The Nature of Labor Reallocation

741 Macroeconomics
Topic 5

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Firm Employment is Log-Linear in TFP

- In Hopenhayn-Rogerson, firm-level employment is given by

$$n = (\underbrace{z^{1-\alpha}}_{\equiv Z} \alpha/w)^{\frac{1}{1-\alpha}}$$

$$\Leftrightarrow \quad \log n = \frac{1}{1-\alpha} \log Z + const$$

- Two implications:
  1. The elasticity of firm employment w.r.t. (firm-level) TFP shock is above 1
  2. The elasticity is symmetric to positive & negative shocks
- Is this true in the data?

Ilut, Kehrig & Schneider (2018)

- Focus on US manufacturing establishments (Census data)
- Construct firm-level TFP using Solow residual:

$$\log sr_{it} = \log y_{it} - \left(\beta_n \log n_{it} + \beta_k \log k_{it} + \beta_m \log m_{it}\right)$$

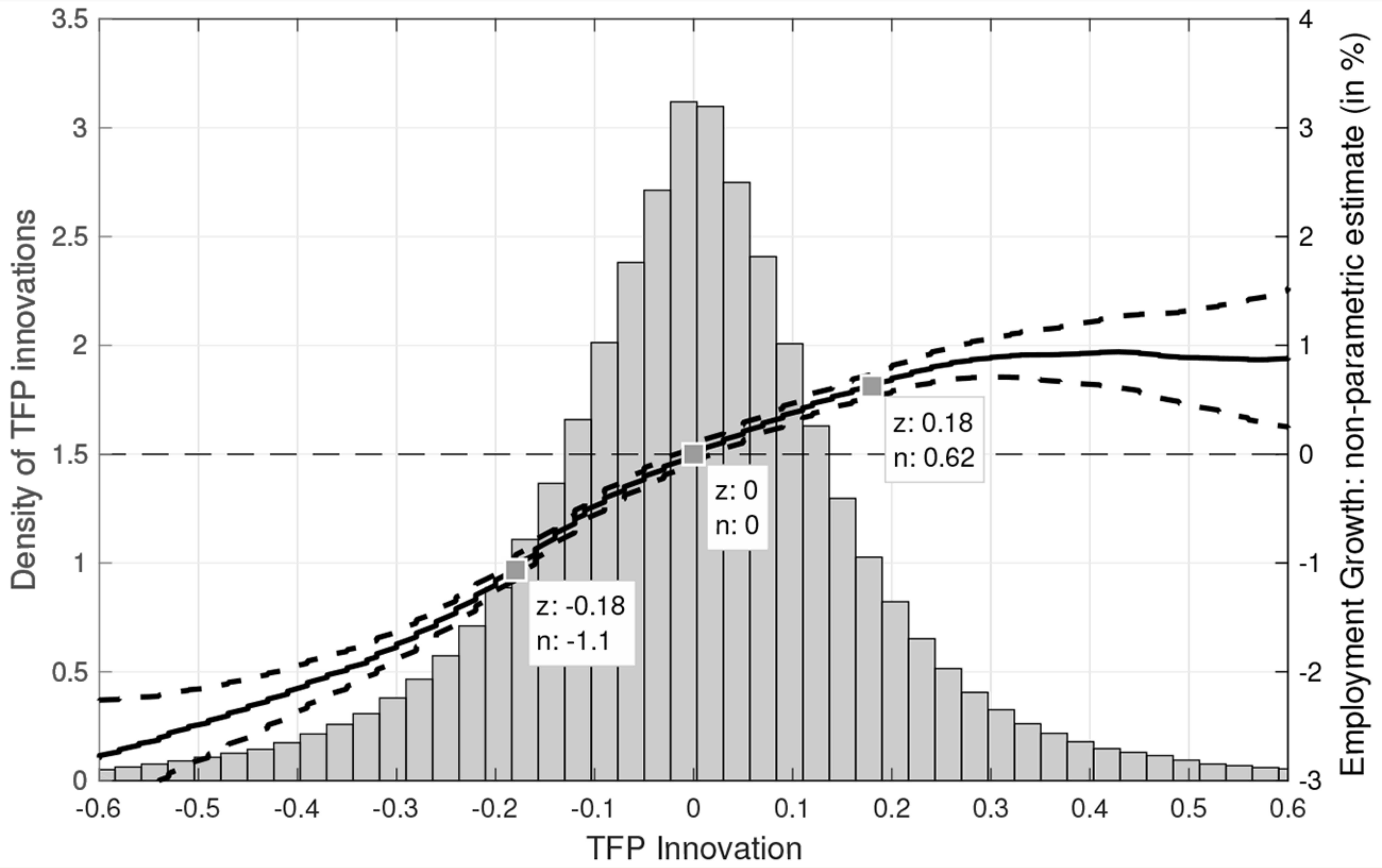
- Construct firm-level TFP shocks, Z_{it}, assuming

$$\log sr_{it} = g \times t + \alpha^i + \log Z_{it}$$

- Q: How does firm-level employment respond to TFP shocks?

$$\Delta \log n_{it} = h(\Delta \log Z_{it}) + \gamma' \boldsymbol{X}_{it} + \epsilon_{it}$$

Firm Employment Response to TFP Shocks



- Positive 1 std shock:

$$\frac{\Delta \ln n}{\Delta \ln z} = \frac{0.0062}{0.18}$$
$$= 0.034$$

- Negative 1 std shock:

$$\frac{\Delta \ln n}{\Delta \ln z} = \frac{0.011}{0.18}$$
$$= 0.061$$

Facts

In the data,

1. The elasticity of firm employment to TFP shock is far below 1
2. Elasticity is two times larger for negative shocks than positive shocks

Hopenhayn-Rogerson with Labor Adjustment Costs

Slow to Hire, Quick to Fire

- The simplest explanation:
  - it is costly to hire workers
  - less so to fire workers

Labor Adjustment Cost

- Suppose that firms face
  - a flow adjustment cost in hiring $h \geq 0$ of the form $\Phi(h, n)$ with $\partial_h \Phi > 0, \partial^2_{hh} \Phi > 0$
  - no cost from firing workers: $\Phi(h, n) = 0$ for $h \leq 0$

  $\Rightarrow$ convex cost in hiring & free firing

- The firm employment evolves $dn_t = hdt$
- Firms never want to jump n upward
  - Why? – The cost of doing so is $\lim_{dt \to 0} \Phi(h, n)dt = \infty$ with $h = \frac{n' - n}{dt}$ and $n' > n$
- But firms may jump n downward

Rest of the Model

- The rest of the model remains the same as before
- The production function is

$$f(z, n) = z^{1-\alpha} n^{\alpha}$$

  and firms incur a fixed operating cost c_f

- Firm's productivity evolves according to a diffusion process

$$dz = \mu(z)dt + \sigma(z)dW$$

Start from Discrete Time

- Start from a discrete-time setup with time interval dt
- The firm's value function is

$$v(n,z) = \max\left\{v^*(n,z), \max\{\underline{v}, v^f(n,z)\}\right\} \tag{1}$$

  - the value of hiring is

$$v^*(n,z) = \max_{h\geq 0}\Big(\underbrace{f(n,z) - wn - c_f}_{\pi(n,z)} - \Phi(h,n)\Big)dt + \underbrace{e^{-rdt}}_{\approx 1 - rdt}\mathbb{E}\left[v(n',z')\right] \tag{2}$$

$$\text{s.t.} \quad n' = n + hdt$$

  - the value of firing is

$$v^f(n,z) = \max_{n^f \leq n} v(n^f, z) \tag{3}$$

  - the value of exit is $\underline{v}$, as before

Continuous Time Limit

- Add and subtract $(1 - rdt)v(n, z)$ and defining $dv(n, z) \equiv v(n', z') - v(n, z)$, we have

$$v^*(n, z) = \max_{h \geq 0} \left(\pi(n, z) - \Phi(h, n)\right) dt + (1 - rdt)\mathbb{E}\left[dv(n, z)\right] + (1 - rdt)v(n, z) \quad (4)$$

$$\text{s.t.} \qquad n' = n + hdt$$

- Apply Ito's lemma to $dv(n, z)$:

$$dv(n, z) = v_n(n, z)\underbrace{dn}_{hdt} + v_z(n, z)\left(\mu(z)dt + \sigma(z)dZ\right) + \frac{1}{2}\sigma(z)^2 v_{zz}(n, z)dt \quad (5)$$

- Substitute (5) back into (4) and dropping dt^2 term

$$v^*(n, z) = \max_{h \geq 0} \left(\pi(n, z) - \Phi(h, n) + v_n(n, z)h + v_z(n, z)\mu(z) + \frac{1}{2}\sigma(z)^2 v_{zz}(n, z)\right) dt$$
$$+ v(n, z) - rdtv(n, z)$$

Bellman Equation in Continuous Time

- Therefore, we have

$$v(n,z) = \max\left\{v^*(n,z), \underline{v}^f(n,z)\right\}$$

where:

$$v^*(n,z) = \max_{h\geq 0}\left(\pi(n,z) - \Phi(h,n) + v_n(n,z)h + v_z(n,z)\mu(z) + \frac{1}{2}\sigma(z)^2 v_{zz}(n,z)\right)dt$$
$$+v(n,z) - rdtv(n,z)$$

$$\underline{v}^f(n,z) = \max\left\{\max_{n'\leq n} v(n',z), \underline{v}\right\}$$

- Three cases

1. Firms do not fire or exit: $v(n,z) > \underline{v}^f(n,z)$ and $v(n,z) = v^*(n,z)$
2. Firms fire workers: $v(n,z) = v^f(n,z) > \underline{v}$, and $v(n,z) > v^*(n,z)$
3. Firms exit: $v(n,z) = \underline{v} > v^f(n,z)$, and $v(n,z) > v^*(n,z)$

HJB-QVI

- Compactly, we can write

$$\min \left\{ \begin{array}{c} rv(n,z) - \max_{h\geq 0}\left(\pi(n,z) - \Phi(h,n) + v_n(n,z)h + v_z(n,z)\mu(z) + \frac{1}{2}\sigma(z)^2 v_{zz}(n,z)\right), \\ v(n,z) - \underline{v}^f(n,z) \end{array} \right\} = 0$$

- This is called HJB Quasi-Variational Inequality (HJB-QVI)
- Distinct from HJB-VI because now the stopping value $\underline{v}^f(n,z)$ is endogenous to $v(n,z)$

Policy Functions of HJB-QVI

$$\min \left\{ \begin{array}{c} rv(n,z) - \max_{h\geq 0}\left(\pi(n,z) - \Phi(h,n) + v_n(n,z)h + v_z(n,z)\mu(z) + \frac{1}{2}\sigma(z)^2 v_{zz}(n,z)\right), \\ v(n,z) - \underline{v}^f(n,z) \end{array} \right\} = 0$$

- When firms hire ($h \geq 0$), the FOC implies $\partial_h \Phi(h,n) = v_n(n,z)$
  - Let $h(n,z)$ denote the policy function
- When firms fire ($h < 0$), firms cut down employment to $n^f(n,z) = \arg\max_{n^f \leq n} v(n^f, z)$
- The employment evolution is

$$dn(n,z) = \begin{cases} h(n,z)dt & \text{if } n \leq n^f(n,z) \\ n^f(n,z) - n & \text{if } n > n^f(n,z) \end{cases}$$

