Modeling Driver Behavior as a Stochastic Hazard-Based Risk-Taking Process
Introduction: Motivation/Framework/Objective/Approach

Background: Major Lane-Changing/Acceleration Models

The Model:
- Tactical Stage:
  - Duration (Hazard-Based) Models
  - Theoretical Framework
  - Data Description and Extraction

- Operational Stage
  - Formulation Logic
  - Model Implementation: Asymptotic Expansion

Numerical Analysis
- Initial Estimates
  - Sensitivity Analysis: Initial Plots

Conclusion
Motivation (Micro-Crash Level):

In 2006, the US. Department of Transportation reported 42,624 traffic crash fatalities with 2,575,000 injuries and 3,014,116,000,000 vehicle-miles traveled.
Motivation (Micro-Crash Level):

Plotting the crash distribution by time of day over the last 8 years:

(U.S. Department of Transportation, National Highway Traffic Safety Administration, Nov. 2006)

Outline

Introduction  Background  The Model:  Tactical Stage  Operational Stage  Numerical Results  Conclusion
Motivation (Macro – Disaster Level):

<table>
<thead>
<tr>
<th>Some Recent Extreme Condition</th>
<th>Date</th>
<th>Countries Affected</th>
</tr>
</thead>
<tbody>
<tr>
<td>New York September Attack</td>
<td>September the 11th, 2001</td>
<td>United States, Indonesia, Sri Lanka, India, Thailand, Somalia, Myanmar, Malaysia</td>
</tr>
<tr>
<td>Indian Ocean Earthquake/Tsunami</td>
<td>December the 26th, 2004</td>
<td>United States, Indonesia, Sri Lanka, India, Thailand, Somalia, Myanmar, Malaysia</td>
</tr>
<tr>
<td>London Bombing</td>
<td>July the 7th, 2005</td>
<td>England</td>
</tr>
<tr>
<td>Hurricane Katrina</td>
<td>August the 29th, 2005</td>
<td>United States</td>
</tr>
<tr>
<td>2008 New York Explosion</td>
<td>March the 6th, 2008</td>
<td>United States</td>
</tr>
<tr>
<td>Iowa/Wisconsin Flooding</td>
<td>June, 2008</td>
<td>United States</td>
</tr>
</tbody>
</table>

Outline

Introduction  Background  The Model:  Tactical Stage  Operational Stage  Numerical Results  Conclusion
Framework: Drivers Decision Models

- Pre-Trip
- Strategic En-Route
- Tactical Route Execution
- Operational Driving
- Vehicle Control

Focus

Time to Make and Execute Decision

- ~ 1 hour
- 30 seconds
- 5 seconds
- Instantaneous

FHWA, 2004
Framework: Human Cognitive Process

- External Stimulus
- Sensory Registers Module
- Working Memory Module
- Decision Making Module
- Execution Module
- Long-Term Memory Module

Elaboration
Retrieval
Forgetting

Hastie and Dawes, 2000
Motivation:

1- Existing car-following and lane-changing models are accident-free where safety constraints are forced.

2- There is a need for a richer complete representation of the cognitive processes underlying driver behavior in different driving conditions (free-flow, congested and extreme conditions)

Objective:

the objective of this research is to:

1- advance the state of knowledge in modeling driver behavior processes and the state of the art of microscopic traffic simulation by incorporating cognitive dimensions of the driver task

2- include risk-perception and risk-taking behaviors under uncertainty (stochastically)

3- capture driver behavior in complex environments such as those associated with congested conditions, accident-prone situations and extreme regimes.
Research Approach/Tasks:

- **Formulation:** Theory and Model Specification
- **Calibration/Validation**
- **Numerical Analysis and Testing**
Research Approach: Formulation

Step 1: Theory

Behavioral Economics Concepts: Hazard-Models
Cognitive Psychology Concepts: Prospect Theory

Step 2: Model Specification
Task 1: Operational Logic: Series of Utility Assumptions and Numerical Approximations
Task 2: Tactical Logic: Identifying Hazard-Based Models in a Traffic Context
Research Approach: Numerical Analysis/Calibration and Validation

