Analysis of tandem fluid queues

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Model: two fluid queues driven by $\varphi(t)$

- CTMC $\varphi(t)$ with finite state space *S*, generator **T**
- Two fluid queues, contents X(t) and Y(t), both $\in [0,\infty)$



First queue X(t) driven by $\varphi(t)$

- $(\varphi(t), X(t))$ is standard fluid queue
- Fluid rates in $\mathbf{R} = diag(r_i)_{i \in S}$

$$rac{d}{dt}X(t) = r_{arphi(t)}$$
 when $X(t) > 0$,
 $rac{d}{dt}X(t) = \max(0, r_{arphi(t)})$ when $X(t) = 0$.

- $S = S_+ \cup S_- \cup S_{\bigcirc}$, e.g. $S_+ = \{i \in S : r_i > 0\}$ (upstates, downstates, zero-states)
- also: $\mathcal{S}_{\ominus} = \mathcal{S}_{-} \cup \mathcal{S}_{\bigcirc}$ ("zero-states at X(t) = 0")
- after ordering,

$$\mathbf{T} = \begin{bmatrix} \mathbf{T}_{++} & \mathbf{T}_{+-} & \mathbf{T}_{+} \\ \mathbf{T}_{-+} & \mathbf{T}_{--} & \mathbf{T}_{-} \\ \mathbf{T}_{0+} & \mathbf{T}_{0-} & \mathbf{T}_{00} \end{bmatrix}$$

Second queue Y(t) driven by $(\varphi(t), X(t))$

- Y(t) increases when X(t) > 0, at rate $\hat{c}_i > 0$
- Y(t) decreases when X(t) = 0, at rate č_i < 0 (unless Y(t) = 0)

So

$$\begin{split} & \frac{d}{dt} Y(t) = \widehat{c}_{\varphi(t)} > 0 & \text{when } X(t) > 0, \\ & \frac{d}{dt} Y(t) = \widecheck{c}_{\varphi(t)} < 0 & \text{when } X(t) = 0, \, Y(t) > 0, \\ & \frac{d}{dt} Y(t) = \widehat{c}_{\varphi(t)} \cdot 1\{\varphi(t) \in \mathcal{S}_+\} & \text{when } X(t) = 0, \, Y(t) = 0. \end{split}$$

•
$$\widehat{\mathbf{C}} = diag(\widehat{c}_i)_{i \in S}$$
 and $\widecheck{\mathbf{C}} = diag(\widecheck{c}_i)_{i \in S}$

Special case: $\mathcal{S}_{\bigcirc} = \emptyset, \ |\mathcal{S}_{+}| = |\mathcal{S}_{-}| = 1, \quad \widehat{\mathbf{C}} = -\widecheck{\mathbf{C}} = \mathbf{I}$



[Kroese and Scheinhardt. Joint Distributions for Interacting Fluid Queues, *Queueing Systems*, 2001]

Qualitative behaviour



Assuming stability (see paper) process ($\varphi(t), X(t), Y(t)$) alternates between:

- (i) periods on x = 0
- (ii) periods on x > 0

Qualitative behaviour (i) on x = 0



(i) periods on x = 0

- Y(t) decreasing, unless at x = 0, y = 0
- $\varphi(t)$ in \mathcal{S}_{\ominus}
- starts at x = 0, y > 0, with $\varphi(t)$ in S_{-}
- ends at $x = 0, y \ge 0$, with $\varphi(t)$ jumping from \mathcal{S}_{\ominus} to \mathcal{S}_{+}

Qualitative behaviour (ii) on x > 0



(ii) periods on x > 0

- Y(t) increasing (while X(t) can either increase or decrease)
- $\varphi(t)$ in \mathcal{S} (any phase)
- starts at $x = 0, y \ge 0$, with $\varphi(t) \in S_+$
- ends at x = 0, y > 0, with $\varphi(t) \in S_{-}$

Stationary distribution

(ii)

has following form (all *vectors* with |S| components):

- (i) 1-dimensional densities $\pi(0, y)$ at x = 0, y > 0
 - point masses **p**(0,0) at (0,0)
 - 2-dimensional densities π(x, y) on {(x, y) : x > 0, y > x ⋅ min_{i∈S+}{ĉ_i/r_i}}
 - 1-dimensional density $\pi^i(x, x\hat{c}_i/r_i)$ on line $y = x\hat{c}_i/r_i$, $i \in S_+$







