

Derivation of coarse-grained models from microscopic CA models of traffic flows

A. Chertock, A. Kurganov, A. Polizzi

C. Hauck, Y. Sun

I. Timofeyev^a

University of Houston

<http://www.math.uh.edu/~ilya/>

^asupport from SAMSI in the Fall 2010 and in the Fall 2011

support from IMA in the Fall 2012

Outline

Main Goal: Systematic Derivation of PDE Models for Traffic Flow

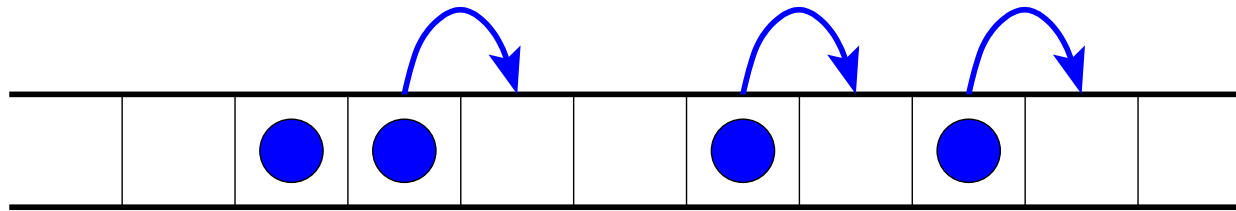
- Microscopic Rules for the Motion of Cars or Pedestrians
- Microscopic CA model for Traffic Flow
- Assumptions for deriving the Coarse-Grained PDE
- Lighthill-Whitham-Richards PDE model
- Equation for the Variance
- Look-Ahead Potential
- One-Dimensional Stochastic Model CA for Pedestrian Traffic
- Explicit Rules for the Interaction of Pedestrians Moving in Opposite Directions

Microscopic Stochastic Lattice Model of Car Traffic

ASEP Dynamics: Spitzer, Derrida, Derrida et al., etc.

L-H Potential: Sopasakis and Katsoulakis, 2006

Approach: One Dimensional $\{0, 1\}$ Lattice Configuration $\sigma_k(t)$, k : cell index. (ASEP: cars moving to the right)



One Step: $k \rightarrow k + 1$ during time-interval Δt

Spin Exchange:

$$[\sigma_k(t) = 1, \sigma_{k+1}(t) = 0] \rightarrow [\sigma_k(t + \Delta t) = 0, \sigma_{k+1}(t + \Delta t) = 1]$$

Two cars cannot occupy the same cell

Microscopic Stochastic Lattice Model

Transition Probability: For cells $[\sigma_k, \sigma_{k+1}]$

$$Pr\{[\sigma_k = 0, \sigma_{k+1} = 1](t + \Delta t) \mid [\sigma_k = 1, \sigma_{k+1} = 0](t)\} \approx c_0 \Delta t$$

where c_0 is the characteristic velocity

Rewrite Transition Probability:

$$Pr\{\text{Transition } \sigma_k(t) \rightarrow \sigma_{k+1}(t + \Delta t)\} \approx \sigma_k(1 - \sigma_{k+1})c_0 \Delta t$$

Goal: Understand Ensemble Simulations

In particular Traffic Density: $\mathbb{E} \sigma_k(t)$

Equation for the Time-Evolution of the Density $\rho_k(t) = \mathbb{E} \sigma_k(t)$:

Only two events are important $k \rightarrow k + 1$ and $k - 1 \rightarrow k$

$$\frac{d}{dt} \mathbb{E} \sigma_k = \mathbb{E} [c_0 \sigma_{k-1} (1 - \sigma_k) - c_0 \sigma_k (1 - \sigma_{k+1})]$$

The equation is exact, but not closed

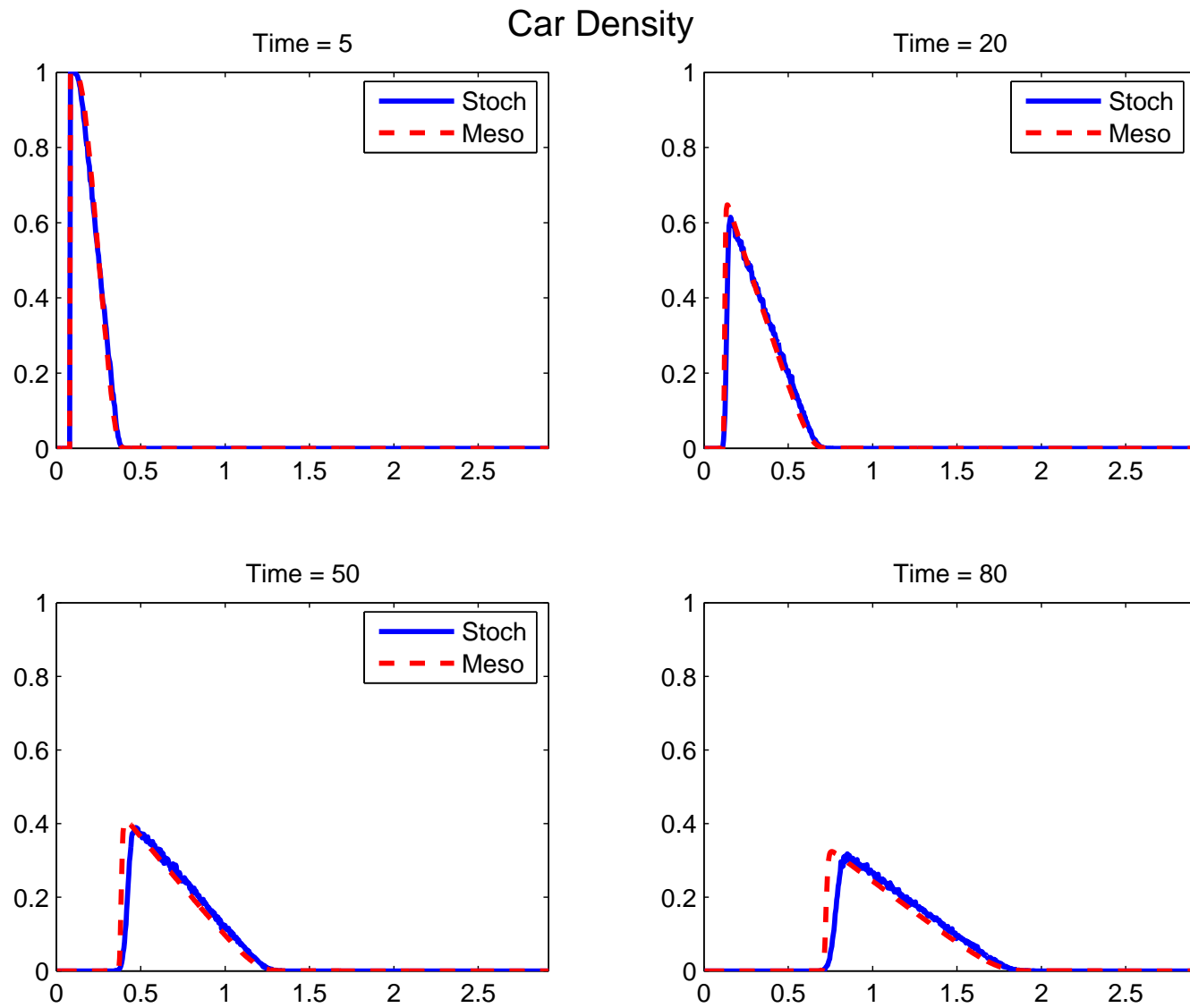
Closure Assumption: Approximate Independence

$$\mathbb{E}[\sigma_k \sigma_{k+1}] \approx \mathbb{E}[\sigma_k] \mathbb{E}[\sigma_{k+1}]$$