- Let $\chi(n,z)$ denote an indicator function of exiting decision

Entry

- When firms enter, they draw (n, z) from cdf $\Psi(n, z)$
- We assume (potentially) inelastic entry:

$$m_t = M \times \left(\frac{1}{\bar{c}^e} \int v(n, z) d\Psi(n, z) \right)^{\nu} \tag{6}$$

Stationary Distribution

- Define $\mathscr{A}_{KFE}$ as the infinitesimal generator defined for a function $f(n,z)$:

$$\mathscr{A}_{KFE}f(n,z) = \mu(z)f_z(n,z) + \frac{1}{2}\sigma(z)^2 f_{zz}(n,z) + (h(n,z) - sn)f_n(n,z)$$
$$+\Lambda^f(n,z)\left[f(n^f(n,z),z) - f(n,z)\right] - \Lambda^e(n,z)f(n,z)$$

  where

$$\Lambda^f(n,z) = \begin{cases} \infty & \text{if } n \geq n^f(n,z) \\ 0 & \text{if } n < n^f(n,z) \end{cases}, \quad \Lambda^e(n,z) = \begin{cases} \infty & \text{if } \mathbb{I}^e(n,z) = 1 \\ 0 & \text{if } \mathbb{I}^e(n,z) = 0 \end{cases}$$

- Let $\mathscr{A}^{\dagger}_{KFE}$ be adjoint operator of $\mathscr{A}_{KFE}$. The steady-state distribution $g(n,z)$ satisfies

$$0 = \mathscr{A}^{\dagger}_{KFE}g(n,z) + m\psi(n,z)$$

Equilibrium Definition

Equilibrium consists of $\{v(n,z), h(n,z), n^f(n,z), \chi(n,z), g(n,z), w, m\}$ such that

1. Value and policy functions $\{v(n,z), h(n,z), n^f(n,z), \chi(n,z)\}$ solve HJB-QVI
2. Stationary distribution $g(n,z)$ solve KFE
3. Entry m is given by (6)
4. Labor market clears: $\int\int ng(n,z)dndz = L$

Numerically Solving HJB-QVI – Nested Howard Algorithm

How to Solve HJB-QVI?

$$\min\left\{ rv(n,z) - \max_{h\geq 0}\left(\pi(n,z) - \Phi(h,n) + v_n(n,z)h + v_z(n,z)\mu(z) + \frac{1}{2}\sigma(z)^2 v_{zz}(n,z)\right), v(n,z) - \underline{v}^f(n,z)\right\} = 0$$

- Relative to the case without adj. costs, there are two additional complications:
  1. optimization w.r.t. h
  2. optimization w.r.t. n^f inside $\underline{v}^f(n,z)$
- Discrezie the state space $n_1, \ldots, n_I$ and $z_1, \ldots, z_J$
- Use short-hand notation of, e.g., $v_{i,j} \equiv v(n_i, z_j)$
- We will use nested Howard's algorithm (Azimzadeh, Bayraktar, Labahn, 2018)

No Firing or Exit

- Start from the case where firms do not fire or exit, $\underline{v}^f_{i,j} = -\infty$

$$rv(n,z) - \max_{h \geq 0} \left(\pi(n,z) - \Phi(h,n) + v_n(n,z)h + v_z(n,z)\mu(z) + \frac{1}{2}\sigma(z)^2 v_{zz}(n,z) \right) = 0$$

- We can solve the above problem using Howard's algorithm:

1. Guess $v^k(n_i, z_j)$ for each (i,j)
2. Compute optimal hiring using the FOC:

$$h^k_{i,j} = \max\{h^*, 0\} \quad \text{where } \partial_h \Phi(h^*, n_i) = \partial_n v^k_{i,j}$$

3. Solve the linear system to obtain $v^{k+1}_{i,j}$

$$rv^{k+1}_{i,j} - \left(\pi_{i,j} - \Phi(h^k_{i,j}, n_i) + \partial_n v^{k+1}_{i,j} h_{i,j} + \mu_j \partial_z v^{k+1}_{i,j} + \frac{1}{2}\sigma_j^2 \partial^2_{zz} v^{k+1}_{i,j} \right) = 0$$

4. Update $v^k_{i,j} := v^{k+1}_{i,j}$ and repeat until convergence

Linear System

- In a matrix form,

$$\underbrace{(r\mathbb{I} - \mathbf{A}^k_{HJB})}_{\mathbf{B}^k}\, \boldsymbol{v}^{k+1} = \boldsymbol{\pi} - \boldsymbol{\Phi}^k \quad \Leftrightarrow \quad \boldsymbol{v}^{k+1} = (\mathbf{B}^k)^{-1}[\boldsymbol{\pi} - \boldsymbol{\Phi}^k]$$

  - $\mathbf{v} \equiv [v_{1,1}, \ldots, v_{I,1}, v_{1,2}, \ldots, v_{I,2}, \ldots, v_{I,j}]'$ is a $(I \times J)$ vector
  - $\mathbf{A}_{HJB}$ is $(I \times J) \times (I \times J)$ matrix, whose elements are

$$[\mathbf{A}_{HJB}]_{ij,kl} = \begin{cases} h_{i,j}\frac{1}{\Delta n} & \text{for } k = i+1, l = j \\ -h_{i,j}\frac{1}{\Delta n} & \text{for } k = i, l = j \\ \frac{1}{2}\sigma_j^2 \frac{1}{(\Delta z)^2} & \text{for } k = i, l = j+1 \\ \mu_j \frac{1}{\Delta z} - \sigma_j^2 \frac{1}{(\Delta z)^2} & \text{for } k = i, l = j \\ -\mu_j \frac{1}{\Delta z} + \frac{1}{2}\sigma_j^2 \frac{1}{(\Delta z)^2} & \text{for } k = i, l = j-1 \end{cases}$$

since $dn = h \geq 0$, we always use forward approximation for $\partial_n v$: $\partial_n v_{i,j} \approx \dfrac{v_{i+1,j} - v_{i,j}}{\Delta n}$

Howard Algorithm with Exit & Firing

- For a fixed value of $\underline{\boldsymbol{v}}^f \equiv [\underline{v}^f_{i,j}]_{i,j}$, we can incorporate exit & firing as follows

1. Guess $\boldsymbol{v}^0$
2. For $k \geq 0$, given $\boldsymbol{v}^k$, construct $\mathbf{B}^k$ as described earlier, and set

$$d_{i,j} = \begin{cases} 0 & [\boldsymbol{B}^k \boldsymbol{v}^k - \boldsymbol{\pi} - \boldsymbol{\Phi}]_i \leq v^k_{i,j} - \underline{v}^f_{i,j} \\ 1 & [\boldsymbol{B}^k \boldsymbol{v}^k - \boldsymbol{\pi} - \boldsymbol{\Phi}]_i > v^k_{i,j} - \underline{v}^f_{i,j} \end{cases}$$

3. Set

$$[\tilde{\boldsymbol{B}}^k]_{ij,lm} = \begin{cases} [\boldsymbol{B}^k]_{ij,lm} & \text{if } d_{i,j} = 0 \\ [\boldsymbol{I}]_{ij,lm} & \text{if } d_{i,j} = 1 \end{cases}, \qquad [\boldsymbol{q}^k]_{i,j} = \begin{cases} [\boldsymbol{\pi} - \boldsymbol{\Phi}]_{i,j} & \text{if } d_{i,j} = 0 \\ \underline{v}^f_{i,j} & \text{if } d_{i,j} = 1 \end{cases}$$

4. Update v^{k+1} solving

$$\tilde{\boldsymbol{B}}^k \boldsymbol{v}^{k+1} = \boldsymbol{q}^k \quad \Leftrightarrow \quad \boldsymbol{v}^{k+1} = [\tilde{\boldsymbol{B}}^k]^{-1} \boldsymbol{q}^k$$

Nested Howard's Algorithm

The outer loop keeps updates $\underline{v}^f$ starting from $\underline{v}^f = -\infty$

1. Set the value of firing to $v_{i,j}^{f,0} = -\infty$ for all i, j
2. For each $k = 0,1,\ldots$
   i. Given $\{v_{i,j}^{f,k}\}_{i,j}$, set $\underline{v}_{i,j}^f \equiv \max\left\{\underline{v}, v_{i,j}^{f,k}\right\}$
   ii. Given $\underline{v}^f \equiv [\underline{v}_{i,j}^f]_{i,j}$, solve HJB-VI (*not* QVI) using Howard's algorithm
   iii. Compute the new value of firing as

$$v_{i,j}^{f,k+1} = \max_{i' \leq i} v_{i,j}$$

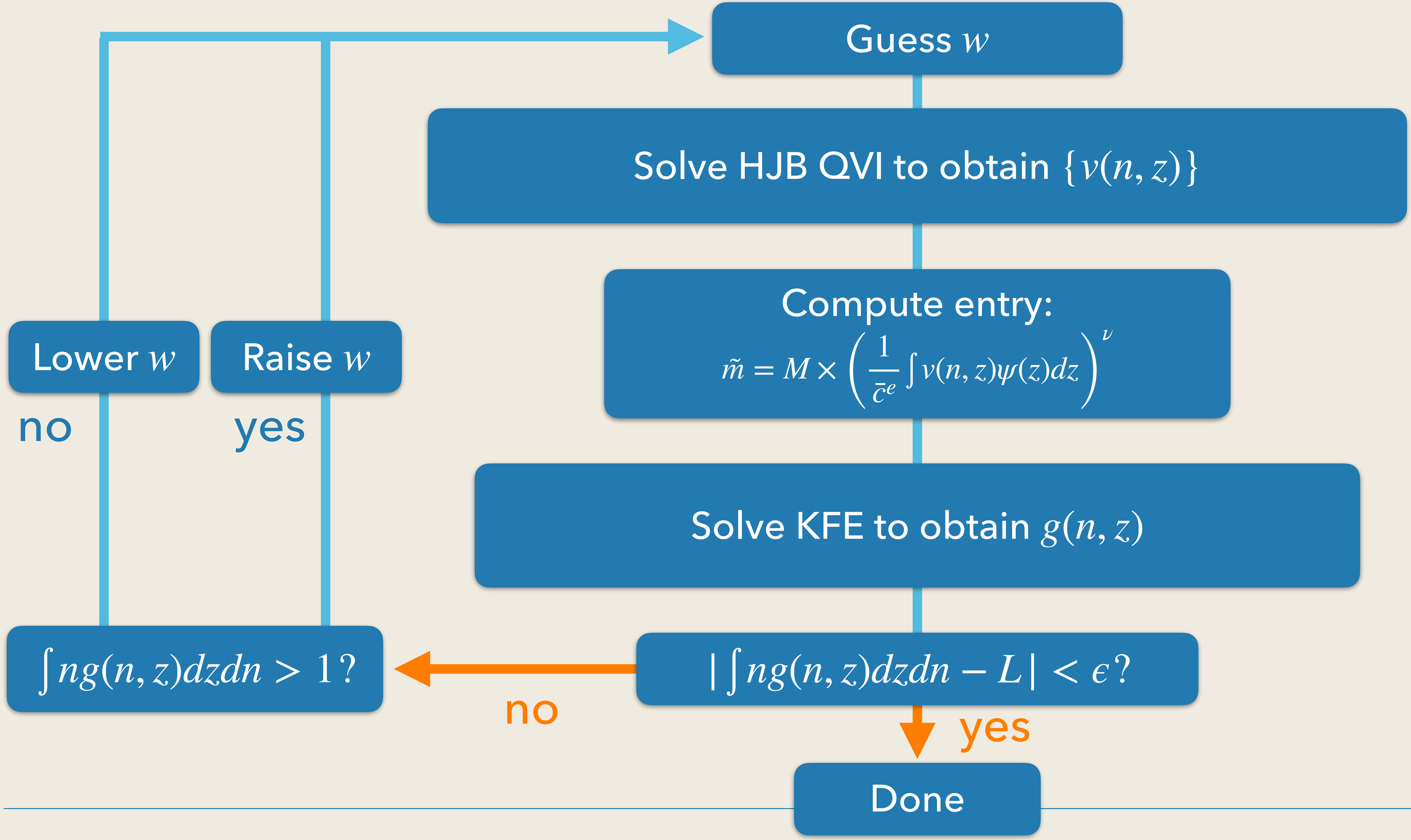
- If $v_{i,j}^{f,k+1}$ is close enough to $v_{i,j}^{f,k}$, we are done.
- Otherwise, set $v_{i,j}^{f,k} := v_{i,j}^{f,k+1}$ and go back to 2.i.

