Endogenous Spatial Production Networks
Quantitative Implications for Trade and Productivity

Piyush Panigrahi
Johns Hopkins University

May 2, 2023

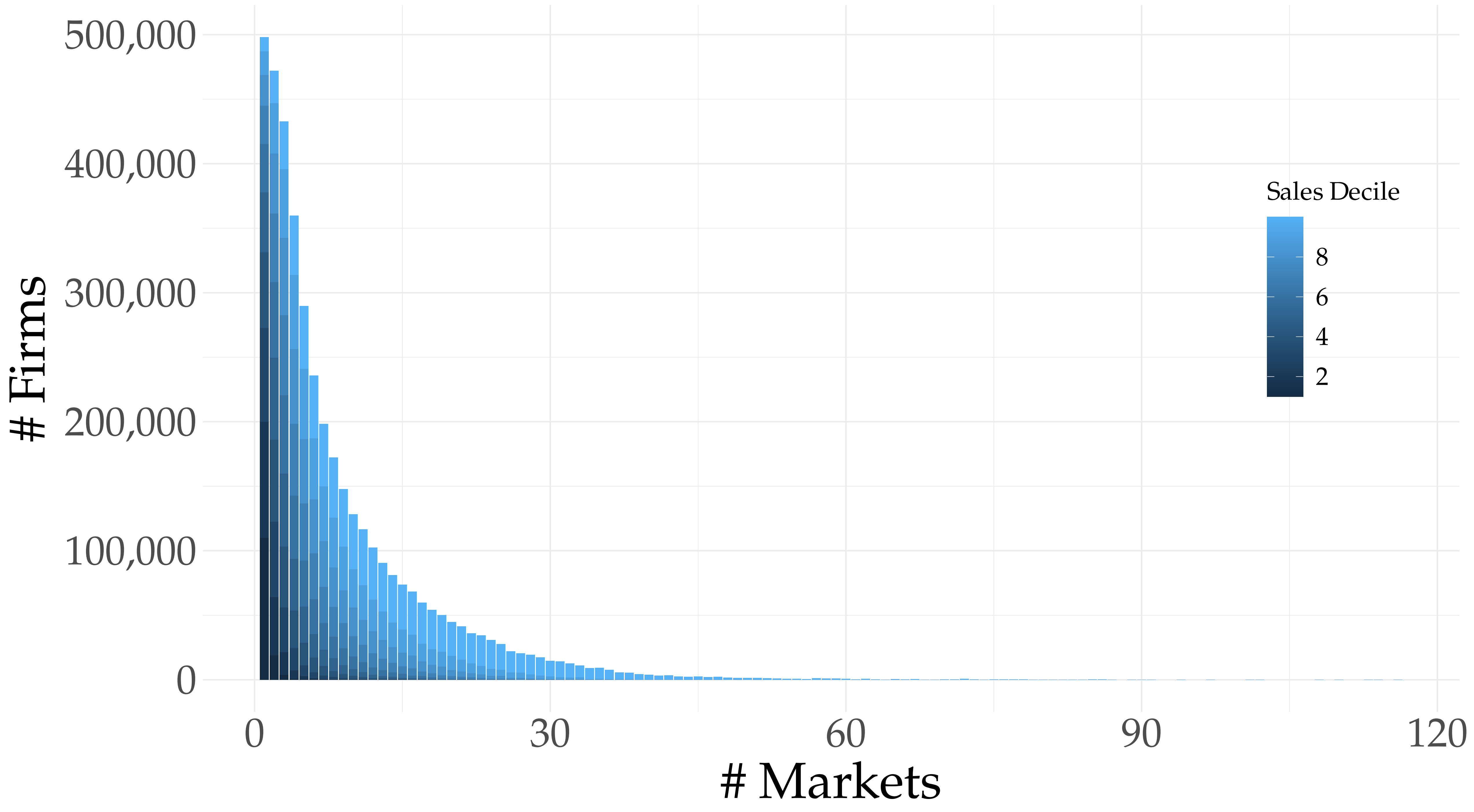
Introduction

- **Large firms** play a **pivotal role** in economic impact of **policy**
- Larger firms **sell more & to more markets** than smaller firms