Mesoscopic Model: $\rho_k(t) = \mathbb{E} \sigma_k(t)$

$$\dot{\rho}_k = c_0 \rho_{k-1} (1 - \rho_k) - c_0 \rho_k (1 - \rho_{k+1})$$

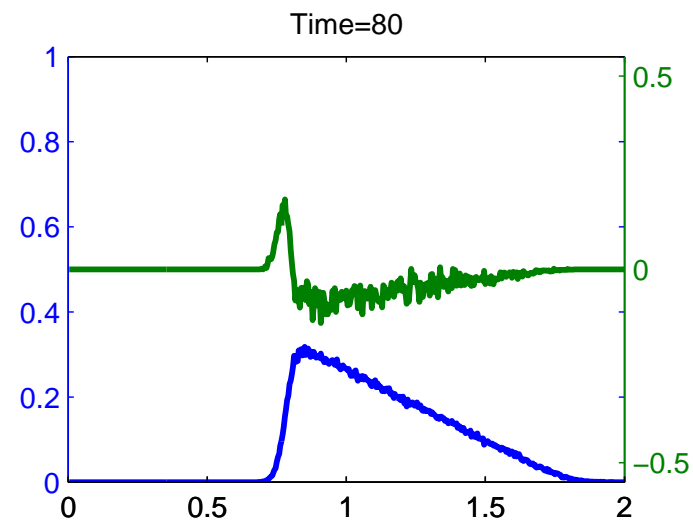
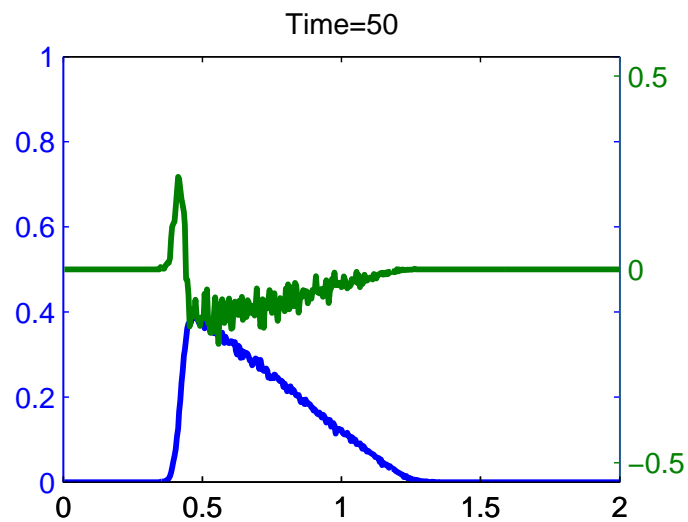
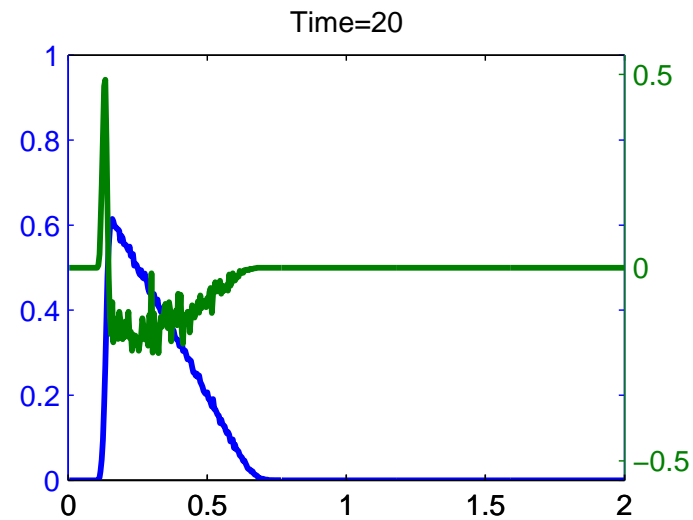
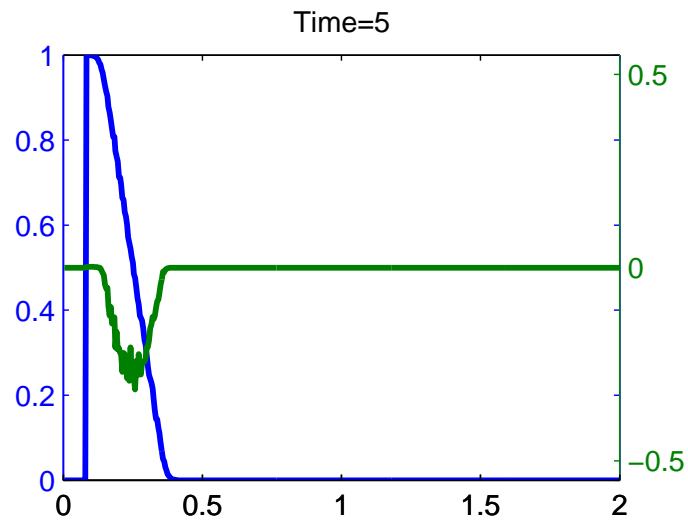
Comparing Microscopic and Mesoscopic Simulations: Car Density



Blue: Stochastic MC Simulations

Red: Mesoscopic Model for $\rho_k(t)$

Testing the Independence Assumption

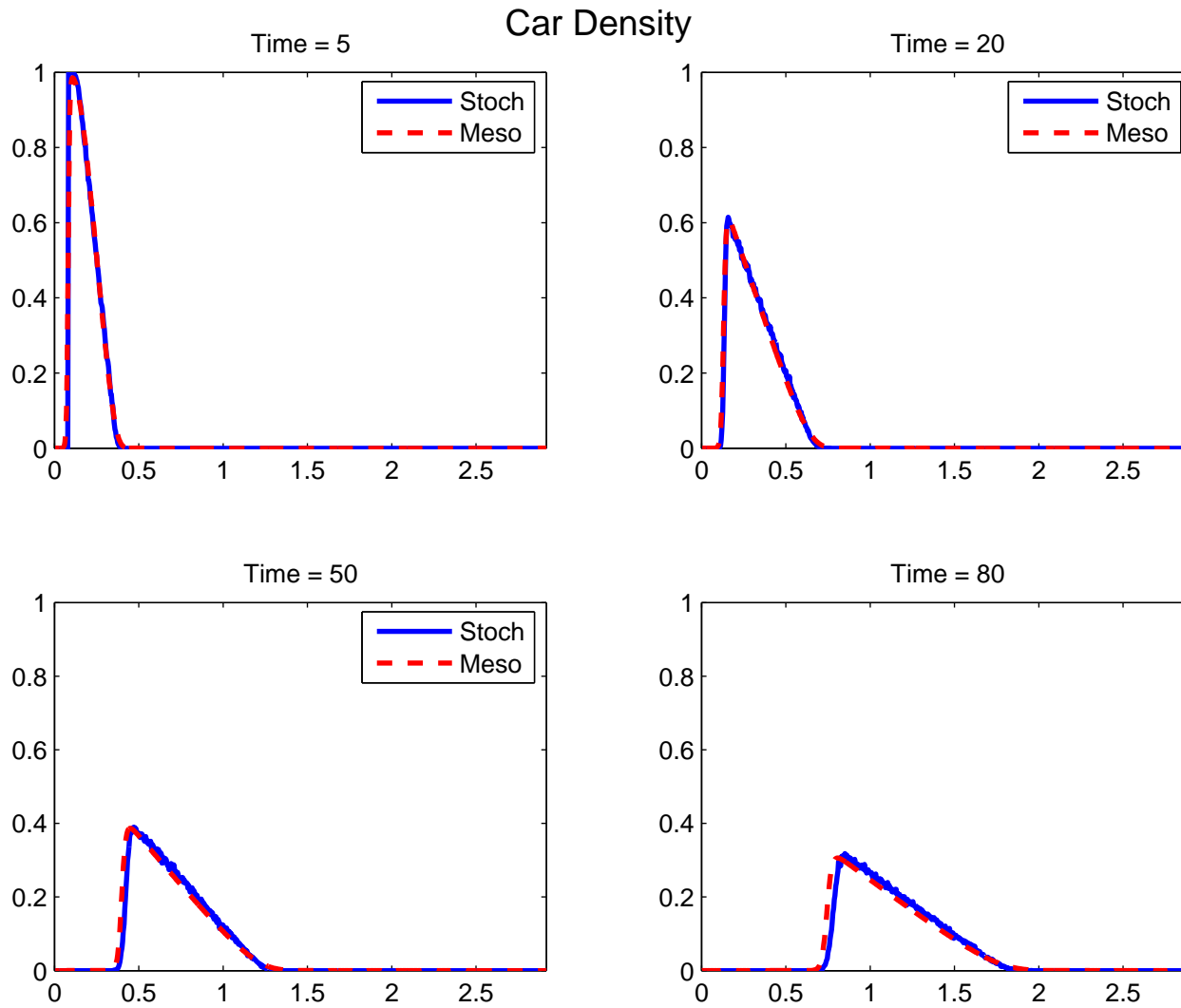


Blue: Car Density

Green: $\mathbb{E}[\sigma_k \sigma_{k+1}] - \mathbb{E}[\sigma_k] \mathbb{E}[\sigma_{k+1}]$

Comparing Microscopic and Mesoscopic Simulations: Car Density

Mesoscopic Model with Diffusion



Blue: Stochastic MC Simulations

Red: Mesoscopic Model for $\rho_k(t)$

Variance in Stochastic Simulations (Hauck, Sun, I.T.)