Can We Do Better?

- Some use algorithms that simultaneously update $\underline{v}^f$ in inner loop
- Never do this. I wasted my entire summer because of it.
- At the same time, the nested Howard algorithm is inefficient
  - Need many outer loop iterations to converge
- Alternative algorithms that improve speeds have been proposed:
  - The most successful one seems to be penalized Howard algorithm (Azimzadeh and Forsyth, 2016; Azimzadeh, Bayraktar, and Labahn, 2018)
  - I tried to implement it but failed
- If you implement Penalized Howard's algorithm, I will count it as a final project

Numerically Computing Steady State Equilibrium

Steady State Algorithm



Discretized Kolmogorov Forward Equation

$$\left[\boldsymbol{D} + (\boldsymbol{A}_{HJB}\boldsymbol{M})'\right]\boldsymbol{g} + m\boldsymbol{\psi} = 0$$

$$[\boldsymbol{M}]_{ij,kl} = \begin{cases} 1 & \text{for } n^f(n_i, z_j) = n_k, \chi(n_i, z_j) = 0, l = j \\ 0 & \text{otherwise} \end{cases}$$

$$[\boldsymbol{D}]_{ij,kl} = \begin{cases} 1 & \text{for } i = k, j = l, n^f(n_i, z_j) < n_i, \chi(n_i, z_j) = 1 \\ 0 & \text{otherwise} \end{cases}$$

- The matrix $\boldsymbol{M}$ takes care of transitions associated with jump in the state variables
- The matrix $\boldsymbol{D}$ ensures that $[\boldsymbol{g}]_{ij} = 0$ for states (n_i, z_j) that are never reached

Macroeconomic Implications of Slow to Hire, Quick to Fire

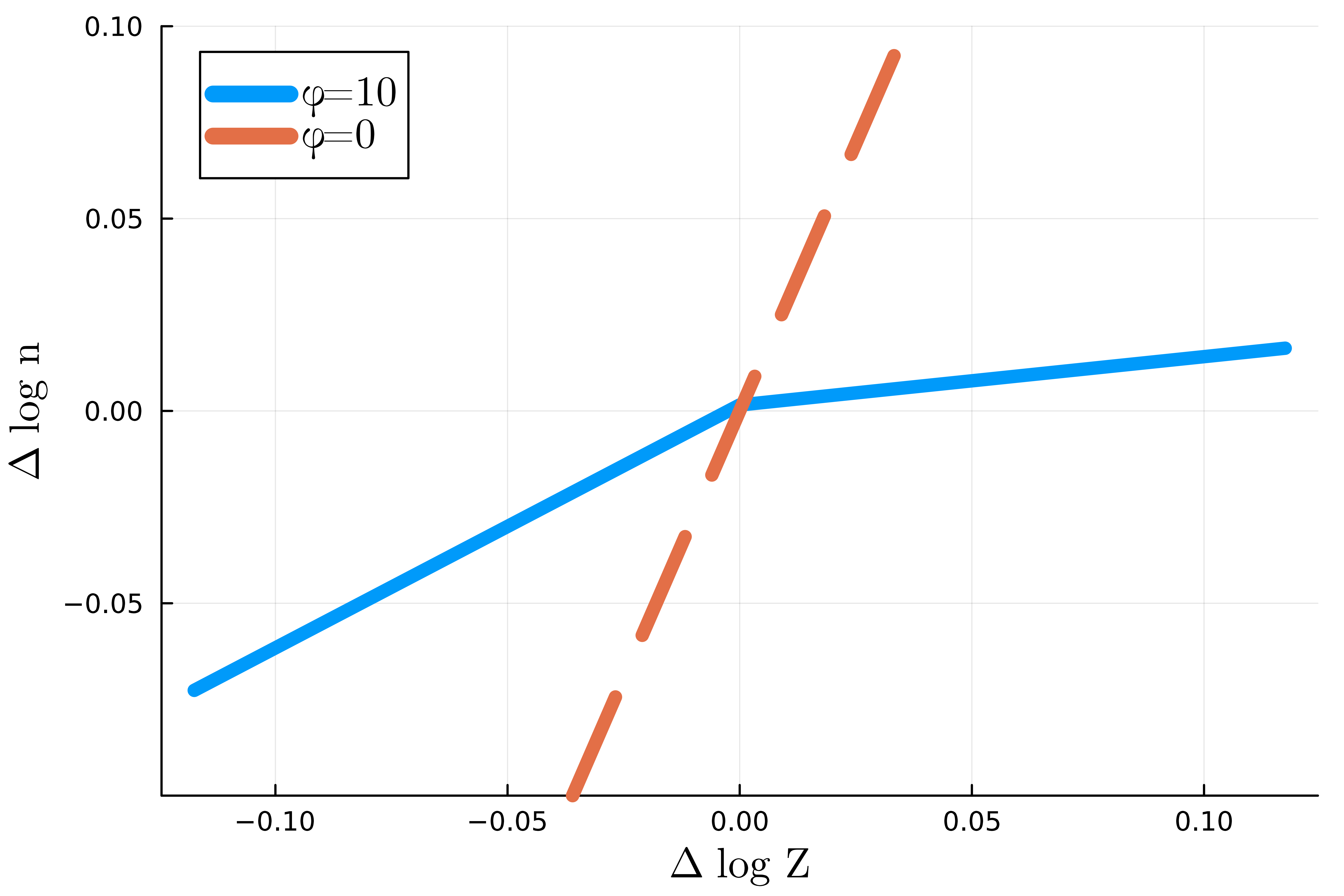
Parameterization

- Assume

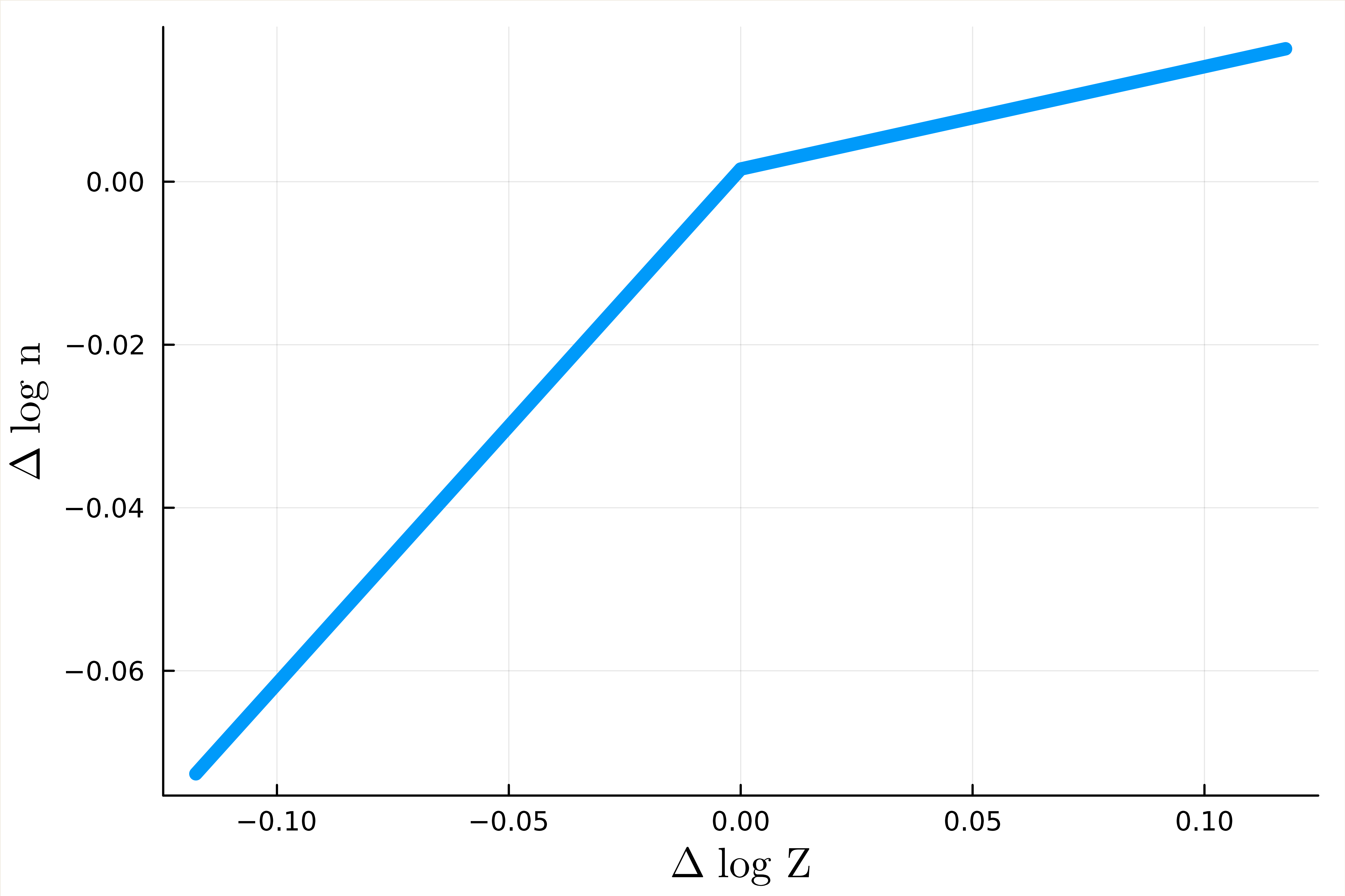
$$\Phi(h,n) = \frac{\phi}{2}\left(\frac{h}{n}\right)^2 n$$