Introduction

— **Large firms** play a **pivotal role** in economic impact of **policy**

— Larger firms **sell more & to more markets** than smaller firms



Source: Indian Firm-to-Firm Network Data from VAT records

Introduction

- **Large firms** play a **pivotal role** in economic impact of **policy**
- Larger firms **sell more & to more markets** than smaller firms
- Production occurs in **large-scale complex networks**
- **Firm-to-firm trade** underlies much of trade across space

Research Questions

- How does **network structure of production** shape firm size dispersion?
- How do **changes in spatial frictions to trade** affect network structure & firm size dispersion?

Preview

How does **network structure of production** shape firm size dispersion?

- firm-to-firm transactions micro-data from Indian VAT records
- endogenous network formation important for firm heterogeneity
- decisions of who to source and how intensively explain 81%

Preview

How do **changes in spatial frictions to trade** affect network structure & firm size dispersion?

- tractable model of network formation between spatially distant firms
- scalable framework for estimation and counterfactual analysis
- evaluate impact of market integration due to India's 2017 GST reform
  - significant reorganization of spatial production network
  - firm connectivity dispersion ↑ but firm size dispersion ↓
  - over half the variation [72%] by endogenous network changes

Related Literature

- Endogenous Production Networks
  [Oberfield (2018), Acemoglu & Azar (2020), Lim (2018), Huneeus (2020), Bernard et al. (2022), Eaton, Kortum & Kramarz (2022)]
  - **Empirically tractable model for large number of firms across space**

- Shocks through Network Economies
  [Acemoglu, Carvalho, Ozdaglar & Tahbaz-Salehi (2012), Baqaee & Farhi (2019, 2020), Bigio & La'O (2020)]
  - **Accommodate endogenous network changes in response to shocks**

- Firm Heterogeneity
  [Luttmer (2007), Arkolakis (2016), Oberfield (2018), Bernard at al. (2022)]
  - **Study heterogeneity arising from input-output linkages across space**

Data

- Universe of within-state firm-to-firm transactions

  [Assembled from commercial tax authorities in 5 Indian states]

  —141 districts:

  Gujarat (25), Maharashtra (35), Tamil Nadu (32), Odisha (30) and West Bengal (19)