Consider: $v_k(t) = \mathbb{E} \sigma_k^2(t)$

Equations for the Mean and Variance:

$$\dot{\rho}_k = c_0 \rho_{k-1} (1 - \rho_k) - c_0 \rho_k (1 - \rho_{k+1})$$

$$\dot{v}_k = c_0 \rho_{k-1} (1 - \rho_k) - c_0 \rho_k (1 - \rho_{k+1})$$

Then:

$$v_k = \rho_k + C_k$$

$$Var_k = \rho_k - \rho_k^2 + C_k$$

Derivation Involves:

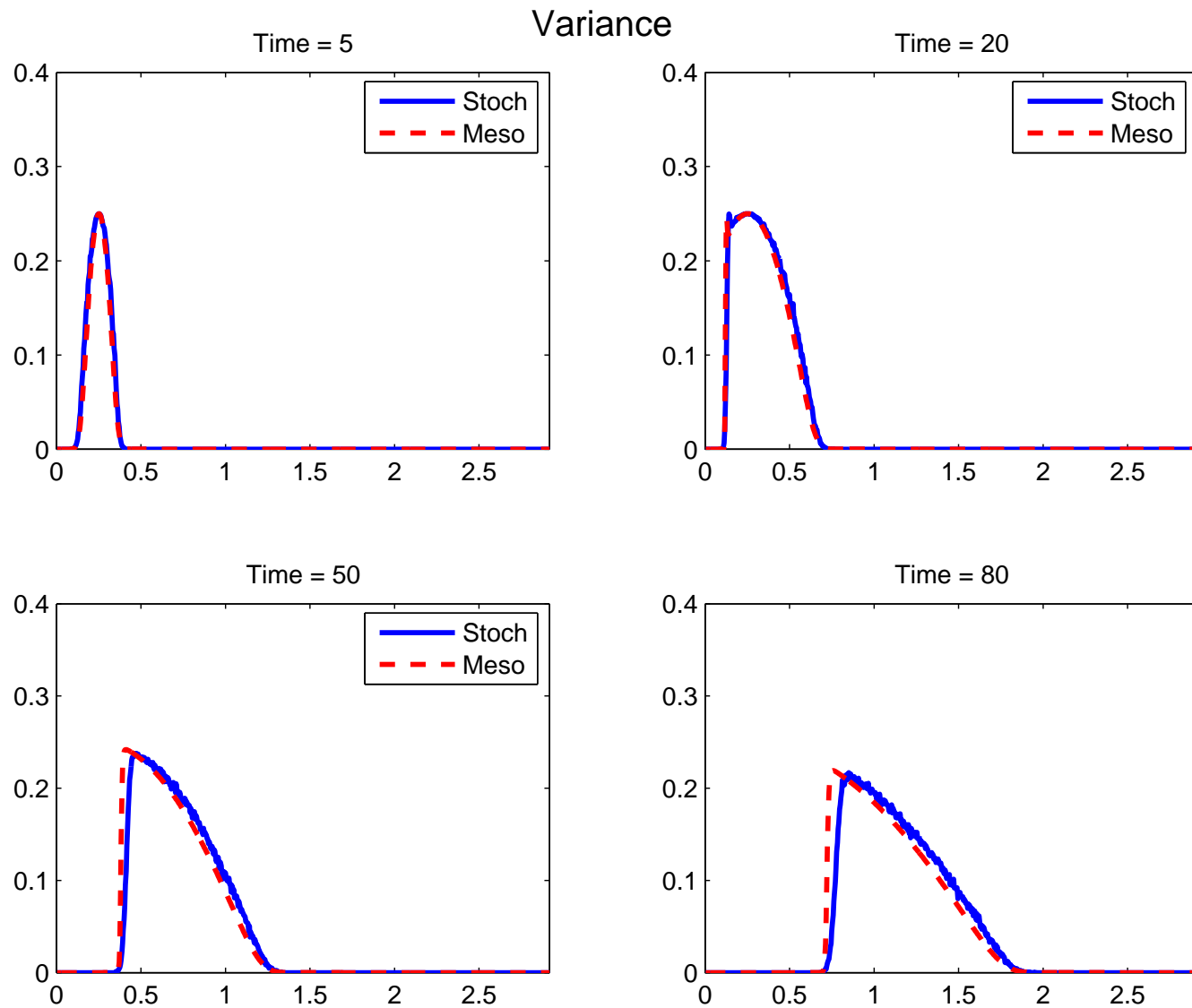
$$Af = \frac{\mathbb{E}[f(\sigma(\Delta t))] - f(\sigma)}{\Delta t}$$

where $f = f(\sigma)$ is any test function on the whole lattice.

To derive equation for ρ_k : $f = \sigma_k$

To derive equation for v_k : $f = \sigma_k^2$

Variance in Stochastic Simulations



Blue: Stochastic MC Simulations

Red: Mesoscopic Model for $\rho_k(t)$

Look-Ahead Potential (Sopasakis & Katsoulakis 06)

Transition Probability: $k \rightarrow k + 1$

$$Pr\{\text{Transition } \sigma_k(t) \rightarrow \sigma_{k+1}(t + \Delta t)\} \approx \sigma_k(1 - \sigma_{k+1})c_0 e^{-\beta J_k} \Delta t$$

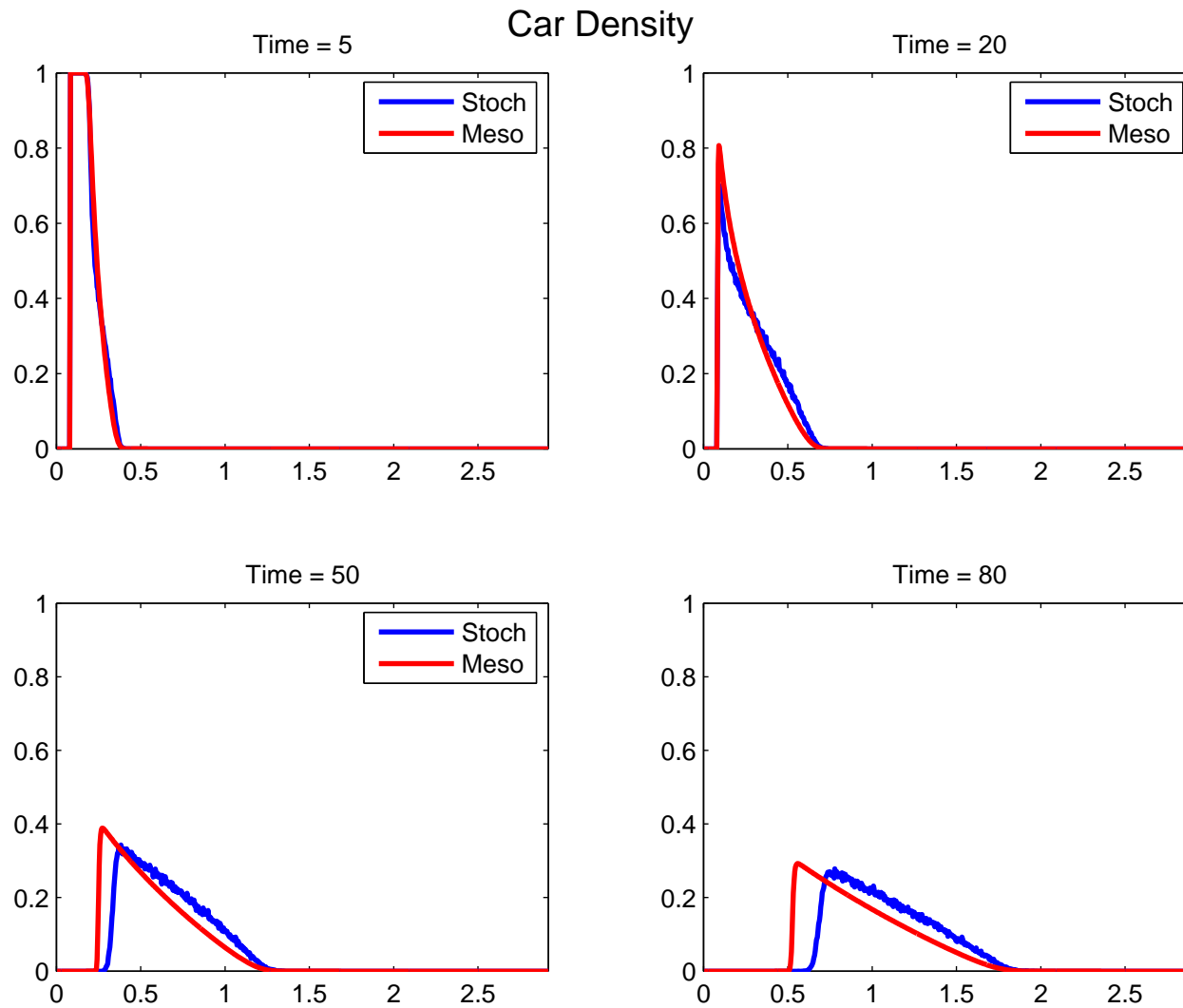
$$J_k = \frac{1}{M} \sum_{l=k+2}^{k+1+M} \sigma_l(t)$$