Step 3: Numerical Analysis:
   Task 3: Initial Estimation of Tactical Model
   Task 4: Numerical Analysis and Sensitivity to test the validity of the formulated operational model in Different Scenarios

Step 4: Calibration/Validation Phase:
   Task 5: Integrate the Tactical and the Operational Logics of the Model
   Task 6: Formulation of a Calibration Procedure for the Joint Model
   Task 7: Operational/Tactical Stages Validation against Real Life Trajectory Data
Background: Car-Following Models/Lane Changing Models
Major car-following models:

1. GHR (GM) (Gazis, Herman and Rothery, 1959)
2. Gipps (Gipps, 1981)
3. CA (Nagel and Shreckenberg, 1992) / (Krauss et al., 1996)
4. SK (Krauss and Wagner, 1997)
5. IDM (Treiber et al., 2000)
6. IDMM (Treiber and Helbing, 2003)
7. Wiedemann (Wiedemann, 1974)

Major lane-changing models

1. Gipps Model (Gipps, 1986)
2. Wiedemann Model (Wiedemann, 1991)
4. Hidas Model (Hidas, 2002)
Model Formulation
Modeling Framework

![Diagram]

- Vehicle \( n \) of Interest
- Stopped Vehicle
- Slow Vehicle
- Free-Flow Episode
- Car-Following Episode
- Acceleration Update Function for Free-Flow/Car-Following Model

Outline:
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Samer H. Hamdar
November the 20th, 2008
Lane Changing Model: Theoretical Framework

(Hamdar and Mahmassani, 2008)
Baseline hazard (1) (Bhat, 2000)

Let $T_i$ be a non-negative random variable representing the duration of car-following/free-flow episode (time) of a driver $i$.

The hazard at time $u$, $\lambda_i(u)$, is the instantaneous probability that the car-following/free-flow duration $T_i$ for a driver $i$ will end in an infinitesimally small time period $\delta$ after time $u$, given that the duration has elapsed until time $u$:

$$\lambda_i(u) = \lim_{\delta \to 0^+} \frac{\Pr(u \leq T_i < u + \delta \mid T_i \geq u)}{\delta}$$

We can related the hazard to the density function $f_i(.)$ and the cumulative distribution function $F_i(.)$ of $T_i$ by:

$$\lambda_i(u) = \frac{f_i(u)}{1 - F_i(u)} = \frac{f_i(u)}{S_i(u)}$$
Baseline hazard (2): Focus on 3 Parametric Functions

- The simplest assumption is having a constant hazard rate $\lambda_i(u) = \sigma$ implying that there is no duration dependence duration time $T_i$ exponentially distributed.

- A two-parameter hazard function is expressed as:

$$\lambda_i(u) = \sigma \alpha \left( \sigma u \right)^{\alpha - 1}$$

Where: $\sigma > 0$ and $\alpha > 0$

- $\alpha > 1$: monotonically increasing dependence (snowballing effect)
- $\alpha < 1$: a monotonically decreasing (inertia effect) dependence
- $\alpha = 0$: no duration dependence.

The distribution of $T_i$ is weibull.
Baseline hazard (3): Focus on 3 Parametric Functions

- For non-monotonic dependence on the duration: the hazard function has the following form:

\[ \lambda_i(u) = \frac{\sigma \alpha (\sigma u)^{\alpha-1}}{1 + ((\sigma u)^\alpha)} \]

- hazard function is monotonic decreasing from infinity when \( \alpha < 1 \)
- monotonic decreasing from \( \sigma \) when \( \alpha = 1 \)
- increasing from zero to a maximum of \( u = [(\alpha - 1)/\sigma]^{1/\alpha} \), and decreasing thereafter when \( \alpha > 1 \)

distribution of \( T_i \) is Log-Logistic
Effect of External Covariates: Proportional Hazard Form

- The advantage of this method is that it can take into account the inter-drivers’ heterogeneity (assumed a gamma heterogeneity).