- I set $\phi = 10$ and contrast with $\phi = 0$
- All the other parameters are unchanged from the lecture note 2

Slow to Hire, Quick to Fire



SS Distribution of Employment Growth



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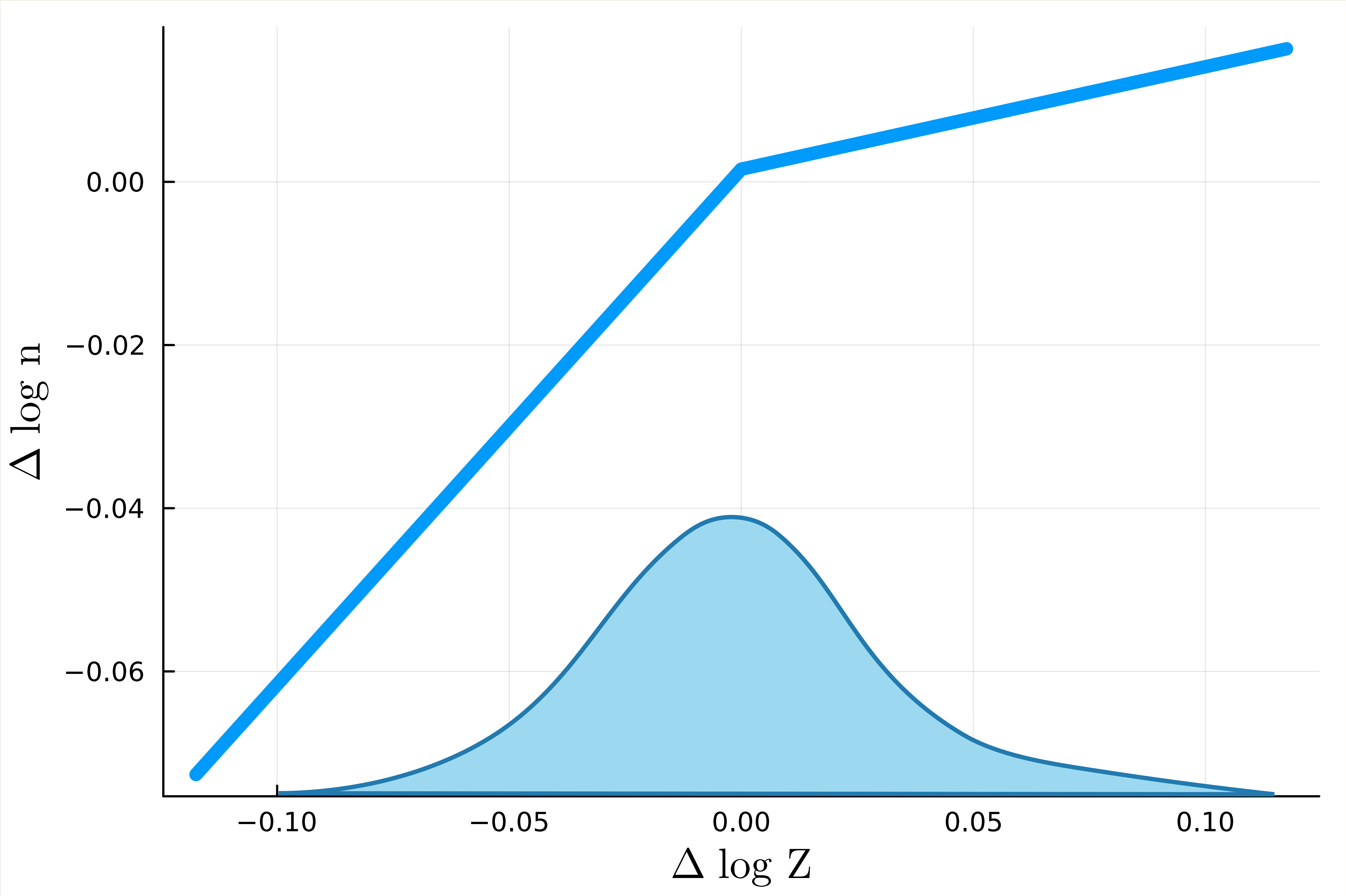

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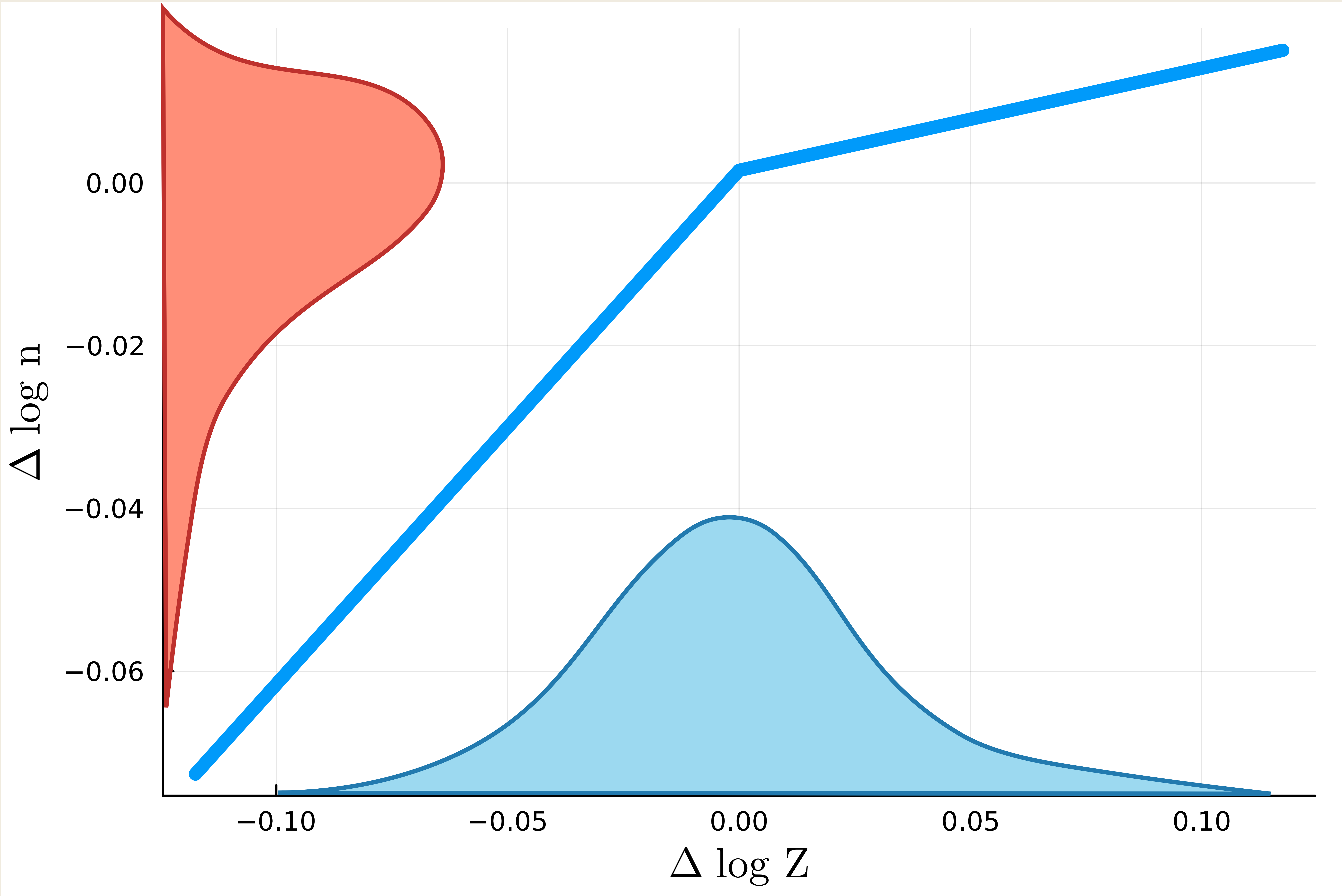
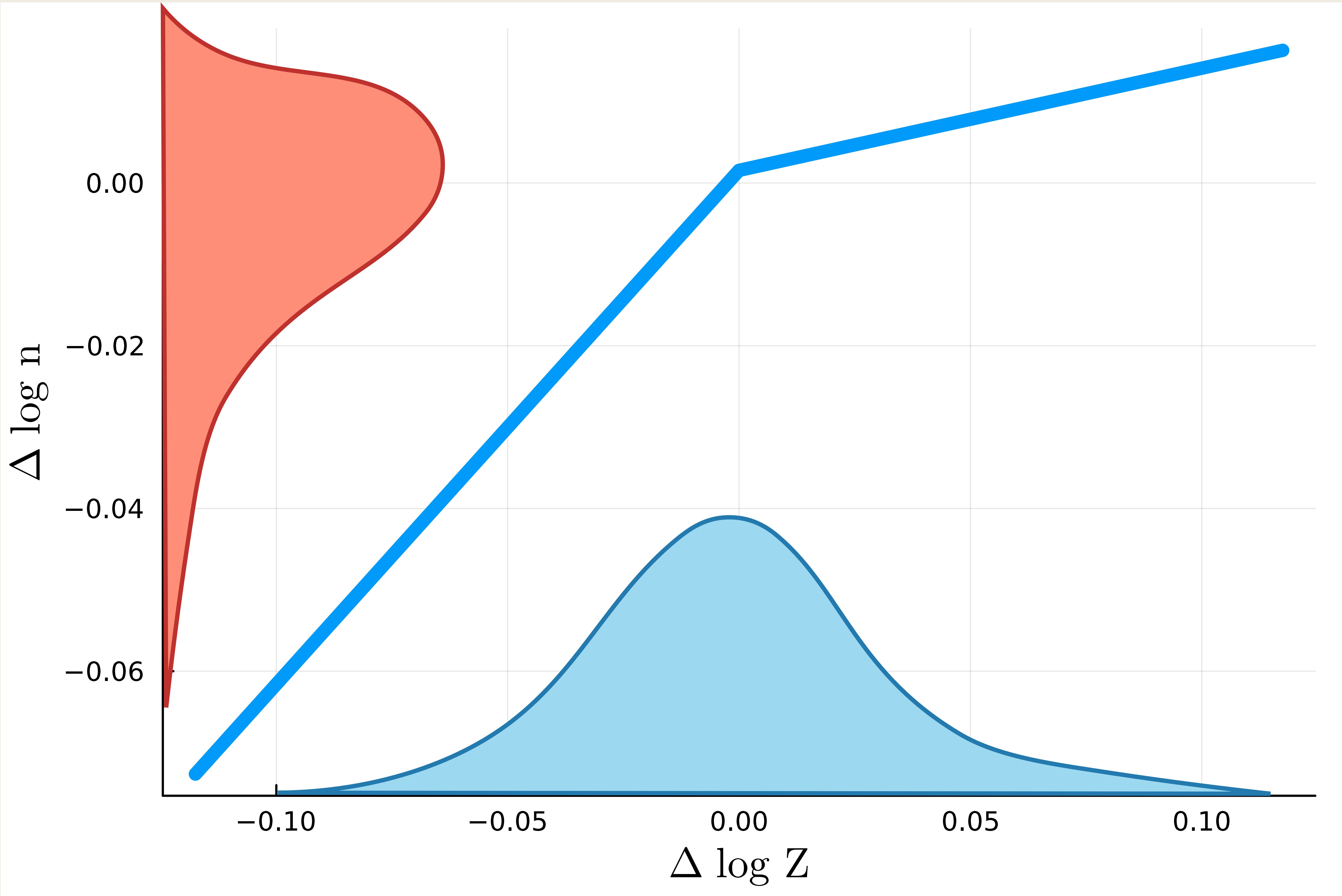