Takes into account presence/absence of cars in cells $k + 2, \dots, k + 1 + M$

Mesoscopic Model

$$\begin{aligned} \dot{\rho}_k &= c_0 \rho_{k-1} (1 - \rho_k) \prod_{i=1}^M \left[1 + \rho_{k+i} (e^{-\beta/M} - 1) \right] - \\ &\quad c_0 \rho_k (1 - \rho_{k+1}) \prod_{i=1}^M \left[1 + \rho_{k+i+1} (e^{-\beta/M} - 1) \right] \end{aligned}$$

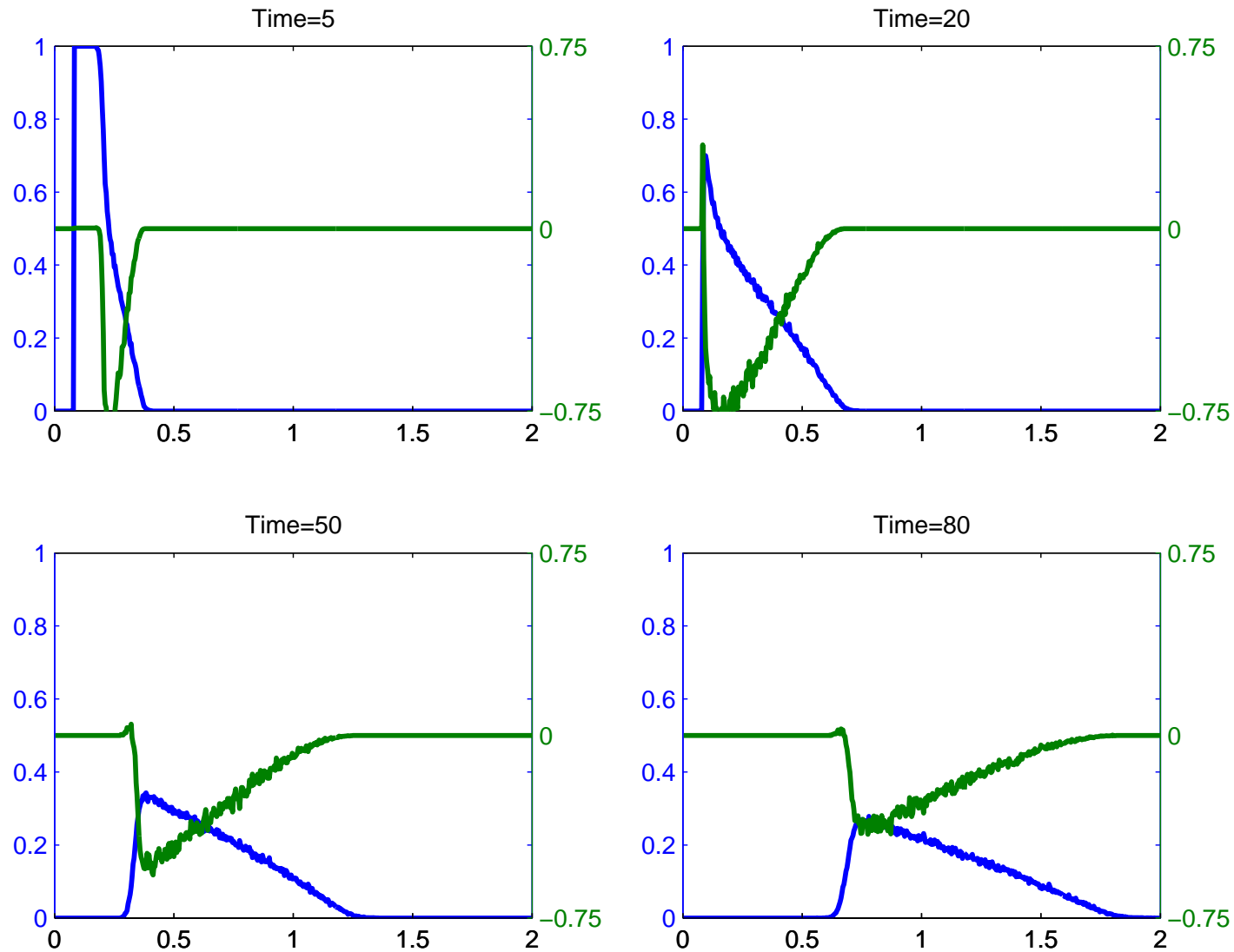
Comparing Microscopic and Mesoscopic Simulations with LH: Car Density



Blue: Stochastic MC Simulations

Red: Mesoscopic Model for $\rho_k(t)$

Testing the Independence Assumption with Look-Ahead Potential

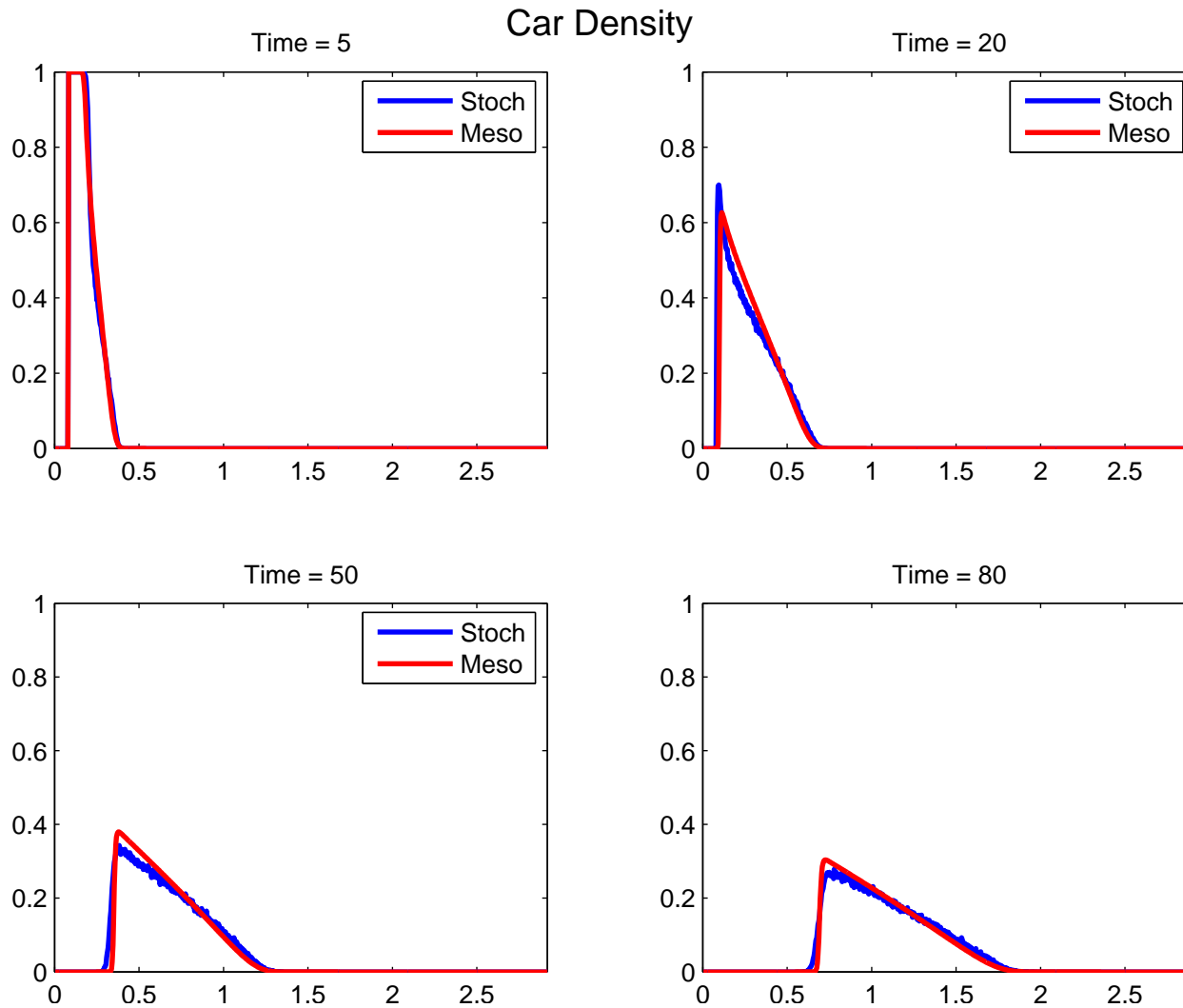


Blue: Car Density

Green: $\mathbb{E}[\sigma_k \sigma_{k+1}] - \mathbb{E}[\sigma_k] \mathbb{E}[\sigma_{k+1}]$

