta^*_1, \tau_3 = \delta^*_1, \tau_4 = \delta^*_1 + \delta^*_2.$$

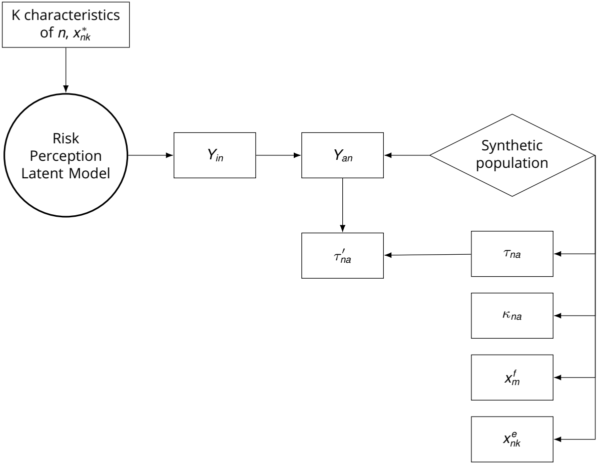
Methodology: Overall framework



We use only the indicators related to the risk perception on activities:

$$i = a$$

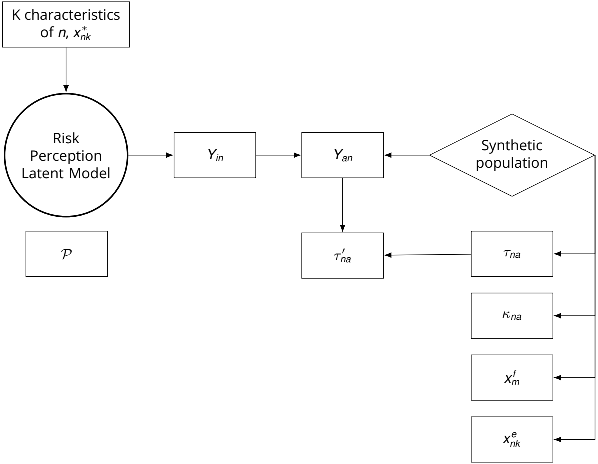
Methodology: Overall framework



Linking the Risk Perception with the ABMR Model:

$$\tau'_a = \tau_a \frac{1}{1 + \exp(-\upsilon_1(Y_{an} - \upsilon_2))}$$

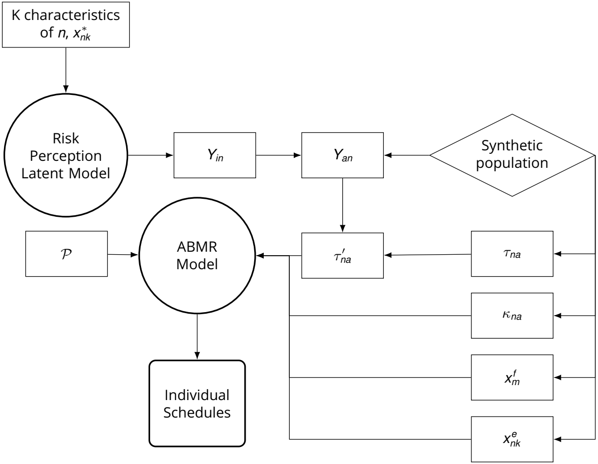
Methodology: Overall framework



Each element of $\mathcal{P}$ is defined as a parameter $\varphi_{\ell,a}$. [1]

[1] $\ell =$ closure restrictions, time slot starting restrictions, time slot closing restrictions, peak hour restrictions, travel time restrictions, curfew restrictions

Methodology: Overall framework



Methodology: Previous Framework Pougala, Hillel, and Bierlaire 2022

Objective function

$$\max_{\omega, Z, x, \tau} \quad U_0 + \sum_{a=0}^{A} Z_a^0 (\chi a + V_a^1 + V_a^2 + \varphi_{5,a} V_{ab}^3) + \sum_{a=0}^{A} \sum_{b=0}^{A} Z_{ab} \cdot \theta_t \cdot \omega_{ab} \tag{1}$$