- The external covariates are multiplicative on an underlying baseline hazard function:

  \[ \lambda_i(u, x_i, \beta, \lambda_0) = \lambda_0(u)\phi(x_i, \beta) \]

Where
\( \lambda_0(u) \) = baseline hazard at time \( u \)
\( x_i \) = vector of explanatory variables corresponding to driver \( i \)
\( \beta \) = vector of parameters corresponding to \( x_i \) to be estimated

- For ease of estimation: \( \phi(x_i, \beta) = \exp(-\beta'x_i + w_i) \); The term \( w_i \) represents the unobserved heterogeneity
Driving: a Multiple Duration Process (1)

- As defined by the authors, driving episodes are of two types: free-flow episode versus car-following episodes.

- A vehicle exits a “free-flow” episode when:
  - it changes lanes (Episode Type 3, \( q = 4 \)). This is rarely expected – unless it is a mandatory lane change towards desired exit.
  - it becomes close enough to the leader entering another “car-following” episode (Episode Type 4, \( q = 3 \)).

- As for the “car-following episodes”, they end when:
  - the corresponding vehicle changes lanes (Episode Type 1, \( q = 2 \)).
  - When the leader of the vehicle of interest is far-enough so it enters a free-flow episode (Episode Type 2, \( q = 1 \)).
Driving: a Multiple Duration Process (2)

- Let $T_{iq}$ represent the continuous duration time to an exiting car-following or free-flow episode corresponding to outcome $q$ ($q = 1, 2 \ldots Q$).

- Based on the “improved formulation”, the outcome-specific hazard function for driver $i$ at some specified time $u$ is:

$$\lambda_{iq}(u) = \lim_{\delta \to 0^+} \frac{\Pr(u \leq T_{iq} < u + \delta \mid T_{iq} \geq u)}{\delta} = \lambda_{0q}(u) \exp(-\beta_q' \chi_{iq})$$

- Two questions dominates the lane-changing model:
  - Is it desirable to change lanes?
  - Is it possible to change lanes?

Captured by the Hazard-Function Above ($q = 1; q = 3$)

Boundary Conditions/MOBIL Model (Treiber et al., 2007)
Lane-Changing Model: Data Description and Extraction
The data set is trajectory data for 5678 vehicles collected as a part of the Federal Highway Administration’s (FHWA) Next Generation Simulation (NGSIM) project.

Data were collected on the 13th of April, 2005, between 4 PM and 5:30 PM, on a segment of the Interstate I-80 in Emeryville, San Francisco, USA.

The semi-poisson headway distribution model (Wasielewski, 1974) is used to determine the threshold $T_{\text{critical}}$ below which a car-following behavior is assumed and above which a free-flow behavior is assumed.
### Exogenous Covariates Included in the Study

<table>
<thead>
<tr>
<th>Exogenous Covariate</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1$ (LCL)</td>
<td>Number of Leaders Changing Lanes During Episode</td>
</tr>
<tr>
<td>$X_2$ (V)</td>
<td>driver’s speed</td>
</tr>
<tr>
<td>$X_3$ (DXL1)</td>
<td>headway between driver i and leader i-1 (front-to-front bumper)</td>
</tr>
<tr>
<td>$X_4$ (DVL1)</td>
<td>relative speed between driver i and leader i-1</td>
</tr>
<tr>
<td>$X_5$ (DXF1)</td>
<td>distance headway between driver i and follower i+1 (front-to-front bumper)</td>
</tr>
<tr>
<td>$X_6$ (DVF1)</td>
<td>relative speed between driver i and follower i+1</td>
</tr>
<tr>
<td>$X_7$ (DXL2)</td>
<td>distance headway between driver i and driver i-2 (front-to-front bumper)</td>
</tr>
<tr>
<td>$X_8$ (DVL2)</td>
<td>relative speed between driver i and driver i-2</td>
</tr>
<tr>
<td>$X_9$ (DXL1R)</td>
<td>distance headway between driver i and the corresponding leader on the right lane</td>
</tr>
<tr>
<td>$X_{10}$ (DVL1R)</td>
<td>relative speed between driver i and the corresponding leader on the right lane</td>
</tr>
<tr>
<td>$X_{11}$ (DXF1R)</td>
<td>distance headway between driver i and the corresponding follower on the right lane</td>
</tr>
<tr>
<td>$X_{12}$ (DVF1R)</td>
<td>relative speed between driver i and the corresponding follower on the right lane</td>
</tr>
<tr>
<td>$X_{13}$ (DXL1L)</td>
<td>distance headway between driver i and the corresponding leader on the left lane</td>
</tr>
<tr>
<td>$X_{14}$ (DVL1L)</td>
<td>relative speed between driver i and the corresponding leader on the left lane</td>
</tr>
<tr>
<td>$X_{15}$ (DXF1L)</td>
<td>distance headway between driver i and the corresponding follower on the left lane</td>
</tr>
<tr>
<td>$X_{16}$ (DVF1L)</td>
<td>relative speed between driver i and the corresponding follower on the left lane</td>
</tr>
<tr>
<td>$X_{17}$ (K)</td>
<td>Driver’s average surrounding density. It is defined as the total density (over the number of lanes)</td>
</tr>
<tr>
<td>$X_{18}$ (KR)</td>
<td>Driver’s average surrounding density in adjacent lane 1 (to the right) if available</td>
</tr>
<tr>
<td>$X_{19}$ (KL)</td>
<td>Driver’s average surrounding density in adjacent lane 2 (to the left) if available</td>
</tr>
</tbody>
</table>
Acceleration Model Formulation