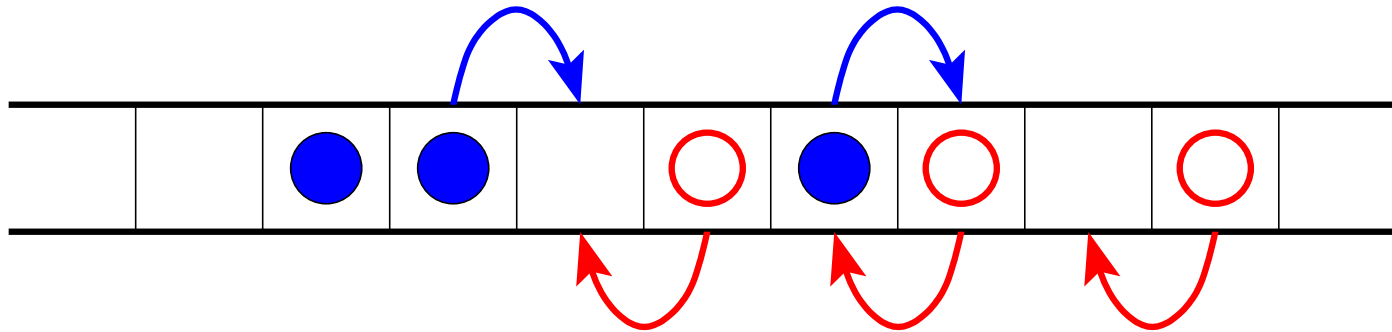
Modified Mesoscopic Model:

$$\dot{\rho}_k = c_0 \rho_{k-1} (1 - \rho_k) \left[1 + \rho_{k+1} (e^{-\beta \rho_{k+1}^d} - 1) \right] - c_0 \rho_k (1 - \rho_{k+1}) \left[1 + \rho_{k+2} (e^{-\beta \rho_{k+2}^d} - 1) \right]$$



Microscopic Stochastic Lattice Model of Pedestrian Traffic

Major Difference: Bi-directional model



Approach: One Dimensional $\{0, 1\}$ Lattice Configuration for

$\sigma_k^+(t)$ – pedestrians moving to the right

$\sigma_k^-(t)$ – pedestrians moving to the left

If no pedestrians in the opposite direction: Equivalent to car traffic models

One Step: $k \rightarrow k + 1$ during time-interval Δt

$$[\sigma_k^+(t), \sigma_{k+1}^+(t)] = [1, 0] \rightarrow [\sigma_k^+(t + \Delta t), \sigma_{k+1}^+(t + \Delta t)] = [0, 1]$$

Two pedestrians moving in the same direction cannot occupy the same cell

Microscopic Stochastic Lattice Model

Transition Probability: For cells $[\sigma_k^+, \sigma_{k+1}^+]$

$$[\sigma_k^-, \sigma_{k+1}^-] = [0, 0] : \quad Pr\{[0, 1](t + \Delta t) \mid [1, 0](t)\} \approx c_0 \Delta t$$

where c_0 is the characteristic velocity

Pedestrians Moving in the Opposite Direction are Present:

$$[\sigma_k^-, \sigma_{k+1}^-] = [1, 0] : \quad Pr\{[0, 1](t + \Delta t) \mid [1, 0](t)\} \approx c_1 \Delta t$$

$$[\sigma_k^-, \sigma_{k+1}^-] = [0, 1] : \quad Pr\{[0, 1](t + \Delta t) \mid [1, 0](t)\} \approx c_2 \Delta t$$

$$[\sigma_k^-, \sigma_{k+1}^-] = [1, 1] : \quad Pr\{[0, 1](t + \Delta t) \mid [1, 0](t)\} \approx c_3 \Delta t$$

where

$$c_0 > c_1 \approx c_2 > c_3$$

Goal

Understand the Density of the Pedestrian Traffic: $\mathbb{E} \sigma_k^+(t)$ and $\mathbb{E} \sigma_k^-(t)$

Equations for the Time-Evolution of the Density $\mathbb{E} \sigma_k^+(t)$: Only two events are important $k \rightarrow k+1$ and $k-1 \rightarrow k$

$$\begin{aligned} \frac{d}{dt} \mathbb{E} \sigma_k^+ &= \mathbb{E} [c_0 \sigma_{k-1}^+ (1 - \sigma_k^+) (1 - \sigma_{k-1}^-) (1 - \sigma_k^-) - \\ &\quad c_0 \sigma_k^+ (1 - \sigma_{k+1}^+) (1 - \sigma_k^-) (1 - \sigma_{k+1}^-) + \\ &\quad c_1 \sigma_{k-1}^+ (1 - \sigma_k^+) \sigma_{k-1}^- (1 - \sigma_k^-) - c_1 \sigma_k^+ (1 - \sigma_{k+1}^+) \sigma_k^- (1 - \sigma_{k+1}^-) + \\ &\quad c_2 \sigma_{k-1}^+ (1 - \sigma_k^+) (1 - \sigma_{k-1}^-) \sigma_k^- - c_2 \sigma_k^+ (1 - \sigma_{k+1}^+) (1 - \sigma_k^-) \sigma_{k+1}^- + \\ &\quad c_3 \sigma_{k-1}^+ (1 - \sigma_k^+) \sigma_{k-1}^- \sigma_k^- - c_3 \sigma_k^+ (1 - \sigma_{k+1}^+) \sigma_k^- \sigma_{k+1}^-] \end{aligned}$$

The equations are exact, but not closed

Closure Assumptions

Approximate Independence:

$$\mathbb{E}[\sigma_{k-1}^+ \sigma_k^+ \sigma_{k-1}^- \sigma_k^-] \approx \mathbb{E}[\sigma_{k-1}^+] \mathbb{E}[\sigma_k^+] \mathbb{E}[\sigma_{k-1}^-] \mathbb{E}[\sigma_k^-]$$

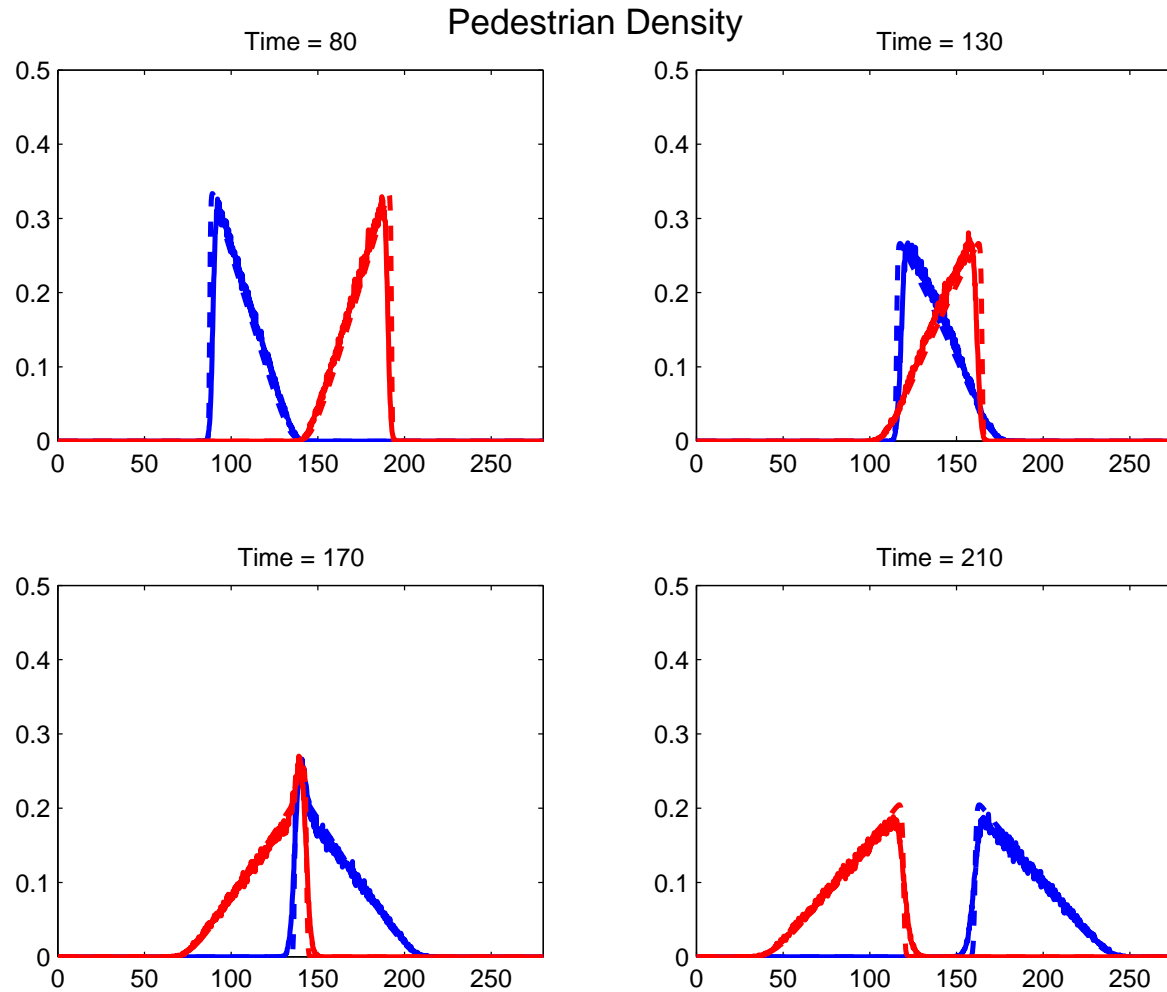
Mesoscopic Model: $\rho_k^\pm(t) = \mathbb{E} \sigma_k^\pm(t)$