Subject to:

$$\sum_a \sum_b (Z_a^0 \cdot x_a^2 + Z_{ab} \cdot \omega_{ab}) = 24 \tag{2}$$

$$\omega_{\text{dawn}} = \omega_{\text{dusk}} = 1 \tag{3}$$

$$x_a^2 \geq Z_a^0 \cdot \tau_a^{\text{min}} \qquad \forall a \in \mathcal{A} \tag{4}$$

$$x_a^2 \leq Z_a^0 \cdot T \qquad \forall a \in \mathcal{A} \tag{5}$$

$$Z_{ab} + Z_{ba} \leq 1 \qquad \forall a, b \in \mathcal{A}, a \neq b \tag{6}$$

$$Z_{a,\text{dawn}} = Z_{\text{dusk},a} = 0 \qquad \forall a \in \mathcal{A} \tag{7}$$

$$\sum_{a} Z_{ab} = z_b^0 \qquad \forall b \in \mathcal{A}, b \neq \text{dawn} \tag{8}$$

$$\sum_{b} Z_{ab} = z_a^0 \qquad \forall a \in \mathcal{A}, a \neq \text{dusk} \tag{9}$$

$$(Z_{ab} - 1) \cdot T \leq x_a^1 + x_a^2 + Z_{ab} \cdot \omega_{ab} - x_b^1 \qquad \forall a, b \in \mathcal{A}, a \neq b, \tag{10}$$

$$(1 - Z_{ab}) \cdot T \geq x_a^1 + x_a^2 + Z_{ab} \cdot \omega_{ab} - x_b^1 \qquad \forall a, b \in \mathcal{A}, a \neq b \tag{11}$$

$$x_a^1 \geq \chi_a^- \qquad \forall a \in \mathcal{A} \tag{12}$$

$$x_a^1 + x_a^2 \leq \chi_a^+ \qquad \forall a \in \mathcal{A} \tag{13}$$

$$\sum_{a \in \mathcal{F}_a} z_a^0 \leq 1 \qquad \forall a \in \mathcal{A} \tag{14}$$

Methodology: ABRM Constraints

Activity-restriction constraints

$$\varphi_{1,a} Z_a^0 = 0 \qquad \forall \varphi_{1,a} \in \mathcal{P}, a \in \mathcal{A} \quad (15)$$

$$\varphi_{2,a} x_a^1 \geq \varphi_{2,a} t_a^{\Theta^1} \qquad \forall \varphi_{2,a} \in \mathcal{P}, a \in \mathcal{A} \quad (16)$$

$$\varphi_{3,a}(x_a^1 + x_a^2) \geq \varphi_{3,a} t_a^{\Theta^2} \qquad \forall \varphi_{3,a} \in \mathcal{P}, a \in \mathcal{A} \quad (17)$$

$$\varphi_{4,a}(x_a^1 + x_a^2) \leq \varphi_{4,a}(t_a^{\Theta^3} + 24 * (1 - Z_2)) \qquad \forall \varphi_{4,a} \in \mathcal{P}, a \in \mathcal{A} \quad (18)$$

$$\varphi_{4,a} x_a^1 \geq \varphi_{4,a}(t_a^{\Theta^4} - 24 * (1 - Z_1)) \qquad \forall \varphi_{4,a} \in \mathcal{P}, a \in \mathcal{A} \quad (19)$$

$$\varphi_{4,a}(Z_1 + Z_2 - 1) \geq 0 \qquad \forall a \in \mathcal{A} \quad (20)$$

$$\varphi_{5,a}(Z_{ab} \cdot \omega_{ab}) \leq \varphi_{5,a} t_a^{\Theta^5} \qquad \forall \varphi_{5,a} \in \mathcal{P}, a \in \mathcal{A} \quad (21)$$

$$\varphi_{6,a} \tau_{\text{dawn}} \leq \varphi_{6,a} t_a^{\Theta^6} \qquad \forall a \in \mathcal{A} \quad (22)$$

$$\varphi_{6,a} x_{\text{dusk}} \geq \varphi_{6,a} t_a^{\Theta^7} \qquad \forall a \in \mathcal{A} \quad (23)$$

$\ell =$ closure restrictions, time slot starting restrictions, time slot closing restrictions,peak hour restrictions, travel time restrictions, curfew restrictions

Results: Case Study - Population of NYC

Study Focus

Our study examines the population of **New York City** (He et al. 2020). Our sample considers a population of **10'000 individuals and 5'489 facilities**).

We prepare the inputs of the model:

Attributes	
Individual	**Facility**
Id Individual	Id Facility
Age	X Coordinate
Gender	Y Coordinate
Employment Status	Type of Facility
Education Level	
Coordinate X Home	
Coordinate Y Home	

Table: Summary of Individual and Facility Attributes

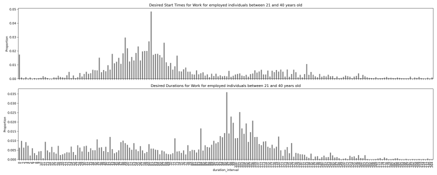


Figure: Distribution of desired start time (above) and desired duration (below) of Work activities for employed individuals between 21 and 40 years old.