Aggregate Positive Productivity Shocks



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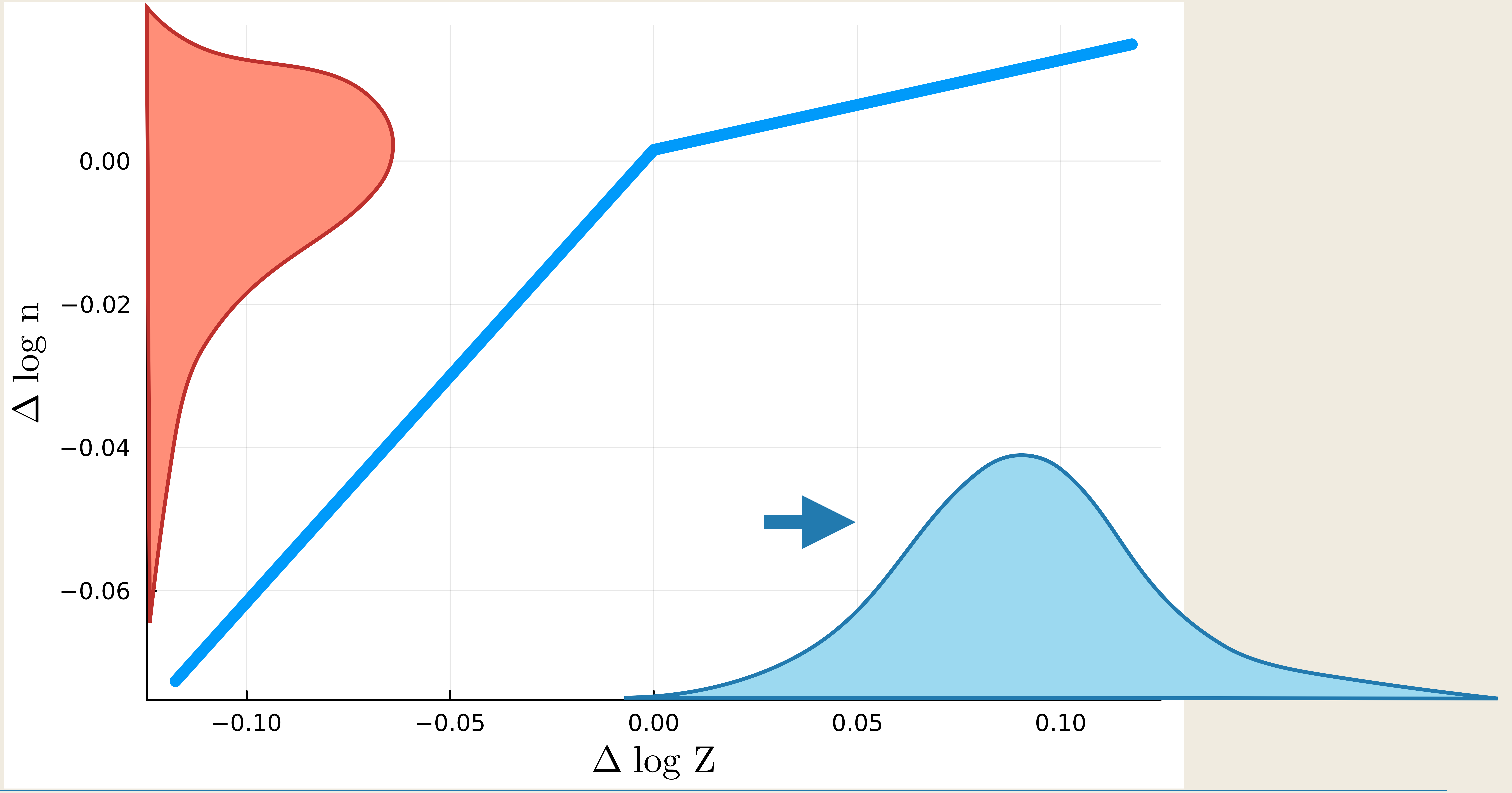

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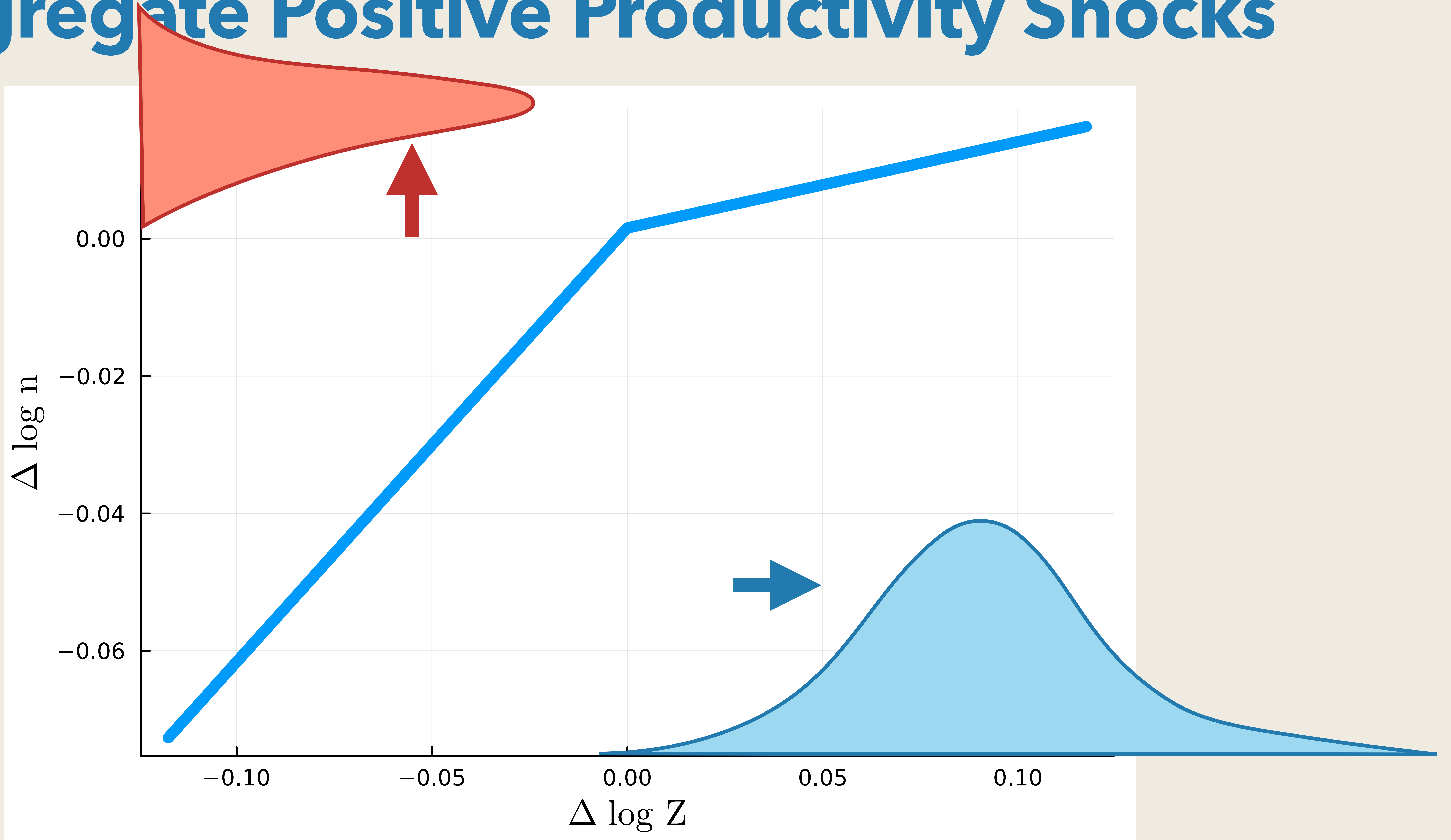

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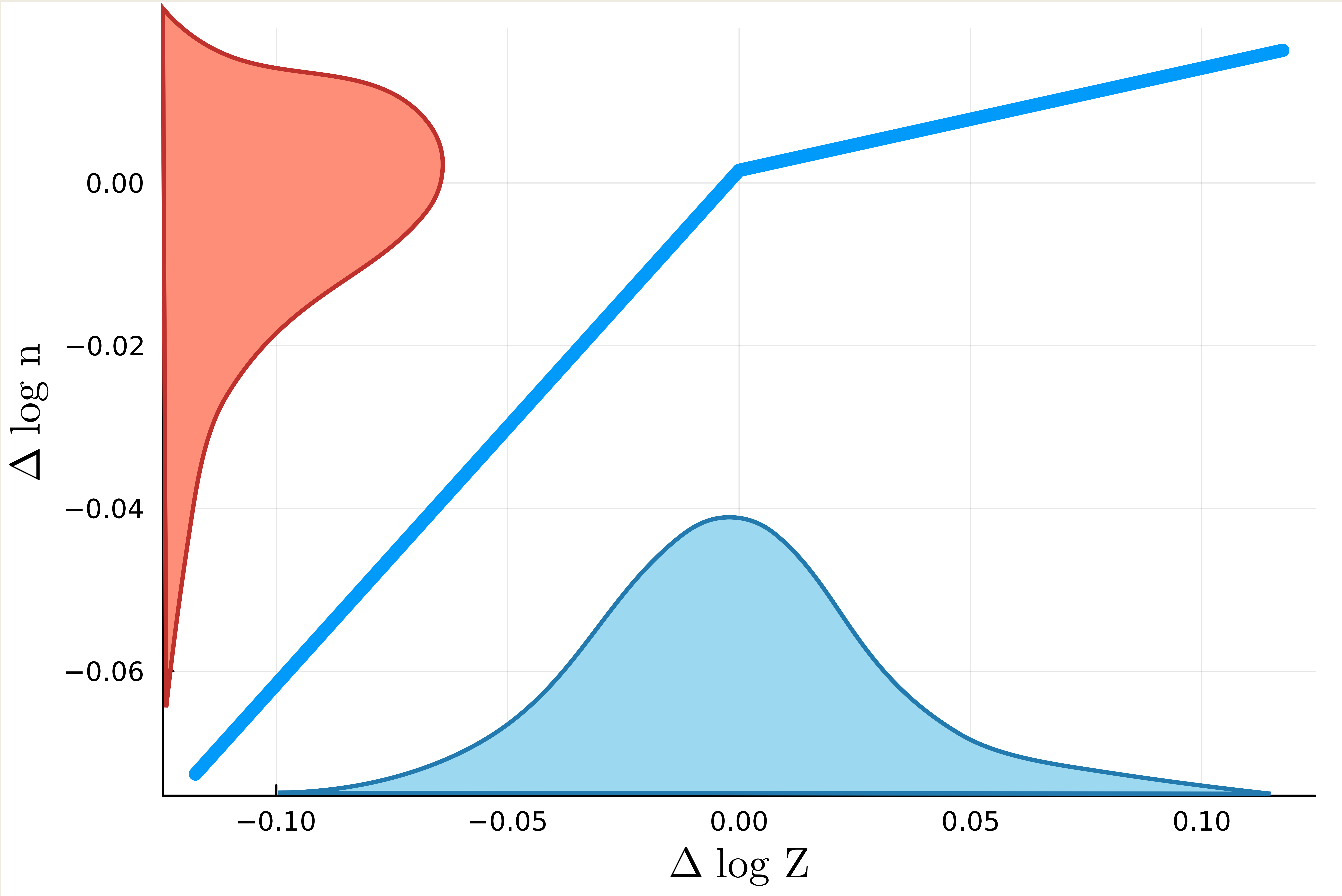