$$\begin{aligned} \frac{d}{dt} \rho_k^+ &= c_0 \rho_{k-1}^+ (1 - \rho_k^+) (1 - \rho_{k-1}^-) (1 - \rho_k^-) - \\ &\quad c_0 \rho_k^+ (1 - \rho_{k+1}^+) (1 - \rho_k^-) (1 - \rho_{k+1}^-) + \\ &\quad c_1 \rho_{k-1}^+ (1 - \rho_k^+) \rho_{k-1}^- (1 - \rho_k^-) - c_1 \rho_k^+ (1 - \rho_{k+1}^+) \rho_k^- (1 - \rho_{k+1}^-) + \\ &\quad c_2 \rho_{k-1}^+ (1 - \rho_k^+) (1 - \rho_{k-1}^-) \rho_k^- - c_2 \rho_k^+ (1 - \rho_{k+1}^+) (1 - \rho_k^-) \rho_{k+1}^- + \\ &\quad c_3 \rho_{k-1}^+ (1 - \rho_k^+) \rho_{k-1}^- \rho_k^- - c_3 \rho_k^+ (1 - \rho_{k+1}^+) \rho_k^- \rho_{k+1}^- \end{aligned}$$

Numerical Comparison of Microscopic and Mesoscopic Models

Weak Slowdown: $\alpha = 1.5$

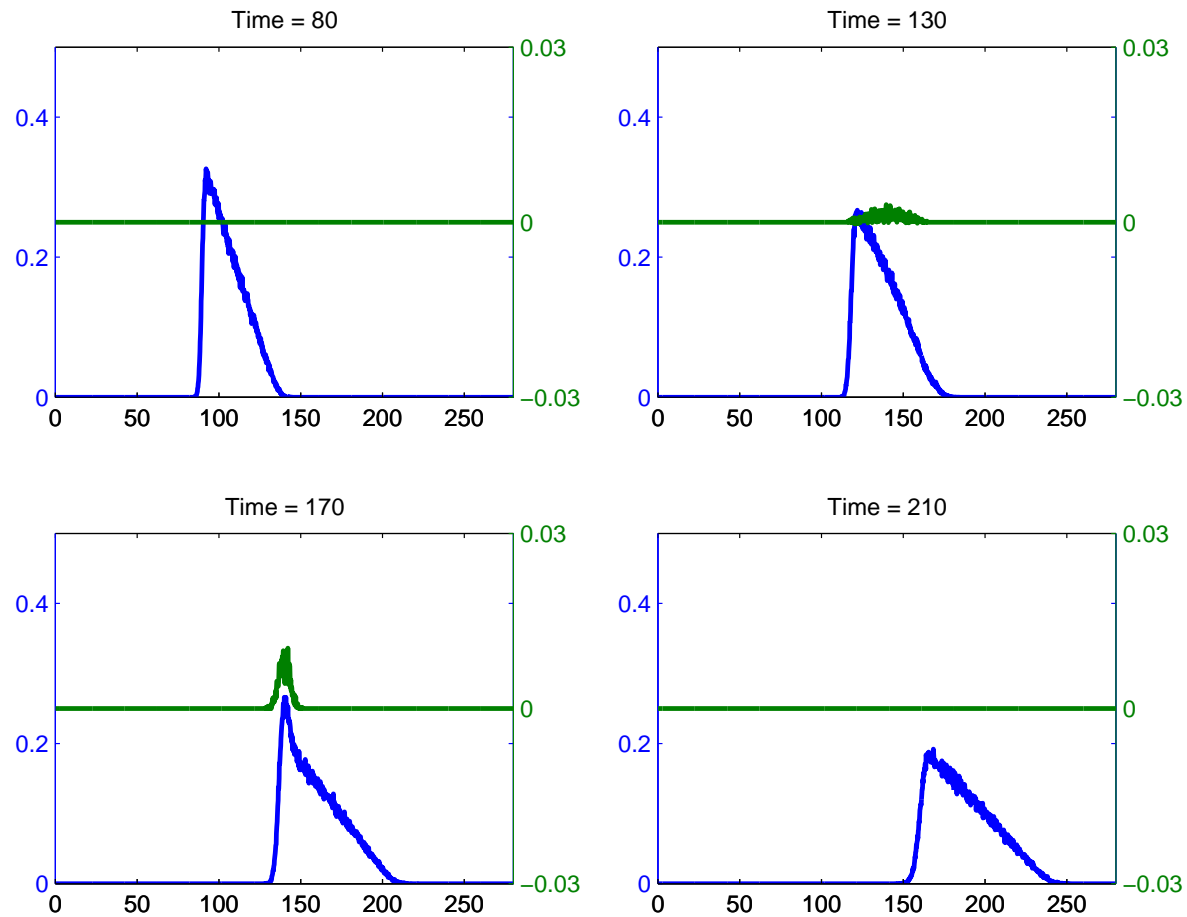
$$c_0 = 0.8m/s, \quad c_1 = c_2 = c_0/\alpha, \quad c_3 = c_0/(2\alpha)$$



Numerical Comparison of Microscopic and Mesoscopic Models

Weak Slowdown: $\alpha = 1.5$

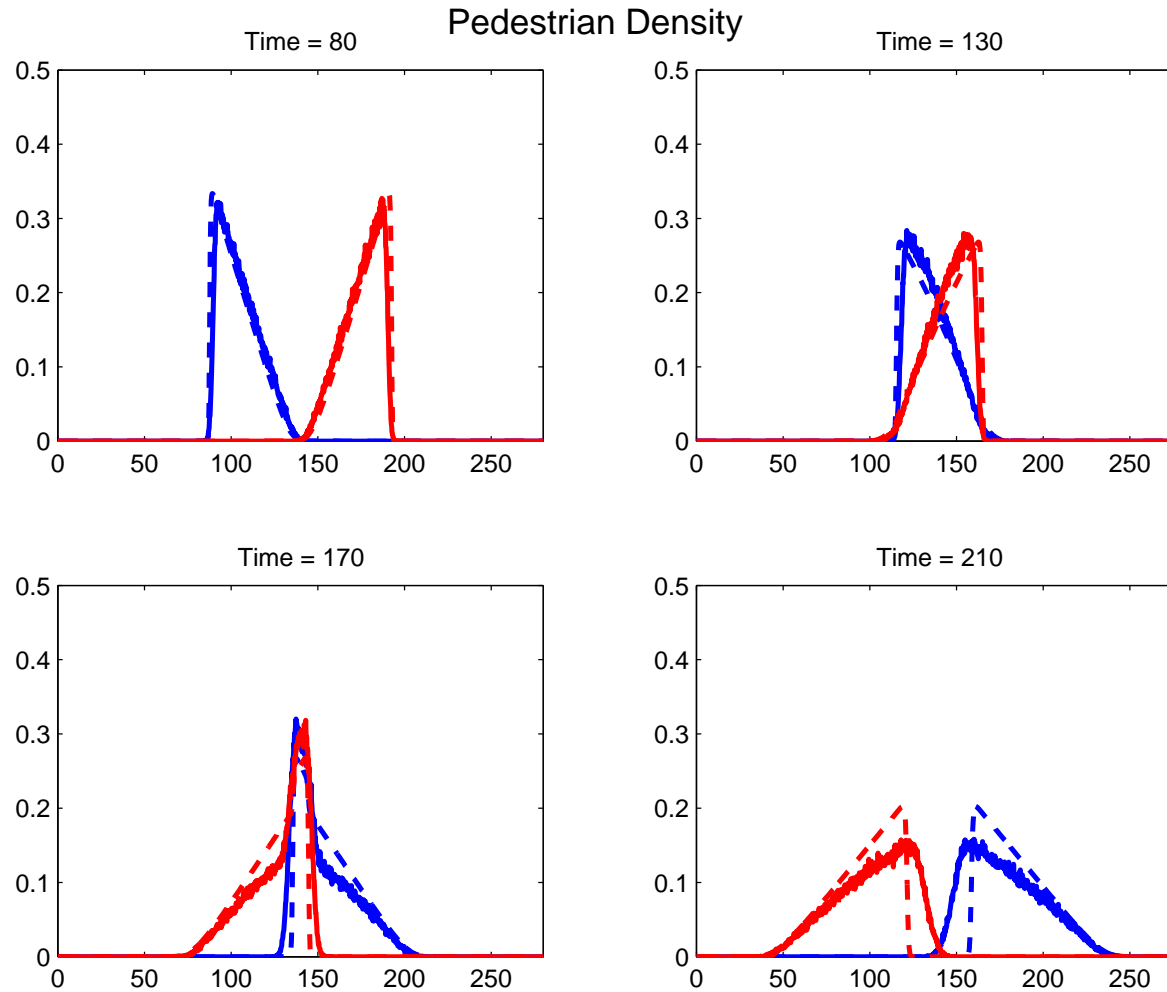
$$c_0 = 0.8m/s, \quad c_1 = c_2 = c_0/\alpha, \quad c_3 = c_0/(2\alpha)$$