  —5 years: FY 2011-12 to 2015-16

  —2.6 million firms and 103 million firm-to-firm connections

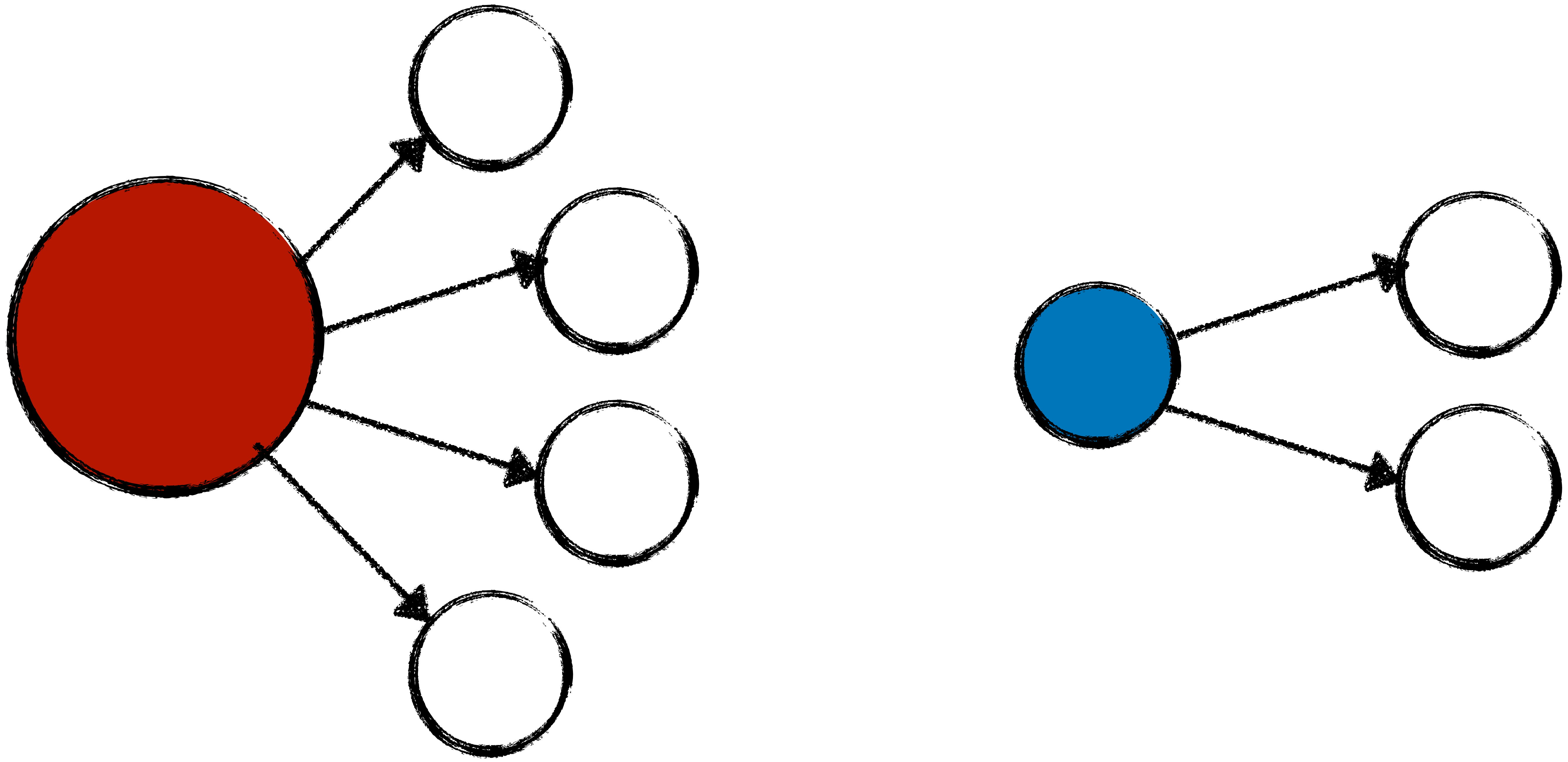
- Universe of cross-state firm-to-firm transactions

  [from Ministry of Finance, Govt. of India]