Approach

Several steps:

- Introduce embedded discrete-time process J_k
- Find its stationary distribution ξ_{γ}
- Take a deep breath...
- Express $\pi(0, y)$ and $\mathbf{p}(0, 0)$ in ξ_y , using down-shift in Y
- Normalise based on knowledge of $(\varphi(t), X(t))$
- Express $\pi(x, y)$ in $\pi(0, y)$ and $\mathbf{p}(0, 0)$, using up-shift in Y
- Express $\pi^i(x, x\hat{c}_i/r_i)$ in $\mathbf{p}(0, 0)$

Mostly as LST's (but not always)

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Approach

Several steps:

- Introduce embedded discrete-time process J_k
- Find its stationary distribution ξ_{v}
- Take a deep breath...
- Express $\pi(0, y)$ and $\mathbf{p}(0, 0)$ in $\boldsymbol{\xi}_{y}$, using down-shift in Y
- Normalise based on knowledge of (φ(t), X(t))
- Express $\pi(x, y)$ in $\pi(0, y)$ and $\mathbf{p}(0, 0)$, using up-shift in Y
- Express $\pi^i(x, x\hat{c}_i/r_i)$ in $\mathbf{p}(0, 0)$

Mostly as LST's (but not always)

Intermezzo (i) on down-shift: $\mathbf{\check{Q}}_{\ominus\ominus}$ and $\mathbf{\check{Q}}_{\ominus+}$

Define generator matrix

$$\check{\boldsymbol{\mathsf{Q}}}_{\ominus\ominus}=(|\check{\boldsymbol{\mathsf{C}}}_{\ominus}|)^{-1}\boldsymbol{\mathsf{T}}_{\ominus\ominus},$$

then for $i, j \in S_{\ominus}$, and z > 0,

$$[e^{\breve{\mathbf{Q}}_{\ominus\ominus}z}]_{ij} = P(\varphi(t_z) = j, \varphi(u) \in \mathcal{S}_{\ominus}, 0 \le u \le t_z \mid \varphi(0) = i, X(0) = 0)$$

Also,

$$\check{\boldsymbol{\mathsf{Q}}}_{\ominus +} = (|\check{\boldsymbol{\mathsf{C}}}_\ominus|)^{-1}\boldsymbol{\mathsf{T}}_{\ominus +},$$

is a matrix of transition rates (w.r.t. level) to phases in S_+ (for times at which *X* and *Y* start increasing)

[Bean, O'Reilly and Taylor. Hitting probabilities and hitting times for stochastic fluid flows, *SPA* 2005]

Intermezzo (ii) on up-shift: $\widehat{\mathbf{Q}}(s)$ and $\widehat{\mathbf{\Psi}}(s)$

Let $\theta = \inf\{t > 0 : X(t) = 0\}$ and $U(t) = \int_{u=0}^{t} \hat{c}_{\varphi(u)} du$, then $U(\theta)$ is total up-shift in *Y* during Busy Period of *X* Its $|S_{+}| \times |S_{-}|$ density matrix $\hat{\psi}(z)$ is given via LST

$$\widehat{\Psi}(s) = \int_{z=0}^{\infty} e^{-sz} \widehat{\psi}(z) dz,$$

as

$$[\widehat{\Psi}(s)]_{ij} = E(e^{-sU(\theta)} \mathbb{1}\{\varphi(\theta) = j\} \mid \varphi(0) = i, X(0) = 0),$$

[Bean and O'Reilly. A stochastic two-dimensional fluid model, *Stochastic Models*, 2013]

Intermezzo (ii) on up-shift: $\widehat{\mathbf{Q}}(s)$ and $\widehat{\Psi}(s)$

To find $\widehat{\Psi}(s)$ define Key generator matrix $\widehat{\mathbf{Q}}(s)$, as