Numerical Comparison of Microscopic and Mesoscopic Models

Intermediate Slowdown: $\alpha = 2$

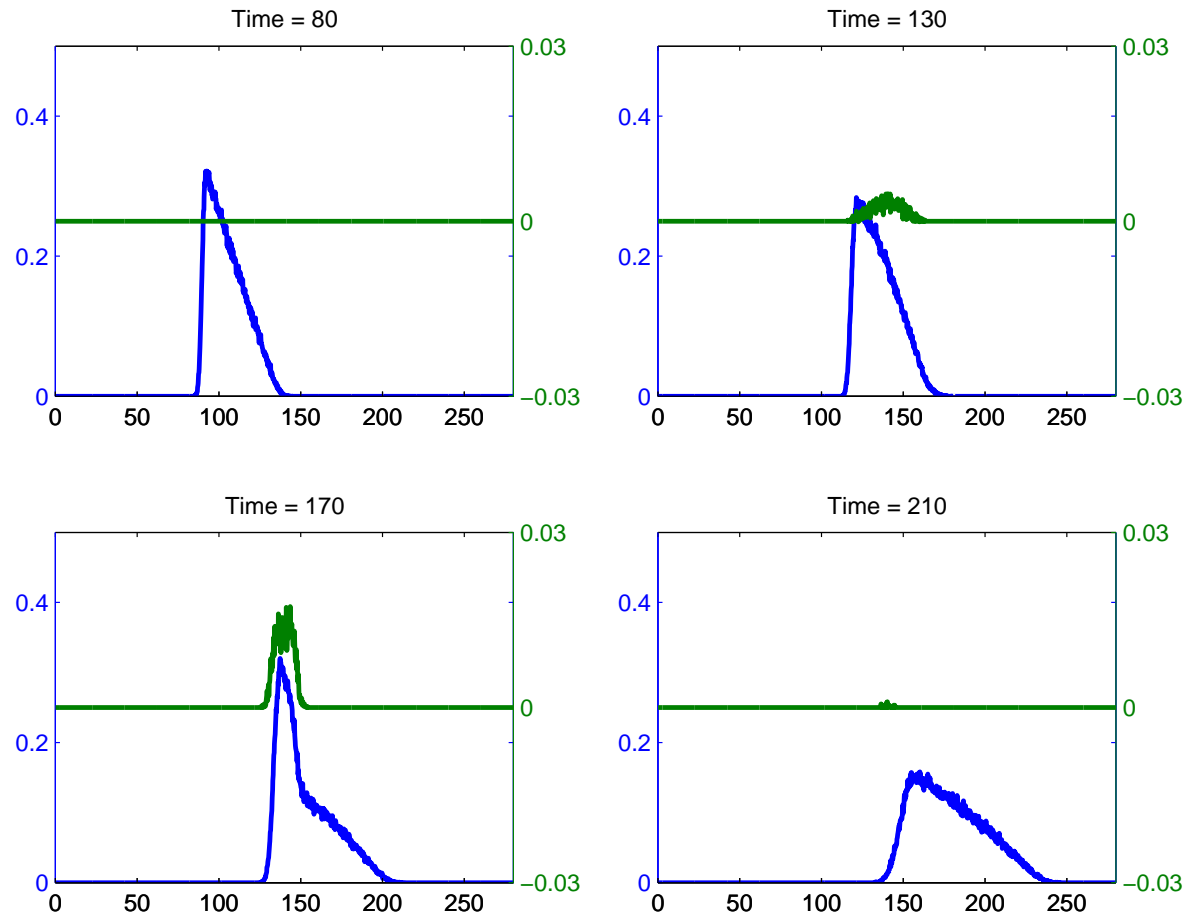
$$c_0 = 0.8m/s, \quad c_1 = c_2 = c_0/\alpha, \quad c_3 = c_0/(2\alpha)$$



Numerical Comparison of Microscopic and Mesoscopic Models

Intermediate Slowdown: $\alpha = 2$

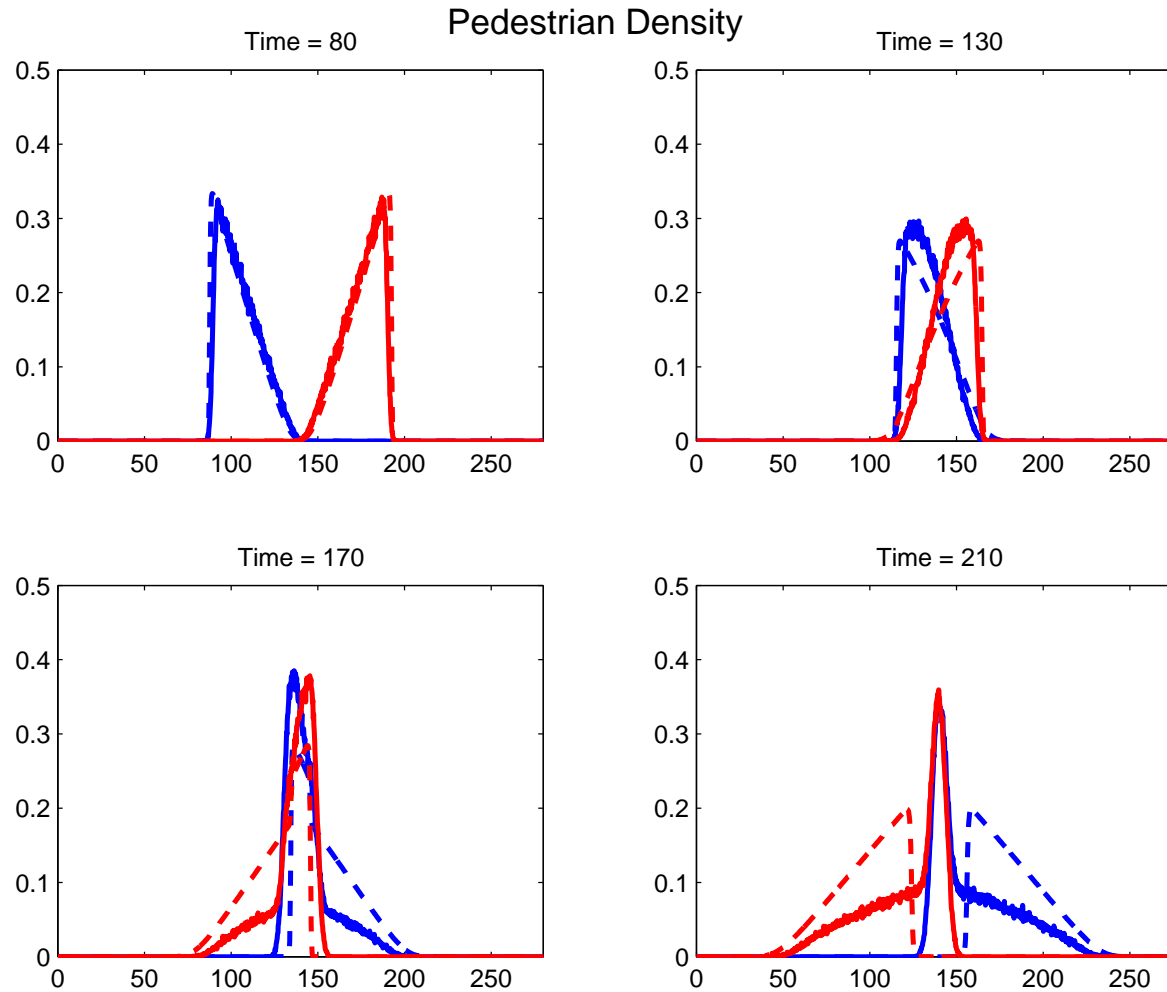
$$c_0 = 0.8m/s, \quad c_1 = c_2 = c_0/\alpha, \quad c_3 = c_0/(2\alpha)$$