  —5 years: FY 2011-12 to 2015-16

Network Structure & Firms' Input Sales

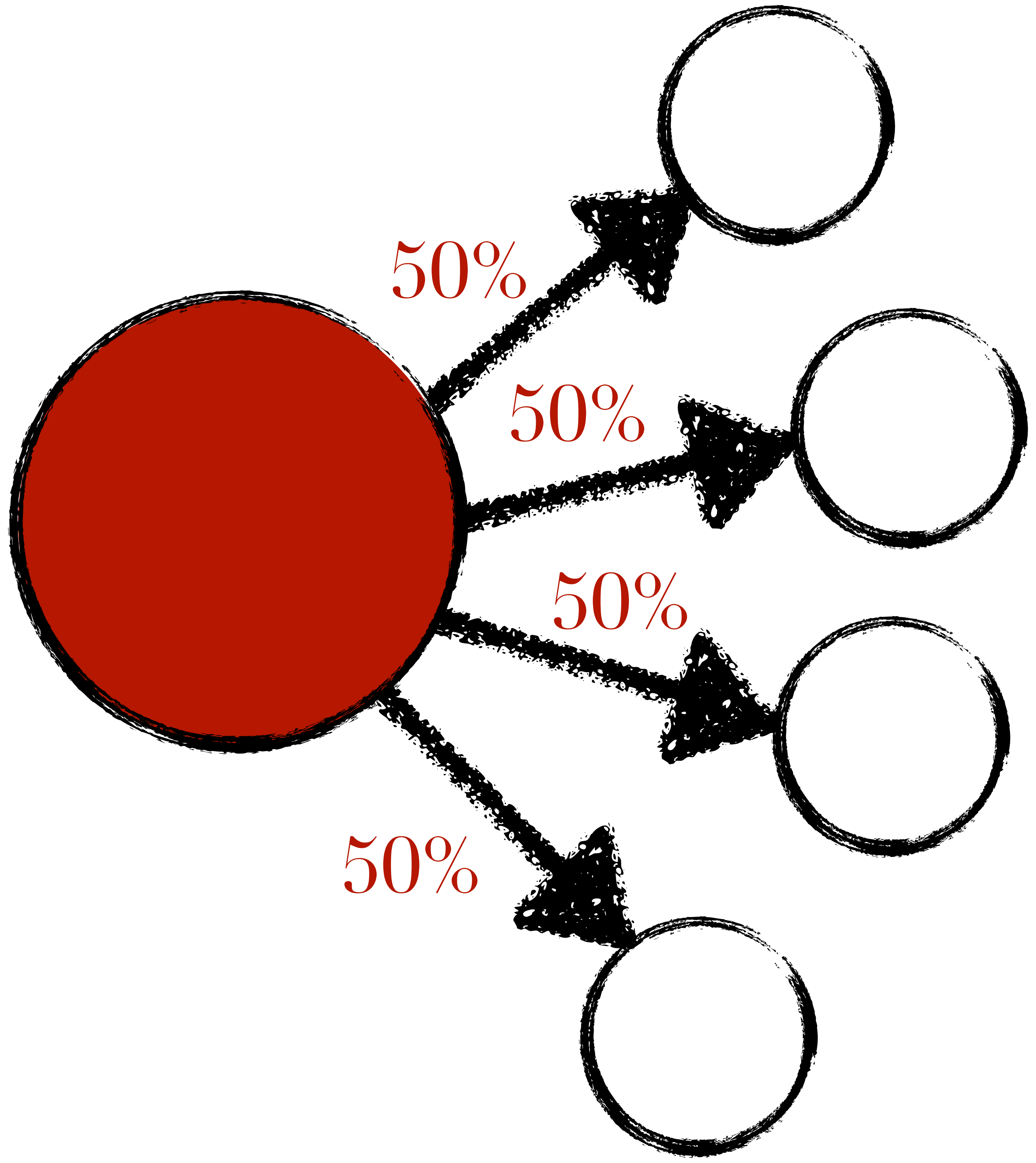
Larger firms tend to have more buyers