Results: Case Study - Population of NYC

We pick the scenario:

Tested Scenarios	Closure			Constraints
	Secondary	Education	Work	Curfew
No restrictions				
Outing limitations	x			
Early curfew				5pm
Economy preservation	x	x		
Work-education balance		x	x	

Tested scenarios, each one considering different NPIs as input to the ABM

Execution Time: Solver

We solve the problem using dynamic programming.

	Execution time [h:mm:ss]	Individuals/second	Seconds/individual
No restrictions	0:54:36	3.05	0.32765
Outing limitations	0:12:52	12.94	0.07725
Early curfew	0:52:42	3.16	0.31624
Economy preservation	0:01:33	107.22	0.00933
Work-education balance	0:37:53	4.40	0.22729
Leisure facilities closure	0:20:40	8.07	0.12396

Table: Execution details for each tested scenario.

Results across scenarios

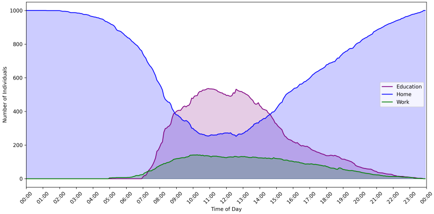


Figure: Outings Limitation scenario.

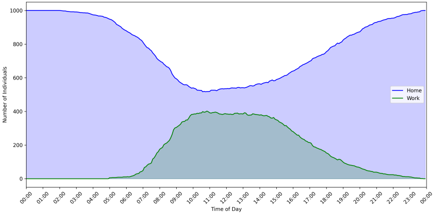


Figure: Only Economy scenario.

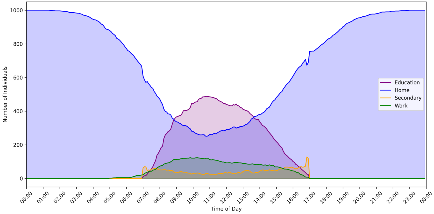


Figure: Early Curfew scenario.

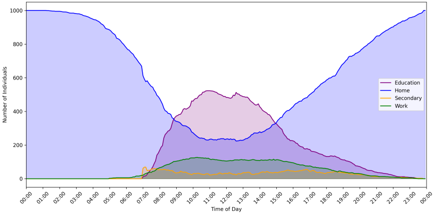
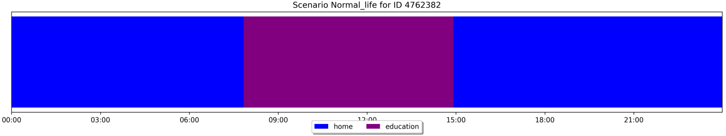
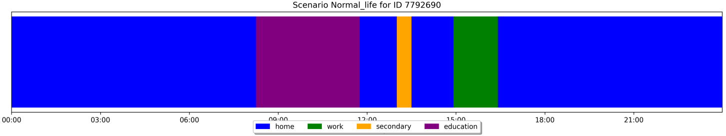
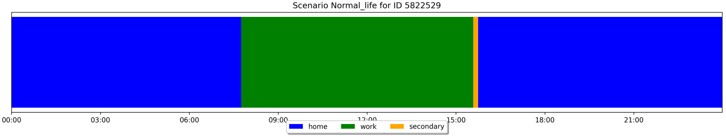


Figure: Normal Life scenario.

Results across individuals: insights on behavior







Aggregated results: insights on activity durations

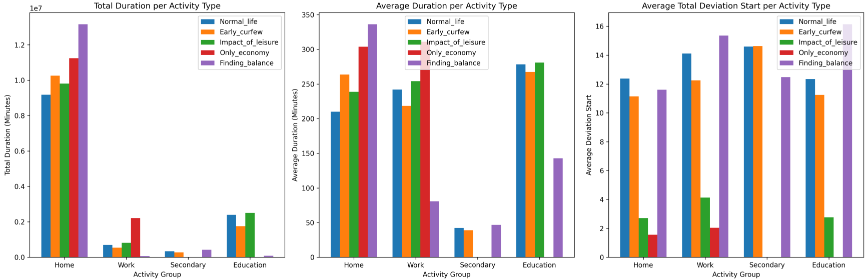


Figure: Total Duration, Average Duration and Average Total Deviation Start per Activity Type .