Numerical Comparison of Microscopic and Mesoscopic Models

Strong Slowdown: $\alpha = 3$

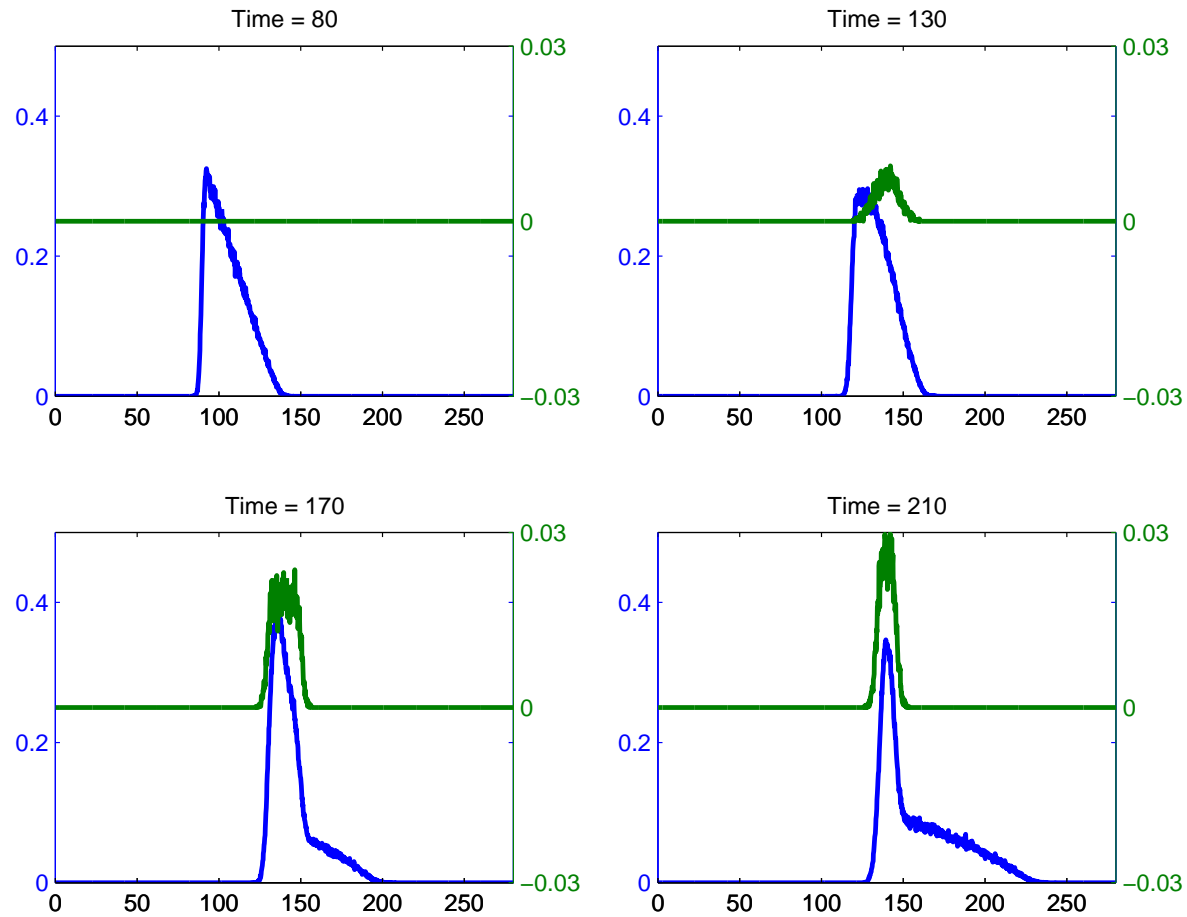
$$c_0 = 0.8m/s, \quad c_1 = c_2 = c_0/\alpha, \quad c_3 = c_0/(2\alpha)$$



Numerical Comparison of Microscopic and Mesoscopic Models

Strong Slowdown: $\alpha = 3$

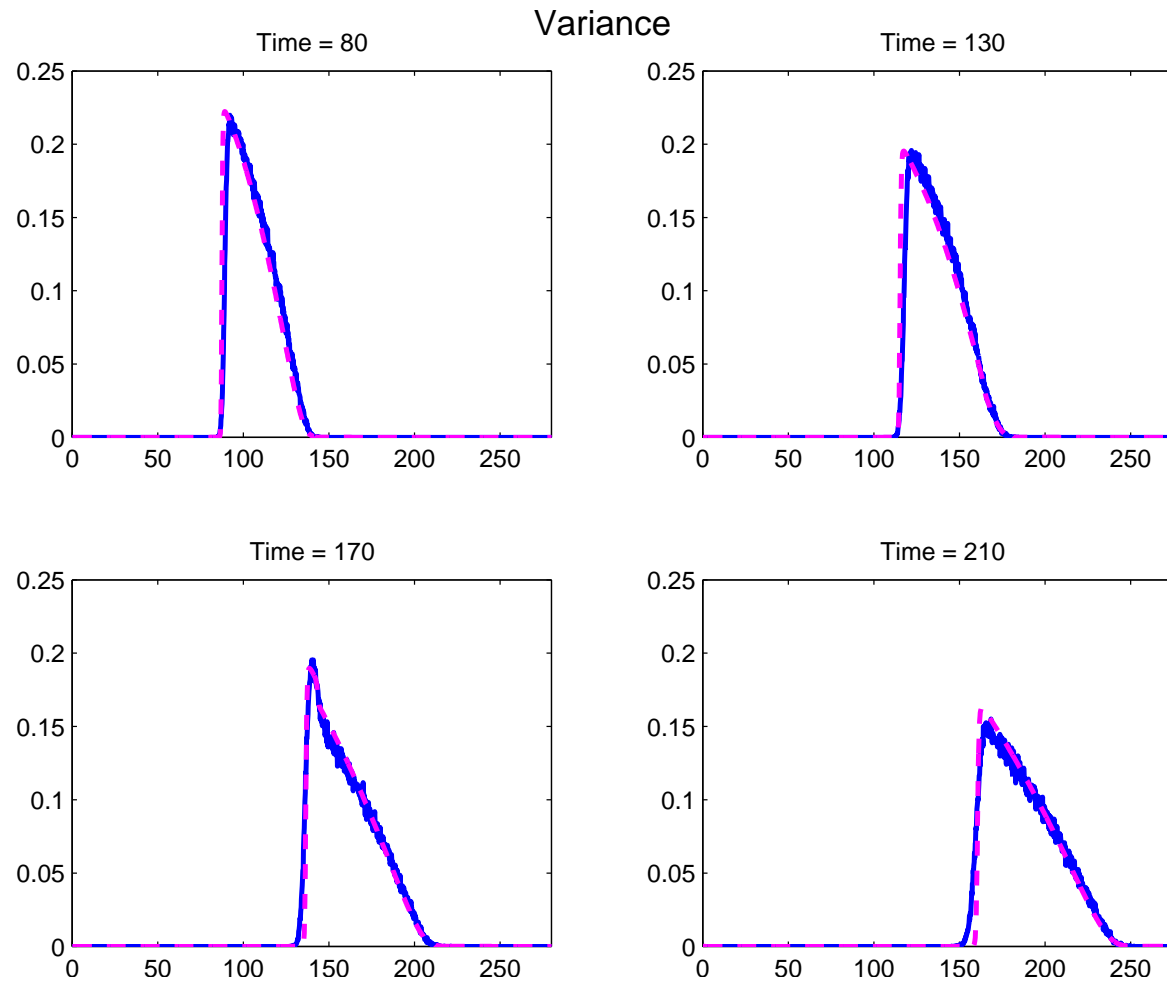
$$c_0 = 0.8m/s, \quad c_1 = c_2 = c_0/\alpha, \quad c_3 = c_0/(2\alpha)$$



Variance in Microscopic and Mesoscopic Models

Weak Slowdown: $\alpha = 1.5$

$$c_0 = 0.8m/s, \quad c_1 = c_2 = c_0/\alpha, \quad c_3 = c_0/(2\alpha)$$



Conclusions

- Explicit Microscopic Interaction Rules Determine the Functional Form of the corresponding PDE model
- Framework for Systematic Derivation of PDE Models
- Look-Ahead information can also be included in the model
- Important to Understand Regime of Validity
- Variance of Stochastic Simulations can be Easily Inferred from the Density