$$\begin{split} \widehat{\mathbf{Q}}(s) &= \begin{bmatrix} \widehat{\mathbf{Q}}(s)_{++} & \widehat{\mathbf{Q}}(s)_{+-} \\ \widehat{\mathbf{Q}}(s)_{-+} & \widehat{\mathbf{Q}}(s)_{--} \end{bmatrix} \\ \widehat{\mathbf{Q}}(s)_{++} &= (\mathbf{R}_{+})^{-1} \left(\mathbf{T}_{++} - s\widehat{\mathbf{C}}_{+} - \mathbf{T}_{+\circ}(\mathbf{T}_{\circ\circ} - s\widehat{\mathbf{C}}_{\circ})^{-1}\mathbf{T}_{\circ+} \right) \\ \widehat{\mathbf{Q}}(s)_{+-} &= (\mathbf{R}_{+})^{-1} \left(\mathbf{T}_{+-} - \mathbf{T}_{+\circ}(\mathbf{T}_{\circ\circ} - s\widehat{\mathbf{C}}_{\circ})^{-1}\mathbf{T}_{\circ-} \right) \\ \widehat{\mathbf{Q}}(s)_{-+} &= (|\mathbf{R}_{-}|)^{-1} \left(\mathbf{T}_{-+} - \mathbf{T}_{-\circ}(\mathbf{T}_{\circ\circ} - s\widehat{\mathbf{C}}_{\circ})^{-1}\mathbf{T}_{\circ+} \right) \\ \widehat{\mathbf{Q}}(s)_{--} &= (|\mathbf{R}_{-}|)^{-1} \left(\mathbf{T}_{--} - s\widehat{\mathbf{C}}_{-} - \mathbf{T}_{-\circ}(\mathbf{T}_{\circ\circ} - s\widehat{\mathbf{C}}_{\circ})^{-1}\mathbf{T}_{\circ-} \right) \\ \text{Then } \widehat{\mathbf{\Psi}}(s) \text{ is minimum nonnegative solution of Riccati eq.} \\ \widehat{\mathbf{Q}}(s)_{+-} &+ \widehat{\mathbf{Q}}(s)_{++} \widehat{\mathbf{\Psi}}(s) + \widehat{\mathbf{\Psi}}(s)\widehat{\mathbf{Q}}(s)_{--} + \widehat{\mathbf{\Psi}}(s)\widehat{\mathbf{Q}}(s)_{-+} \widehat{\mathbf{\Psi}}(s) = \mathbf{0}, \end{split}$$

[Bean and O'Reilly. A stochastic two-dimensional fluid model, *Stochastic Models*, 2013]

Back on track... Embedded process J_k

Let $J_k = (\varphi(\theta_k), Y(\theta_k))$, with state space $\mathcal{S}_- \times (0, \infty)$, where θ_k is k-th time that $(\varphi(t), X(t), Y(t))$ hits x = 0

Lemma

The transition kernel of J_k is given by

$$\begin{aligned} \mathbf{P}_{z,y} &= \int_{u=[z-y]^+}^{z} \begin{bmatrix} \mathbf{I} & \mathbf{O} \end{bmatrix} e^{\check{\mathbf{Q}}_{\ominus\ominus} u} \check{\mathbf{Q}}_{\ominus+} \widehat{\psi}(y-z+u) du \\ &+ \begin{bmatrix} \mathbf{I} & \mathbf{O} \end{bmatrix} e^{\check{\mathbf{Q}}_{\ominus\ominus} z} (-\check{\mathbf{Q}}_{\ominus\ominus})^{-1} \check{\mathbf{Q}}_{\ominus+} \widehat{\psi}(y). \end{aligned}$$

where $[x]^+$ denotes max(0, x), and $\begin{bmatrix} I & O \end{bmatrix}$ is a $|S_-| \times |S_{\ominus}|$ matrix.

Embedded process J_k

Proof. Based on Lindley-type recursion,

$$Y(\theta_{k+1}) = [Y(\theta_k) - D_k]^+ + U_k, \qquad (1)$$

where

$$D_k = \int_{u= heta_k}^{ au_k} |\check{c}_{\varphi(u)}| du, \quad U_k = \int_{u= au_k}^{ heta_{k+1}} \widehat{c}_{\varphi(u)} du$$

So (i) Y(t) first has down-shift -D, as long as $\varphi(t) \in S_{\ominus}$ (ii) after jump $S_{\ominus} \rightarrow S_+$, Y(t) has up-shift U, during busy period of X.

Then use previous knowledge; note that J_k moves from (i, z) to (j, y) without or with returning to 0 during (θ_k, θ_{k+1}) .