Results after applying the Risk Perception Latent state

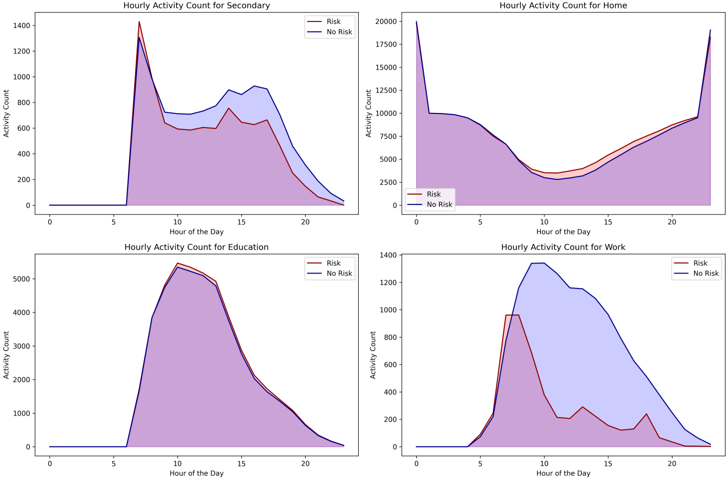


Figure: Changes in Hourly Count of Individuals per activity when including the Risk Perception Latent Model.

Conclusion and Future Work

Conclusions:

1. Computationally efficient tool to model individual schedules for **epidemiological models**, capable of running 10,000 individuals with 5,000 facilities in 50 minutes.
2. Able to capture the **’swapping-activities’** effect.
3. Able to model government-**imposed mobility restrictions** and **self-imposed** changes due to perceived risks.

Future work:

1. Expand the sample to **300,000 individuals** and calibrate the latent model with more socioeconomic variables.
2. Embed the activity-based model into an **epidemiological model** to optimize **policies** using Cortes Balcells, Krueger, and Bierlaire 2021.
3. **Validate** the model with **real data**.

Thank you for your attention

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Results Risk Perception Latent Model

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
B_att_covid_5	-0.668	0.0521	$-12 \cdot 8$	0
B_att_covid_2	0.375	0.049	7.65	$1.98e-14$
B_att_covid_1	0.275	0.0534	5.15	$2.64e-07$
B_att_covid_3	0.451	0.0523	8.61	0
B_risk_percp_1	0.39	0.0545	7.16	$8.31e-13$
B_risk_percp_2	0.106	0.0389	2.74	0.00623
B_risk_percp_3	0.19	0.0431	4.4	$1.1e-05$
B_risk_percp_5	0.101	0.0362	2.78	0.00539
B_risk_percp_6	0.291	0.0447	6.5	$7.85e-11$
INTERSECT_att_covid_5	-0.167	0.0307	-5.43	$5.62e-08$
INTERSECT_att_covid_2	-0.318	0.0302	-10.5	0
INTERSECT_att_covid_1	-0.0736	0.0323	-2.28	0.0229
INTERSECT_att_covid_3	-0.302	0.0325	-9.29	0
INTERSECT_risk_percp_1	0.199	0.0326	6.1	$1.09e-09$
INTERSECT_risk_percp_2	0.0404	0.0228	1.77	0.0764
INTERSECT_risk_percp_3	-0.35	0.0268	$-13 \cdot 1$	0
INTERSECT_risk_percp_5	-0.0892	0.0222	-4.02	$5.88e-05$
INTERSECT_risk_percp_6	-0.305	0.0278	-11	0
SIGMA_STAR_att_covid_5	0.806	0.0167	48.4	0
SIGMA_STAR_att_covid_2	0.639	0.0164	39.1	0
SIGMA_STAR_att_covid_1	0.696	0.0161	43.2	0
SIGMA_STAR_att_covid_3	0.768	0.0178	43.3	0
SIGMA_STAR_risk_percp_1	0.6	0.0144	41.6	0
SIGMA_STAR_risk_percp_2	0.402	0.00955	42.2	0
SIGMA_STAR_risk_percp_3	0.513	0.0133	38.6	0
SIGMA_STAR_risk_percp_5	0.448	0.0106	42	0
SIGMA_STAR_risk_percp_6	0.535	0.0133	40.2	0
coef_bachelors_or_more	-0.244	0.0474	-5.14	$2.8e-07$
coef_gender_female	-0.376	0.0408	-9.22	0
coef_intercept	-0.239	0.0464	-5.15	$2.55e-07$
coef_zone_West	0.156	0.0402	3.88	0.000106
delta_1	0.209	0.0049	42.7	0
delta_2	0.48	0.0103	46.8	0

Table: Results parameters Latent model