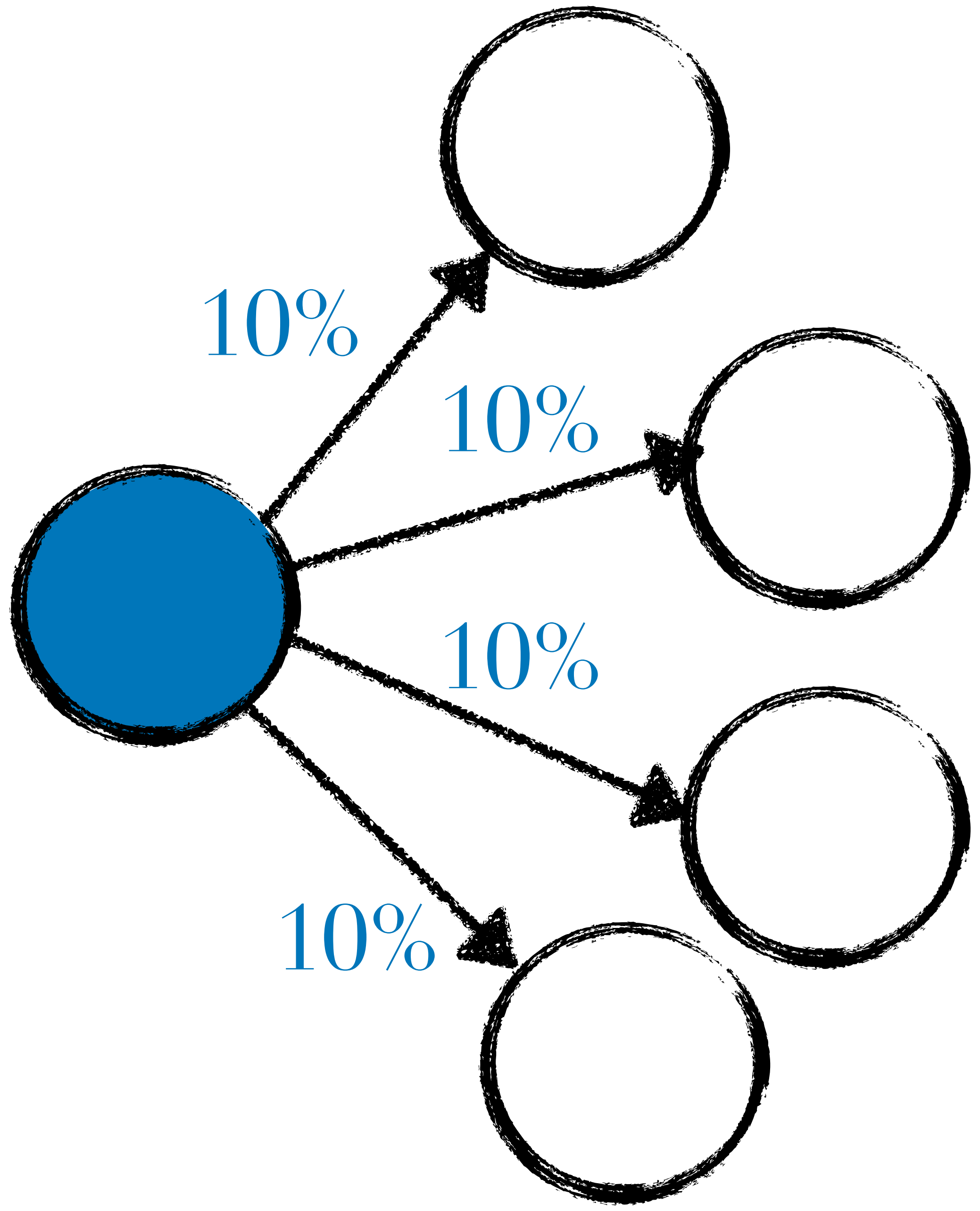


$$\frac{Cov[\ln(\text{sales}), \ln(\#\text{ buyers})]}{Var[\ln(\text{sales})]} = 35\%$$