Embedded process J_k

Corollary

The Laplace-Stieltjes transform of $\mathbf{P}_{z,y}$ w.r.t. y is given by

$$\begin{split} \mathbf{P}_{z,\cdot}(s) &= \begin{bmatrix} \mathbf{I} & \mathbf{O} \end{bmatrix} e^{-sz} \left(\widecheck{\mathbf{Q}}_{\ominus\ominus} + s\mathbf{I} \right)^{-1} \left(e^{\left(\widecheck{\mathbf{Q}}_{\ominus\ominus} + s\mathbf{I} \right)z} - \mathbf{I} \right) \\ &\times \widecheck{\mathbf{Q}}_{\ominus+} \widehat{\Psi}(s) \\ &+ \begin{bmatrix} \mathbf{I} & \mathbf{O} \end{bmatrix} e^{\widecheck{\mathbf{Q}}_{\ominus\ominus}z} (-\widecheck{\mathbf{Q}}_{\ominus\ominus})^{-1} \widecheck{\mathbf{Q}}_{\ominus+} \widehat{\Psi}(s). \end{split}$$

Proof. Using lemma, or based on (1) directly

Embedded process J_k – stationary distribution ξ_v

Stationary distribution of J_k is given by row vector $\boldsymbol{\xi}_z = [\xi_{i,z}]_{i \in S_-}$ of densities, satisfying

$$\begin{cases} \int_{z=0}^{\infty} \xi_z \mathbf{P}_{z,y} dz = \xi_y \\ \int_{y=0}^{\infty} \xi_y dy \mathbf{1} = \mathbf{1}, \end{cases}$$

Will be solved numerically.

Next step (after deep breath):

Express stationary distribution of $(\varphi(t), X(t), Y(t))$ at level x = 0 in terms of ξ_z .

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Expressing $\pi(0, y)$ and $\mathbf{p}(0, 0)$ in ξ_y



Expressing $\pi(0, y)$ and $\mathbf{p}(0, 0)$ in ξ_y

Lemma

We have $\pi(0,y)=\left[egin{array}{cc} m{0} & \pi(0,y)_{\ominus} \end{array}
ight]$, where

$$\pi(0,y)_{\ominus} = \alpha \int_{z=y}^{\infty} \begin{bmatrix} \xi_z & \mathbf{0} \end{bmatrix} e^{\mathbf{\check{Q}}_{\ominus\ominus}(z-y)} (|\mathbf{\check{C}}_{\ominus}|)^{-1} dz$$

and $\boldsymbol{p}(0,0) = \left[\begin{array}{cc} \boldsymbol{0} & \boldsymbol{p}(0,0)_{\ominus} \end{array} \right]$, where

$$\mathbf{p}(0,0)_{\ominus} = \alpha \int_{z=0}^{\infty} \begin{bmatrix} \boldsymbol{\xi}_z & \mathbf{0} \end{bmatrix} e^{\mathbf{\tilde{Q}}_{\ominus\ominus}z} dz (-\mathbf{T}_{\ominus\ominus})^{-1}$$

Here, α is a normalization constant In fact α is the total rate of hitting x = 0.

Expressing $\pi(0, y)$ and $\mathbf{p}(0, 0)$ in ξ_y

Proof. Consider "cycles" defined by hitting times of x = 0, and condition on where previous hit took place.

[Latouche and Taylor. A stochastic fluid model for an ad hoc mobile network, *Queueing Systems*, 2009]

Expressing $\pi(0, y)$ and $\mathbf{p}(0, 0)$ in ξ_y

LST of density part: let

$$\pi(0,\cdot)(s)=\int_{z=0}^{\infty}e^{-sy}\pi(0,y)dy$$

Corollary

We have $\pi(0,\cdot)(s) = \left[egin{array}{c} \mathbf{0} & \pi(0,\cdot)(s)_\ominus \end{array}
ight]$, where

$$\begin{aligned} \pi(\mathbf{0},\cdot)(\boldsymbol{s})_{\ominus} &= \alpha \int_{z=0}^{\infty} \left[\boldsymbol{\xi}_{z} \quad \mathbf{0} \right] \boldsymbol{e}^{\breve{\mathbf{Q}}_{\ominus\ominus}z} (\breve{\mathbf{Q}}_{\ominus\ominus} + \boldsymbol{s}\mathbf{I})^{-1} \\ &\times \left(\mathbf{I} - \boldsymbol{e}^{-(\breve{\mathbf{Q}}_{\ominus\ominus} + \boldsymbol{s}\mathbf{I})z} \right) (|\breve{\mathbf{C}}_{\ominus}|)^{-1} dz. \end{aligned}$$

Proof. Straightforward.