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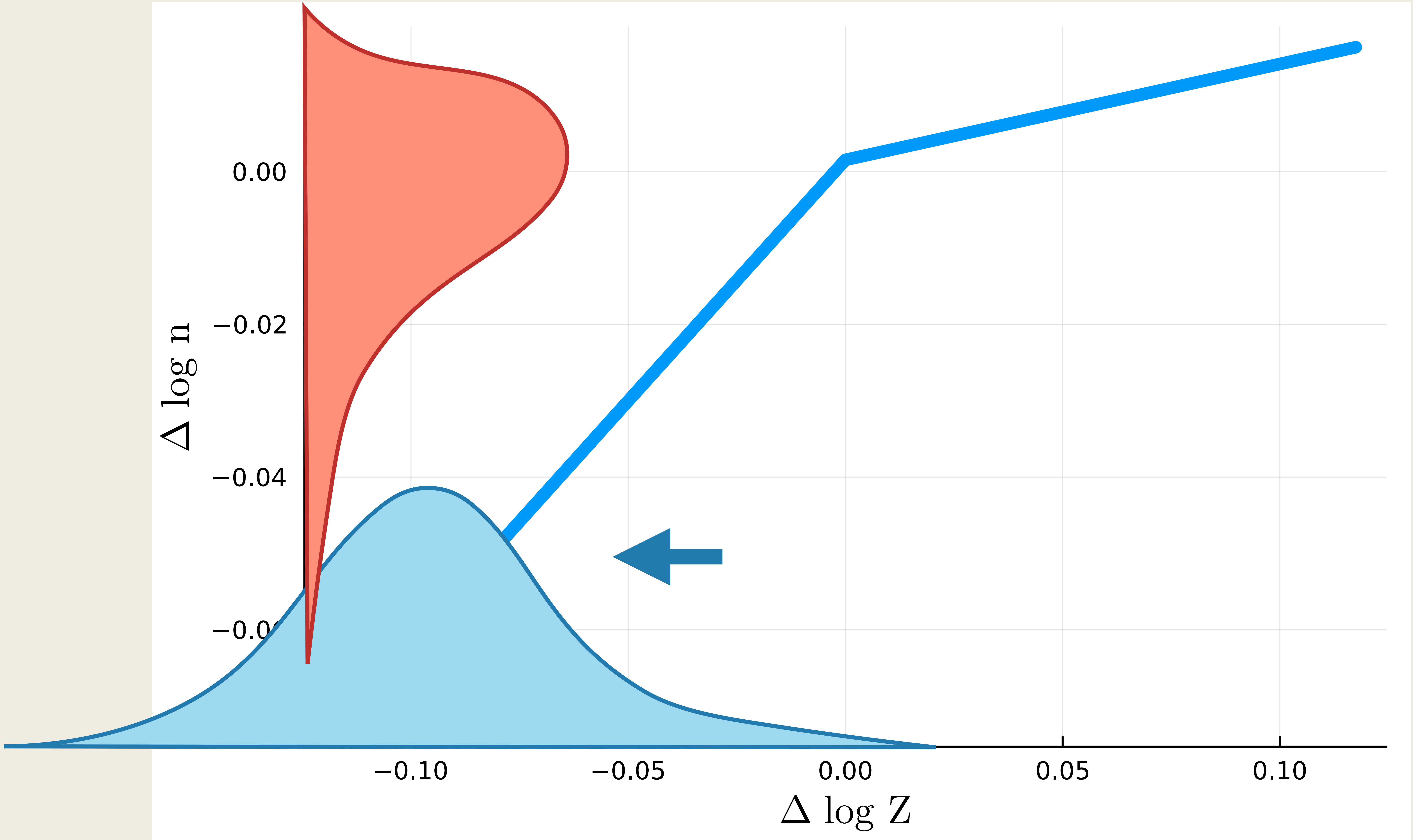

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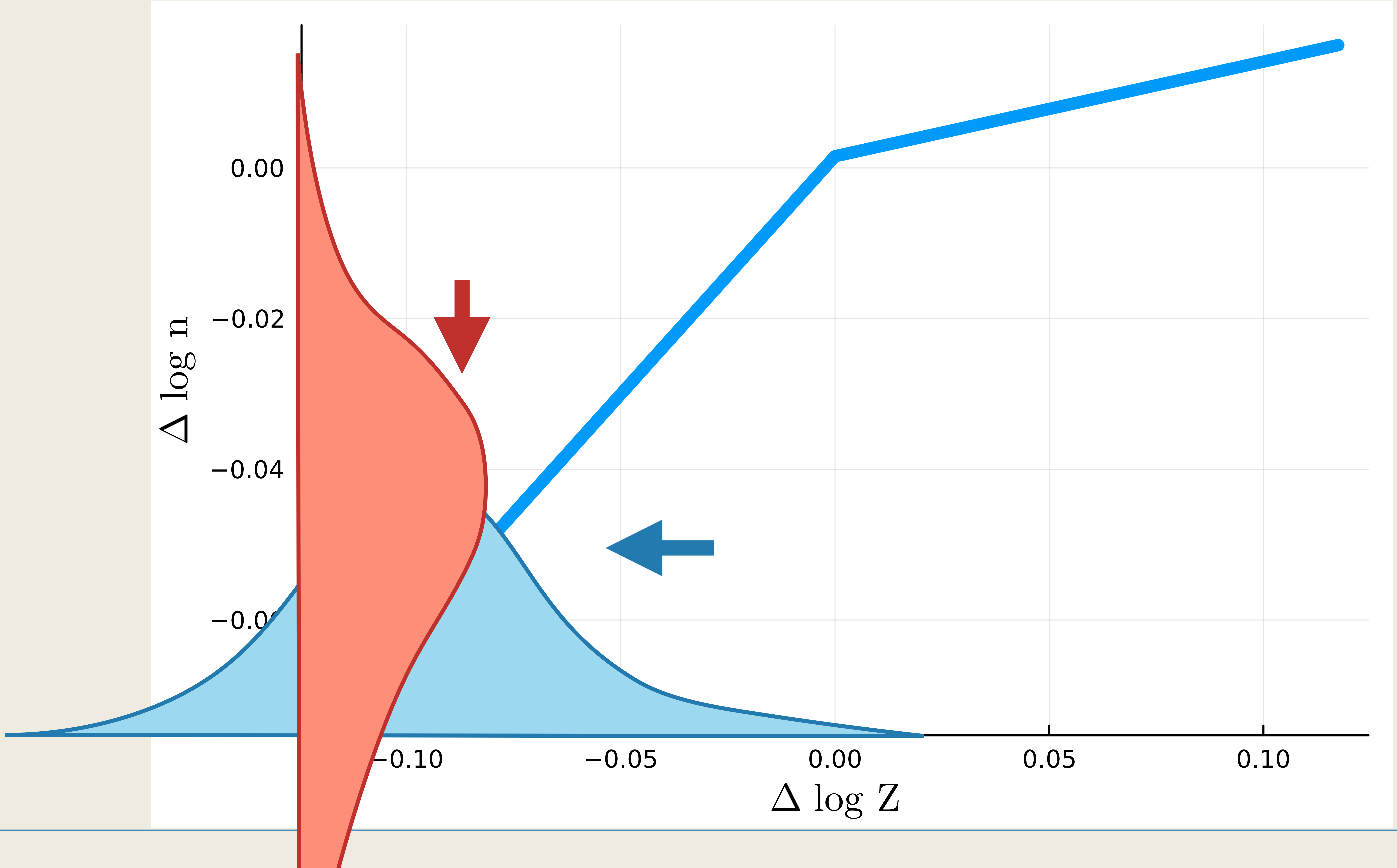
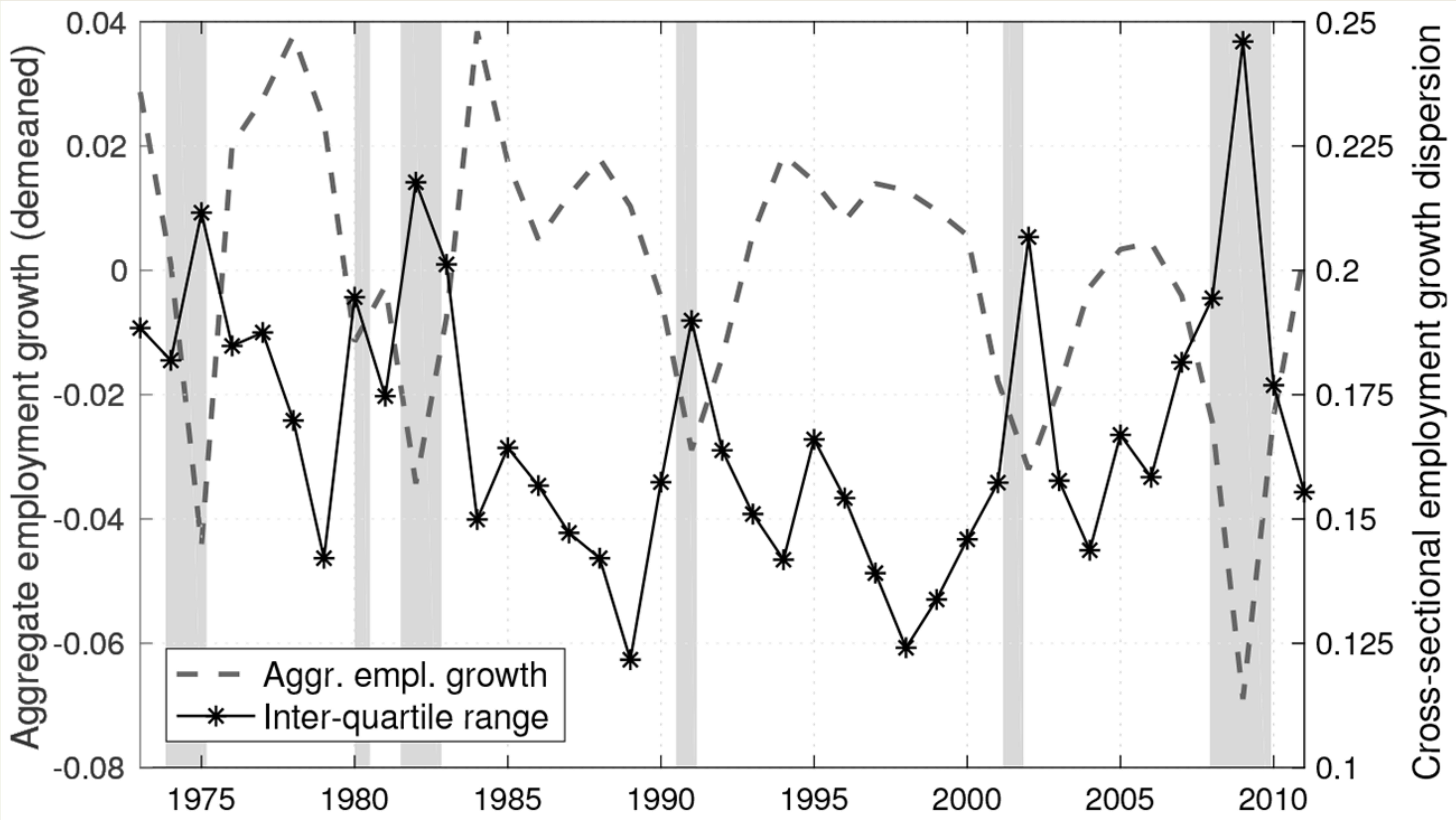