(Hamdar, Treiber, Kesting and Mahmassani, 2008)
Model Background (Wallsten et al., 2005): Psychology Experiment

2 Decision Alternatives

- Fill the Balloon with more Air
- Stop

Balloon does not explode: Increase Reward

Cash in Existing Amount of Money

Balloon Explodes: Loses all Amount of Money

Which Decision to be Made?

Depends on:
1- Value function: how decision makers evaluate alternatives
2- Estimated Probability of Balloon Explosion

Decision Maker

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Behavioral Framework (1): Model Structure

- In the Car-Following Process, three behaviors are possible:
  1. Drivers accelerate
  2. Drivers decelerate
  3. Drivers keep the same speed

- Choosing between these three behaviors is choosing between a set of acceleration values between $a_{\text{min}}$ and $a_{\text{max}}$.

- Driver $n$ sequentially evaluate the collision risk involved in choosing the acceleration $a_n$ and the corresponding gain or loss:
  1. The risk is represented by a collision probability
  2. The gain and losses are evaluated using a “prospect theory” value function allocated to each acceleration value
Prospect theory allows choosing between different set of alternatives (acceleration values) presented for individual \( n \) (driver) at time \( t \): \( C_n(t) \).

Each alternative has a measured “objective” utility \( O(C_n(t)) \).

A value function \( U_{PT}[O(C_n(t))] \) is used to transform the “objective” utility into a perceived “subjective” value. The value function can represent:

1. Risk seeking versus aversion attitudes expressed by humans (drivers).
2. Asymmetry in weighing gains and losses.
3. The tendency to measure gains and losses not in terms of absolute values but with respect to a reference point.

A probability \( P(C_n(t)) \) is associated to each alternative.

A prospect function \( \pi[P(C_n(t))] \) transforms the probability terms to prospects.

Based on the prospect of each alternative, the alternative with the highest \( \pi[P(C_n(t))] U_{PT}[O(C_n(t))] \) is chosen.
Estimation of Collision Probability (1)

What is the future speed of my leader?

$v_{n-1}^{est}(t)$: estimated (subjective) future speed of lead vehicle $n-1$ as perceived by driver $n$ over anticipated time span $\tau_n$

Follows normal distribution with standard deviation $\sigma(v_{n-1})$, and mean equal to actual velocity of the leader $v_{n-1}(t)$.

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The crash probability $p_n(t + \tau_n)$ is given by the probability that the gap $s_n(t + \tau_n) = x_{n-1}(t + \tau_n) - x_n(t + \tau_n) - L_{n-1}$ at time $t + \tau_n$ is $\leq 0$.