Normalise, based on 1-dim fluid queue ($\varphi(t), X(t)$)

Lemma

The normalisation constant α is given by

$$\begin{aligned} \alpha &= \left\{ \left[\begin{array}{c} \boldsymbol{\xi} & \boldsymbol{0} \end{array} \right] (-\boldsymbol{T}_{\ominus\ominus})^{-1} \left(\boldsymbol{1} \\ &+ \boldsymbol{T}_{\ominus+} \boldsymbol{K}^{-1} \left[\begin{array}{c} (\boldsymbol{R}_{+})^{-1} & \boldsymbol{\Psi}(|\boldsymbol{R}_{-}|)^{-1} \end{array} \right] \\ &\times \left(\boldsymbol{1} + \boldsymbol{T}_{\pm \bigcirc} (-\boldsymbol{T}_{\bigcirc \bigcirc})^{-1} \boldsymbol{1} \right) \right) \right\}^{-1}, \end{aligned}$$

where, $\xi = \int_{z=0}^{\infty} \xi_z dz$, $\Psi = \widehat{\Psi}(s)|_{s=0}$ and $\mathsf{K} = \widehat{\mathsf{K}}(s)|_{s=0}$ with

$$\widehat{\mathsf{K}}(s) = \widehat{\mathsf{Q}}(s)_{++} + \widehat{\Psi}(s)\widehat{\mathsf{Q}}(s)_{-+}.$$

Normalise, based on 1-dim fluid queue ($\varphi(t), X(t)$)

Proof. Integrating $\pi(0, y)$ and adding $\mathbf{p}(0, 0)$ yields the probability mass vector of $\varphi(t)$ at x = 0, which is also known from 1-dim fluid queue:

$$\begin{bmatrix} \mathbf{p}_{-} & \mathbf{p}_{\bigcirc} \end{bmatrix} = lpha \begin{bmatrix} \boldsymbol{\xi} & \mathbf{0} \end{bmatrix} (-\mathbf{T}_{\ominus\ominus})^{-1}$$

Similarly, we have expression for density $\pi(x)$ at x > 0. Now solve α from

$$\mathbf{p1} + \int_{x=0}^{\infty} \pi(x) dx \mathbf{1} = 1$$

Expressing $\pi(x, y)$ in $\pi(0, y)$ and $\mathbf{p}(0, 0)$

Lemma

We have

$$\pi(x,\cdot)(s)=\left[egin{array}{cc} \pi(x,\cdot)(s)_+ & \pi(x,\cdot)(s)_- & \pi(x,\cdot)(s)_\odot \end{array}
ight]$$

$$egin{array}{lll} \left[egin{array}{lll} \pi(x,\cdot)(s)_+ & \pi(x,\cdot)(s)_- \end{array}
ight] = (\pi(0,\cdot)(s)_\ominus + \mathbf{p}(0,0)_\ominus) \ imes \mathbf{T}_{\ominus +} e^{\widehat{\mathbf{k}}(s)x} imes \left[egin{array}{lll} (\mathbf{R}_+)^{-1} & \widehat{\mathbf{\Psi}}(s)(|\mathbf{R}_-|)^{-1} \end{array}
ight], \end{array}$$

and

with

$$\begin{aligned} \pi(x,\cdot)(s)_{\bigcirc} &= & \left[\begin{array}{cc} \pi(x,\cdot)(s)_{+} & \pi(x,\cdot)(s)_{-} \end{array} \right] \\ &\times \mathsf{T}_{\pm \bigcirc}(s\widehat{\mathsf{C}}_{\bigcirc} - \mathsf{T}_{\bigcirc \bigcirc})^{-1}. \end{aligned}$$

Expressing $\pi(x, y)$ in $\pi(0, y)$ and $\mathbf{p}(0, 0)$

Let $\pi(\cdot, \cdot)(v, s) = \int_{x=0}^{\infty} e^{-vx} \pi(x, \cdot)(s) dx$.