Countercyclical Volatility



Source: Ilut, Kehrig & Schneider (2018)

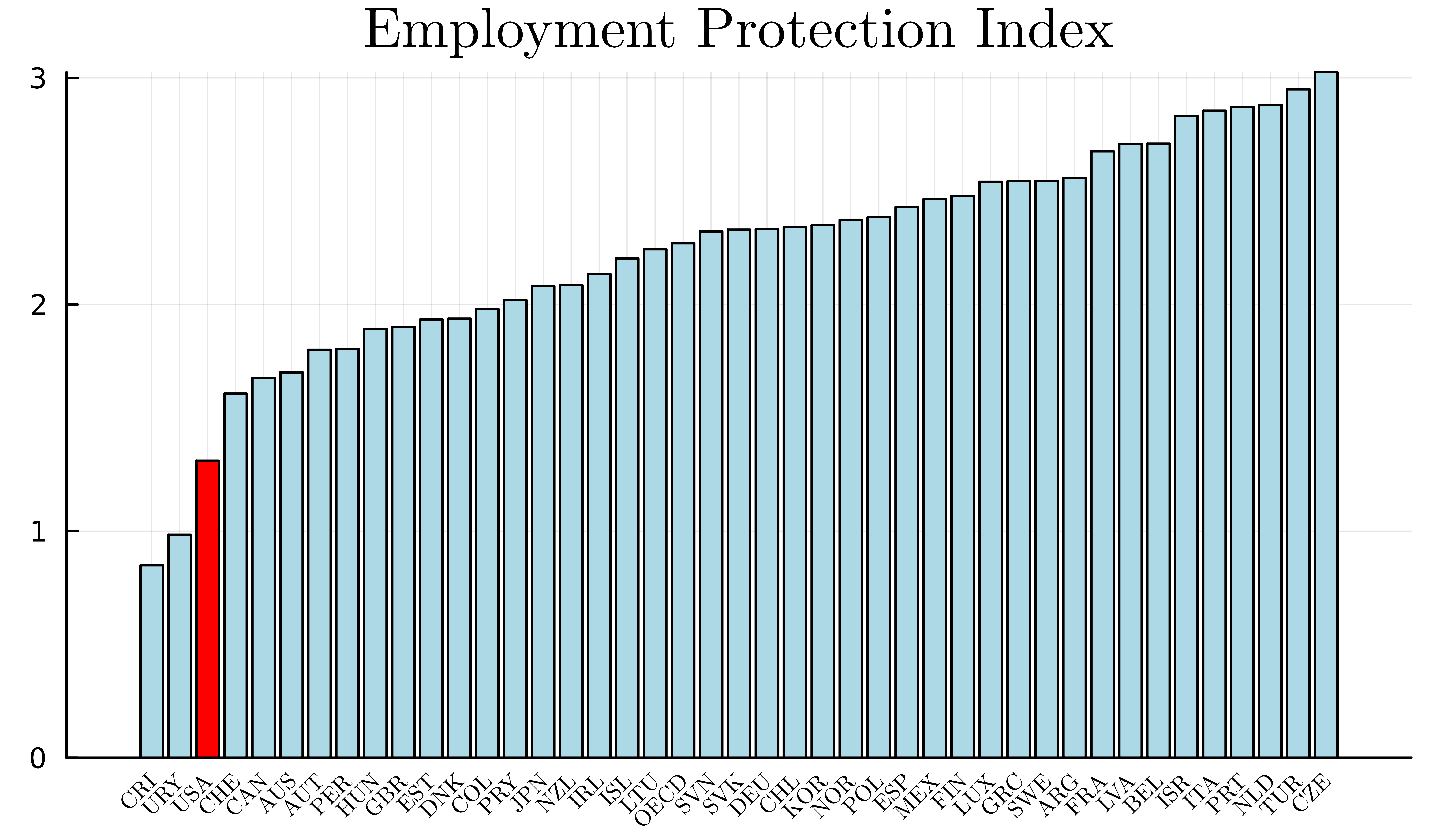
Countercyclical Volatility & Skewness

Moments	$\frac{\text{IQR}(n^i \mid u^a = -\sigma^a)}{\text{IQR}(n^i \mid u^a = +\sigma^a)}$ (1)
Data	1.278
Linear hiring	1
Concave hiring	1.220

Source: Ilut, Kehrig & Schneider (2018)

Firing Cost and Misallocation – Hopenhayn & Rogerson (1993)

Employment Protection Index



Data source: OECD

Question

- What is the cost of strict firing regulations?
- Suppose that in order to fire a worker, firms have to pay $\tau \times$ annual wage salary
  - US: $\tau = 0$
  - Europe: high τ
- Firing costs take the form of taxes
- The collected tax revenue is rebated back to households as lump-sum transfers

HJB-QVI

$$\min\left\{ rv(n,z) - \max_{h\geq 0}\left(\pi(n,z) - \Phi(h,n) + v_n(n,z)h + v_z(n,z)\mu(z) + \frac{1}{2}\sigma(z)^2 v_{zz}(n,z)\right), v(n,z) - \underline{v}^f(n,z)\right\} = 0$$

$$\underline{v}^f(n,z) = \max\left\{ \max_{n^f\leq n} v(n^f,z) - \tau w(n-n^f), \underline{v}\right\}$$

- This is the only modification
- No firing tax when exiting (maybe I should have assumed otherwise)

HJB-QVI

$$\min\left\{rv(n,z)-\max_{h\geq 0}\left(\pi(n,z)-\Phi(h,n)+v_n(n,z)h+v_z(n,z)\mu(z)+\frac{1}{2}\sigma(z)^2v_{zz}(n,z)\right), v(n,z)-\underline{v}^f(n,z)\right\}=0$$

$$\underline{v}^f(n,z)=\max\left\{\max_{n^f\leq n} v(n^f,z)-\tau w(n-n^f), \underline{v}\right\}$$

firing tax

- This is the only modification
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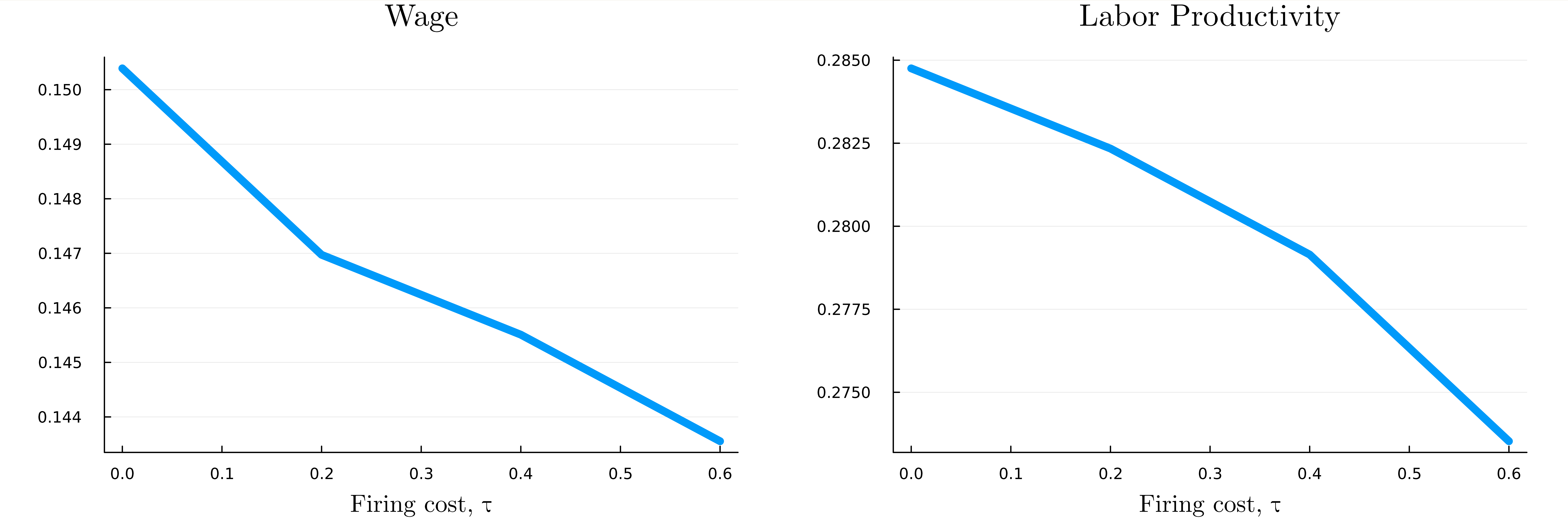
Misallocation Cost of Firing Regulations



- Firing costs lead to the misallocation of workers because
  1. Unproductive firms cannot downsize
  2. Productive firms become hesitant to expand

Idiosyncratic Distortion

- Firing tax is a distortion at the aggregate level
- There is no shortage of reasons to expect firms to face idiosyncratic distortions
  - Corruption, firm-level taxes/subsidies, financial frictions, incomplete contracts
- Restuccia & Rogerson (2008) consider *wedges* in the form of

$$(1+\tau_i)z^{1-\alpha}n^{\alpha}$$

where $\tau_i = \begin{cases} \tau & \text{with prob } 1/2 \\ -\tau & \text{with prob } 1/2 \end{cases}$

- τ_i is assigned when firm i is born and fixed over time

Misallocation from Idiosyncratic Distorton

Table 3
Effects of idiosyncratic distortions—uncorrelated case

Variable	τ_t			
	0.1	0.2	0.3	0.4
Relative Y	0.98	0.96	0.93	0.92
Relative TFP	0.98	0.96	0.93	0.92

Source: Restuccia & Rogerson (2008)

Non-Parametric Identification of Misallocation

– Carrillo, Donaldson, Pomeranz, & Singhal (2023)

What is the Cost of Misallocation?