Given constant acceleration for the follower (driver in question) and constant velocity for the leader:

$$x_{n-1}(t + \tau_n) = x_{n-1}(t) + \tau_n v_{n-1}^{est}(t)$$
$$x_n(t + \tau_n) = x_n(t) + v_n(t)\tau_n + \frac{1}{2}a_n\tau_n^2$$

$$p_n(t + \tau_n) = P\left( v_{n-1}^{est}(t) < \frac{v_n(t)\tau_n + \frac{1}{2}a_n\tau_n^2 - s_n(t)}{\tau_n} \right)$$

Writing $v_{n-1}^{est}(t)$ in terms of standardized normal distribution, we get:

$$v_{n-1}^{est}(t) = v_{n-1}(t) + \sigma (v_{n-1}) Z$$

$$p_n(t + \tau_n) = P\left( Z < \frac{\Delta v_n(t)\tau_n + \frac{1}{2}a_n\tau_n^2 - s_n(t)}{\sigma(v_{n-1})\tau_n} \right) = \Phi\left( \frac{\Delta v_n(t)\tau_n + \frac{1}{2}a_n\tau_n^2 - s_n(t)}{\sigma(v_{n-1})\tau_n} \right)$$

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Evaluation Process (1)

- The gain and losses are expressed here in terms of gains and losses in speed from the previous acceleration instance i-1.

- If the gain and losses are expressed in terms of an abscissa $\Delta\dot{v} = \Delta v = a_n \times \tau_n$, the value function $U_{PT}(a_n)$ is defined as follows:

$$U_{PT}(a_n) = \frac{\left( w^+(1-w^-) \cdot \tanh \left( \frac{a_n}{a_0} \right) + 1 \right)}{2} \cdot \sqrt{\frac{a_n}{a_0}}$$

- In a collision, the loss is assumed to be related to a seriousness term weighted by $w_c$: when the seriousness of the driver increases, $w_c$ increases. $k(w_c)$ represents the sensitivity to the loss caused by an accident.

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The value Function is:

\[ U(a_n) = (1 - p_{n,i}) U_{PT}(a_n) - p_{n,i} w_c k(v, \Delta v) + \varepsilon_n \]

Where

- \( U_{PT}(a_n) \) = PT value function
- \( p_{n,i} \) = probability of colliding with rear-end bumper of lead vehicle given that no collision took place in the \( i-1 \)th acceleration instance
- \( \varepsilon_n \) = driver specific error term assumed to have Weibull distribution

Using a continuous logit model, the stochastic car-following acceleration \( a_{n,\text{car-following}}(t) \) of vehicle n is retrieved from the following probability density function:

\[
f(a_n) = \begin{cases} 
\frac{\exp(\beta \times U(a_n))}{\int_{a_{min}}^{a_{max}} \exp(\beta \times U(a')) \, da'} & \text{if } a_{min} \leq a_n \leq a_{max} \\
0 & \text{otherwise}
\end{cases}
\]

where \( \beta \) is a free parameter (\( \beta > 0 \)) that reflects the sensitivity of choice to the utility.
Accelaration Model:
Preliminary Implementation
All $N+1$ drivers ($n = 0, 1, \ldots N$) are assumed to have identical parameters where $s$ is the corresponding gap and $\Delta v$ is the relative speed (positive when approaching).

The estimation uncertainty $\sigma (v_i) = \alpha v_i$ of the velocity of the leader is proportional to the velocity itself, i.e., the relative error (variation coefficient) $\alpha$ is constant.

The anticipation time horizon $\tau$ is assumed to be the minimum between the time-to-collision $\tau_{TTC} = (s / \Delta v)$ and some maximum value $\tau_{max}$:

$$\tau = \tau(s, \Delta v) = \begin{cases} \frac{s}{\Delta v} & \Delta v \geq \frac{s}{\tau_{max}} \\ \tau_{max} & \text{otherwise} \end{cases}$$
Asymptotic Expansion

- an asymptotic expansion of the acceleration probability distribution of this model will give:
  \[
  \dot{v} = a \approx N(a^*, \sigma_a^2)
  \]

→ the distribution of accelerations is approximately given by a Gaussian distribution whose moments are:
  \[
  a^* = \arg(\max(U(a))), \quad \sigma_a^2 = \frac{-1}{\beta U''(a^*)}
  \]

- \( U'(a) \) and \( U''(a) \) can be calculated analytically (given by derivatives of \( \Phi(z) \) that is a density of a Gaussian). The value \( a^* \) itself needs to be calculated numerically (Iterative Procedure with Newtonian Method).
Numerical Analysis

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Lane-Changing Model: Testing Results
Minor Multiple-Duration Effect:

- Not surprisingly, using the calculated $T_{\text{critical}}$ thresholds, the majority of the headways observed are in the car-following mode.