Corollary

We have

$$\pi(\cdot,\cdot)({\it v},{\it s})=\left[egin{array}{cc} \pi(\cdot,\cdot)({\it v},{\it s})_+ & \pi(\cdot,\cdot)({\it v},{\it s})_- & \pi(\cdot,\cdot)({\it s})_\odot \end{array}
ight]$$

with

$$\begin{bmatrix} \pi(\cdot, \cdot)(\nu, s)_{+} & \pi(\cdot, \cdot)(\nu, s)_{-} \end{bmatrix} = (\pi(0, \cdot)(s)_{\ominus} + \mathbf{p}(0, 0)_{\ominus})$$
$$\times \begin{bmatrix} \mathbf{T}_{-+} \\ \mathbf{T}_{-+} \end{bmatrix} (-\widehat{\mathbf{K}}(s) + \nu \mathbf{I})^{-1} \begin{bmatrix} (\mathbf{R}_{+})^{-1} & \widehat{\mathbf{\Psi}}(s)(|\mathbf{R}_{-}|)^{-1} \end{bmatrix}$$

and

$$egin{array}{rll} \pi(\cdot,\cdot)(m{s})_{\bigcirc} &=& \left[egin{array}{cc} \pi(\cdot,\cdot)(m{s})_+ & \pi(\cdot,\cdot)(m{s})_- \end{array}
ight] \mathbf{T}_{\pm \bigcirc} \ & imes (m{s}\widehat{\mathbf{C}}_{\bigcirc} - \mathbf{T}_{\bigcirc \bigcirc})^{-1}. \end{array}$$

Expressing $\pi^i(x, x\hat{c}_i/r_i)$ in **p**(0,0)

Lemma

For all $i \in S_+$,

$$\pi^i(x, x\widehat{c}_i/r_i) = \sum_{j \in \mathcal{S}_{\ominus}} \mathbf{p}_j(0, 0) T_{ji} \exp(-(T_{ii}/r_i)x)/r_i$$

Proof. Consider "cycle" starting when (0, 0) is left, and consider expected number of visits to $(i, x, x\hat{c}_i/r_i)$ before return to (0, 0).

Main result

Theorem

Stationary distribution of $(\varphi(t), X(t), Y(t))$ is found, as mixture of densities and LSTs.

Numerical scheme

• Discretize the DTMC J_k and truncate its state space:

$$\tilde{\mathbf{P}}_{\ell m} = \int_{y=m\Delta u}^{(m+1)\Delta u} \mathbf{P}_{\ell\Delta u,y} dy, \quad \ell, m = 0, 1, 2, \dots L$$

- Normalize this to obtain $\mathbf{P}_{\ell m}$ with $\sum_{m=0}^{L} \mathbf{P}_{\ell m} \mathbf{1} = \mathbf{1}$. Find $\bar{\boldsymbol{\xi}}_{\ell} = [\bar{\boldsymbol{\xi}}_{j;\ell}]_{j\in\mathcal{S}_{-}}$ by solving $\bar{\boldsymbol{\xi}}\mathbf{P} = \bar{\boldsymbol{\xi}}, \quad \bar{\boldsymbol{\xi}}\mathbf{1} = \mathbf{1}$.

Use this to approximate e.g.

$$\mathbf{p}(0,0)_{\ominus} = \alpha \int_{z=0}^{\infty} \boldsymbol{\xi}_{z} e^{\mathbf{\tilde{Q}}_{\ominus\ominus} z} dz (-\mathbf{T}_{\ominus\ominus})^{-1}$$
$$\approx \alpha \sum_{\ell=0}^{L} \mathbf{\bar{\xi}}_{\ell} e^{\mathbf{\tilde{Q}}_{\ominus\ominus} \ell \Delta u} (-\mathbf{T}_{\ominus\ominus})^{-1}.$$

- Similar for $\pi(0, y)$ etc; invert using Abate and Whitt
- Work in progress

Numerical scheme

$\widehat{\mathbf{\Psi}}(s)$						
\downarrow						
$\mathbf{P}_{Z,\cdot}(s)$		$\boldsymbol{\xi}(\boldsymbol{s})$		$\pi(0,\cdot)(s)$	\rightarrow	$\pi(x,\cdot)(s)$
\downarrow				\uparrow		\downarrow
$\mathbf{P}_{z,y}$	\rightarrow	ξ_z	\rightarrow	$\pi(0, y)$		$\pi(x,y)$

Conclusions and future work

- Stationary distribution found, as mixture of densities and LSTs (as opposed to closed form LST in special case)
- Finish numerical scheme
- Consider dual model