- How large is the cost of misallocation in the data?
- Let us step back and consider a static model with a fixed mass of firms
- Each firm i produces using

$$y_i = f_i(n_i) \tag{7}$$

- The efficient allocation solves

$$Y^* \equiv \max_{\{n_i\}} \int f_i(n_i) di$$

$$\text{s.t.} \quad \int n_i di = L$$

- The solution features equalization of MPL:

$$f_i'(n_i) = w \quad \text{for all } i$$

Variance of MPL

- Take arbitrary allocation $\{n_i\}$. Up to a second order around the efficient allocation

$$\frac{Y - Y^*}{Y^*} \approx -\frac{1}{2}\int \lambda_i \epsilon_i \log(MPL_i/w)^2 di$$

where $MPL_i = f_i'(n_i)$, $\lambda_i = w_i n_i / Y^*$ and $\epsilon_i \equiv -\frac{d \log MPL_i}{d \log n_i}$

- (Weighted) variance of MPL is the key moment for the cost of misallocation

- Testing the presence of misallocation ⇔ testing Var$(MPL_i) = 0$

- How do we get the distribution of MPL?

1. Assume $f_i(n_i) = Z_i n_i^\alpha$, and then $MPL_i = \alpha \frac{y_i}{n_i}$ (Hsieh & Klenow, 2009)
2. Nonparametrically identify the distribution of MPL (Carrillo et al. 2023)

Nonparametric Identification

- Taking the first-order approximation of equation (7),

$$\Delta y_i = \beta_i \Delta n_i + \epsilon_i$$

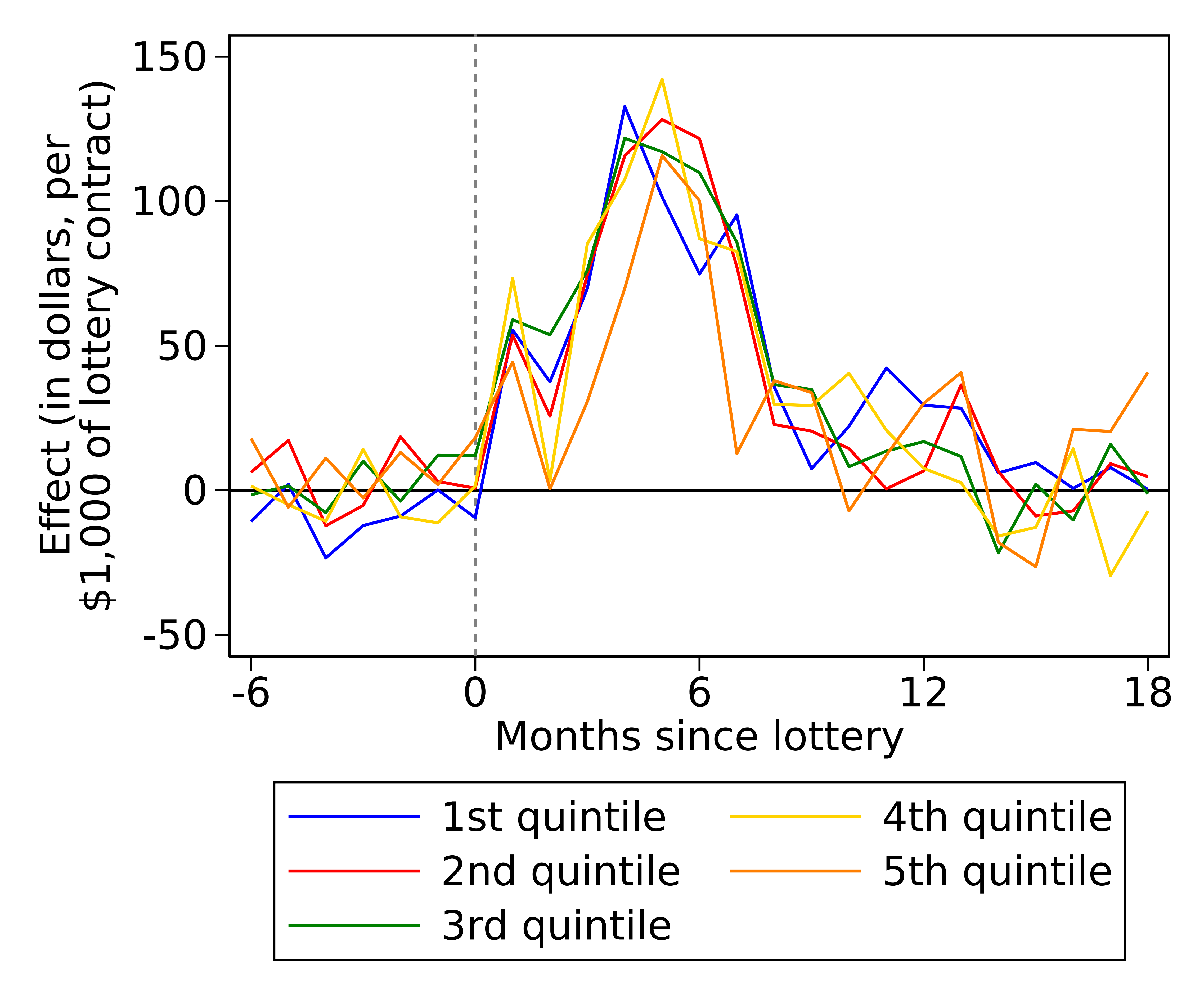
  - ϵ_i: technology shocks (i.e., changes in $f_i(\cdot)$)
  - $\beta_i = f_i'(n_i) = MPL_i$: treatment effect of exogenously increasing n_i on y_i
- With suitable instruments Z_i that exogenously shift n_i, $\mathbb{E}[\beta_i^k]$ ($k = 1,2,\ldots$) are identified (Masten & Torgovitsky, 2016)

Empirical Implementation

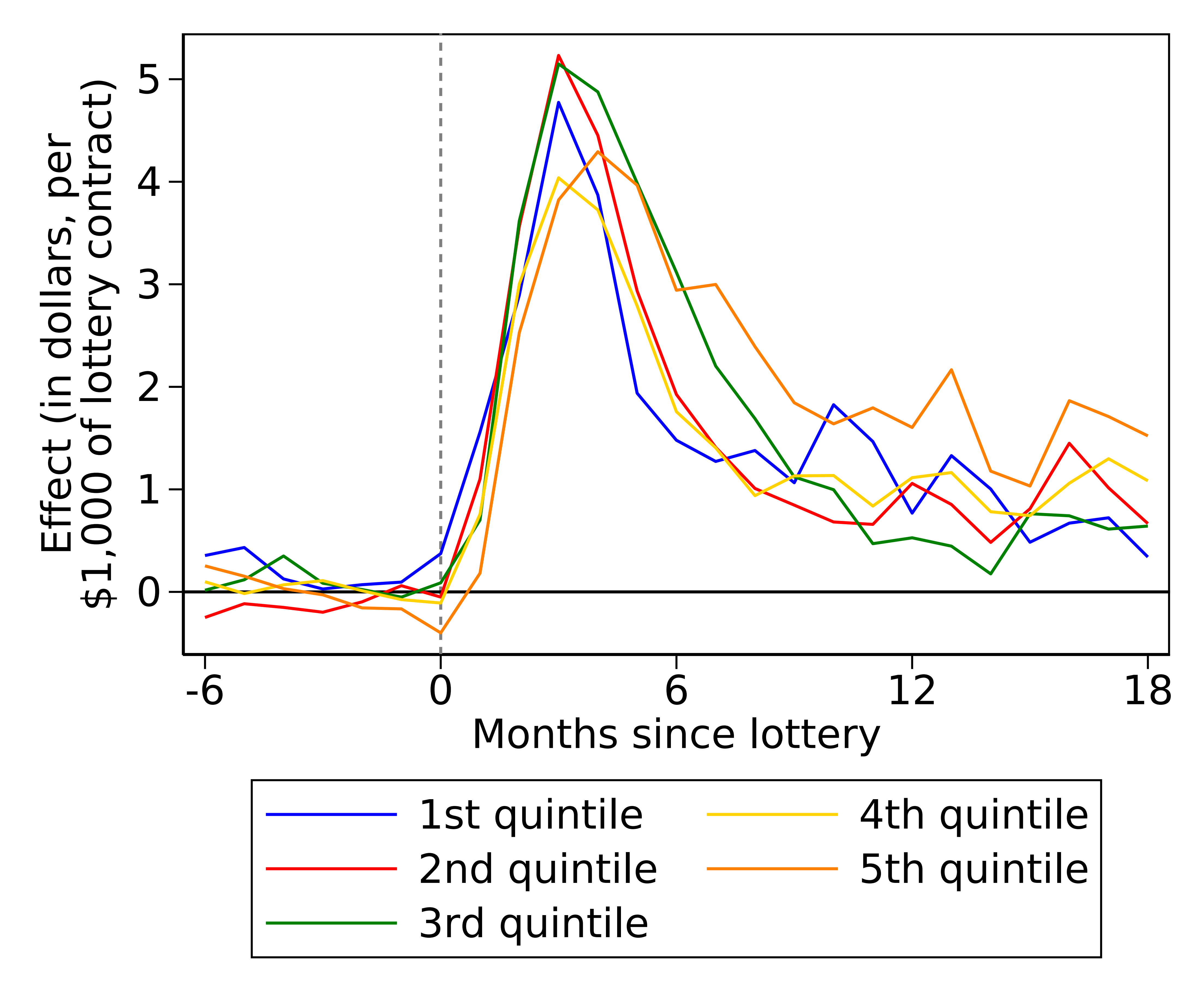
- Construction sector in Ecuador, 2009-2014
- Public construction projects were allocated through a randomized lottery
- Lottery serves as an ideal instrument
  - exogeneity: orthogonal to technology shocks ϵ_i or MPL_i
  - relevance: winning a lottery does shift n_i

Heterogenous Treatment Effects by Firm Size?

Sales



Labor Inputs



Small Cost of Misallocation

Table 4: Estimated Cost of Misallocation

	$\mathbb{E}_{\bar{\lambda}}[\bar{\mu}]$	$\mathbb{V}ar_{\bar{\lambda}}[\bar{\mu}]$	$\frac{\Delta W}{W}$
	(1)	(2)	(3)
Panel (a): IVCRC estimates			
Baseline	1.126	0.014	0.016
	[1.093, 1.161]	[0, 0.341]	[0, 0.261]
Panel (b): Alternative procedure assuming common scale elasticities			
Constant returns-to-scale ($\gamma = 1$)	1.240	0.611	0.479
	[1.223, 1.257]	[0.544, 0.730]	[0.427, 0.572]

- Assume $\epsilon_i = 3$ for all i
- The welfare cost of misallocation is 1.6%
- Hsieh-Klenow type calculation implies 48% of welfare loss in the same dataset

Questions

- Laissez-faire of Hopenhayn-Rogersion with labor adjustment costs is efficient
- But, MPL is not equalized in a static sense
- Firms hire workers until

  (present discounted value of hiring a worker) = (hiring cost today)
- Hiring a worker is an investment
- How do we incorporate dynamics without imposing strong assumptions?
- How do we incorporate entry & exit dynamics?