- This is expected since the data were collected at peak hour PM on a major free-way section: drivers are leaving the business districts of San-Francisco, San Jose (through the Bay Bridge) as well as Oakland for the residential areas in the Northern Part of the Bay Area.

  Accordingly, all significant episodes are assumed car-following episodes ending either by changing lanes or by leaving the study area.

- The multiple duration effect is minor; in this study, the duration model is seen as a descriptive lane-changing model.
General Statistics:

- 6450 Episodes:
  - 4465 are left censored.
  - 1250 right censored episodes and thus cannot be supported by LIMDEP Software in the estimation process.
  - 735 non-censored ones.

- For the data description, the non-censored episodes (735) were used:

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Duration Model (1): Weibull

<p>| Parameters of underlying density at data means: |</p>
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sigma</td>
<td>0.1858</td>
<td>0.00088</td>
<td>0.169 to 0.203</td>
</tr>
<tr>
<td>Alpha</td>
<td>2.09356</td>
<td>1.2276</td>
<td>1.0529 to 2.3342</td>
</tr>
<tr>
<td>Median</td>
<td>48.22723</td>
<td>2.29176</td>
<td>43.7354 to 52.7191</td>
</tr>
</tbody>
</table>

Percentiles of survival distribution:

<table>
<thead>
<tr>
<th>Survival</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.75</td>
<td>71.90</td>
</tr>
<tr>
<td>0.95</td>
<td>48.23</td>
</tr>
</tbody>
</table>

The statistically significant variables are LCL, V, DXL2, DVL2 and DXF1. The variables related to followers (anisotropy of traffic) and second leaders (anticipation) have a significant influence on the probability of ending an episode and thus, changing lanes.

>1 (2.09): snowballing effect. This is a sign of an increase of impatience level while driving in congested conditions.
### Duration Model (2): Log-logistic

<table>
<thead>
<tr>
<th>Parameters of underlying density at data means:</th>
<th>Parameter Estimate</th>
<th>Std. Error</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sigma</td>
<td>0.02062</td>
<td>0.00072</td>
<td>0.0192 to</td>
</tr>
<tr>
<td>Alpha</td>
<td>2.50077</td>
<td>0.09263</td>
<td>2.3100 to</td>
</tr>
<tr>
<td>Median</td>
<td>48.50207</td>
<td>1.68598</td>
<td>45.1976 to</td>
</tr>
</tbody>
</table>

#### Percentiles of survival distribution:

<table>
<thead>
<tr>
<th>Survival</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25</td>
<td>75.26</td>
</tr>
<tr>
<td>0.50</td>
<td>48.50</td>
</tr>
<tr>
<td>0.75</td>
<td>31.26</td>
</tr>
<tr>
<td>0.95</td>
<td>14.94</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Coeff.</th>
<th>Std.Err.</th>
<th>t-ratio</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ONE</td>
<td>2.72893</td>
<td>0.203488</td>
<td>13.4108</td>
</tr>
<tr>
<td>LCL</td>
<td>0.164709</td>
<td>0.018776</td>
<td>8.77255</td>
</tr>
<tr>
<td>V</td>
<td>-0.05908</td>
<td>0.004191</td>
<td>-14.0969</td>
</tr>
<tr>
<td>DXL1</td>
<td>-0.00107</td>
<td>0.002011</td>
<td>-0.53421</td>
</tr>
<tr>
<td>DVL1</td>
<td>0.00961</td>
<td>0.009127</td>
<td>1.05290</td>
</tr>
<tr>
<td>DXF1</td>
<td>0.001514</td>
<td>0.00066</td>
<td>2.29388</td>
</tr>
<tr>
<td>DVF1</td>
<td>0.000421</td>
<td>0.006962</td>
<td>0.060488</td>
</tr>
<tr>
<td>DXL2</td>
<td>0.009351</td>
<td>0.001516</td>
<td>6.16687</td>
</tr>
<tr>
<td>DVL2</td>
<td>0.014860</td>
<td>0.006841</td>
<td>2.17349</td>
</tr>
<tr>
<td>K</td>
<td>0.0001438</td>
<td>0.000263</td>
<td>6.99801</td>
</tr>
</tbody>
</table>

The remarks regarding the external covariates in the Weibull Model remains the same in the Log-Logistic Model. The only difference is adding the density as a significant external covariate.
Duration Model (3): Log-logistic

- $\alpha$ is greater than 1 (2.5)

- the hazard function increases with the duration until the duration is equal to $u = \left[\left(\alpha - 1\right)^{1/\alpha}\right] / \sigma$. The probability of ending an episode (changing lanes) starts decreasing afterward. This may reflect the driver being used to travel on a given lane after a specific amount of time.

- It should be noted that this does not pose any conflict with the Weibull Model since most episodes have a duration less than $u = \left[\left(\alpha - 1\right)^{1/\alpha}\right] / \sigma \sim 1$ minute.
Acceleration Model: Testing Results
## Initial Plots (1)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Typical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum anticipation time horizon</td>
<td>$t_{\text{max}} = 5$ s</td>
</tr>
<tr>
<td>Velocity uncertainty variation coefficient</td>
<td>$\alpha = 0.1$</td>
</tr>
<tr>
<td>Logit uncertainty parameter (higher for smaller uncertainty)</td>
<td>$\beta = 3$</td>
</tr>
<tr>
<td>Accident weighing factor</td>
<td>$\omega_c = 40$</td>
</tr>
<tr>
<td>Exponents of the PT utility</td>
<td>$\gamma = 0.5$</td>
</tr>
<tr>
<td>Weighing factor for the negative PT utility</td>
<td>$\omega^- = 2$</td>
</tr>
<tr>
<td>Minimum acceleration</td>
<td>$a_{\text{min}} = -8$ m/s$^2$</td>
</tr>
<tr>
<td>Maximum acceleration</td>
<td>$a_{\text{max}} = 4$ m/s$^2$</td>
</tr>
<tr>
<td>Acceleration normalizing factor</td>
<td>$a_0 = 1$ m/s$^2$</td>
</tr>
</tbody>
</table>
Initial Plots (2)

- Several Relationships (Value Function versus Space Headway, Value Function versus Speed, Value Function versus Relative Speed) were tested.

- Remarkably, in stochastic equilibrium, approximate time headways of 1.5 seconds are kept constant in the car-following regime (mainly influenced by $\alpha \tau_{\text{max}}$).
Contour plots of the acceleration probability density (equation 2) as a function of $v$, $s$ and $\Delta v$ (top left, top right and bottom right). Contour for a situation with a standing vehicle or a red traffic light, $v = \Delta v$ for $s = 30$ m (bottom right).

### Outline
- Introduction
- Background
- The Model: Tactical Stage
- Operational Stage
- Numerical Results
- Conclusion
all vehicles use the maximal deceleration values when

\[ 18 \text{ (m/s)} \leq v \leq 40 \text{ (m/s)} \quad \text{and} \quad 7 \text{ (m/s)} \leq \Delta v \leq 20 \text{ (m/s)} \]

The lowest variances are observed mostly for small “v” and when \( \Delta v \) decreases below zero: less disturbances is caused by accelerating (mostly related to the vehicle properties) then decelerating (mostly related to a drivers’ personality).
Conclusions
Conclusion

- There is a need for translating psychology cognitive concepts to the transportation traffic modeling field (anisotropy, anticipation, risk averseness)

- Transforming the complicated psychology-based model into an efficient logic possible to calibrate and implement.

- To do so, the author incorporates crash-inducing (collision probability and accident weighing parameter) risk-taking (probabilistic choice under uncertainty) behavior into the microscopic operational simulation framework.

- A hazard framework is offered for the tactical stage: the driving process is a continuous process governed by the experiences encountered during the “duration” of different episodes (stochasticity, tracking survival/impatience rates, estimating reaction times, understanding local impact on driving behaviour through anticipation and anisotropy)

- Based on the initial estimation, tactical models showed a snow-balling effect especially during the first minute of an episode: impatience levels decrease afterward.

- In terms of stochastic equilibrium, the operational model exhibits promising properties.
Thank you!

Questions?