Network Structure & Firms' Input Sales

Larger firms tend to be used more intensively by buyers

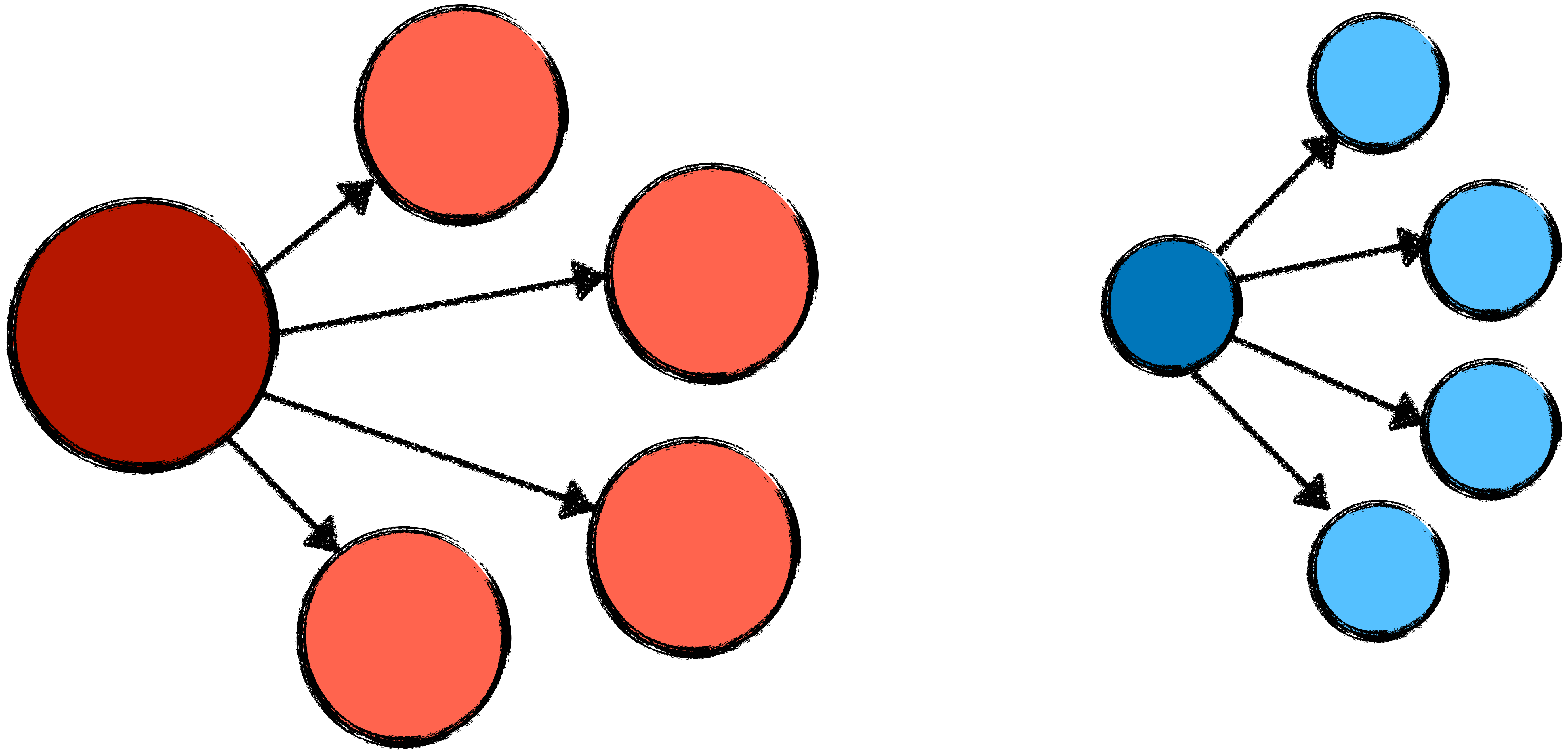




$$\frac{Cov[\ln(\text{sales}), \ln(\text{average intensity})]}{Var[\ln(\text{sales})]} = 46\%$$

Network Structure & Firms' Input Sales

Larger firms tend to have larger buyers



$$\frac{Cov[\ln(\text{sales}), \ln(\text{average buyer size})]}{Var[\ln(\text{sales})]} = 19\%$$

Network Structure & Firms' Input Sales

Exact Decomposition of Intermediate Input Sales

more buyers [35%]	larger share of buyers' costs [46%]	larger buyers [19%]

$$\text{sales}(s) = \#\,\text{buyers}(s) \times \underbrace{\left(\frac{\sum_b \text{share}(s,b)}{\#\,\text{buyers}(s)}\right)}_{\text{average intensity}(s)} \times \underbrace{\left(\frac{\sum_b \text{share}(s,b) \times \text{costs}(b)}{\sum_b \text{share}(s,b)}\right)}_{\text{average buyer size}(s)}$$

Network Structure & Firms' Input Sales

Accounting for Spatial Frictions

more buyers [23%]	larger share of buyers' costs [57%]	larger buyers [20%]

$$\text{sales}(s, d) = \#\ \text{buyers}(s, d) \times \text{average intensity}(s, d) \times \text{average buyer size}(s, d)$$

Network Structure & Firms' Input Sales

Within Firm Across Destination Markets

more buyers [37%]	larger share of buyers' costs [56%]	larger buyers [7%]

$$\frac{\text{sales}(s,d)}{\text{sales}(s)} = \frac{\#\ \text{buyers}(s,d)}{\#\ \text{buyers}(s)} \times \frac{\text{average intensity}(s,d)}{\text{average intensity}(s)} \times \frac{\text{average buyer size}(s,d)}{\text{average buyer size}(s)}$$

Towards the Model

<table>
<tr><td colspan="2">higher intensity of use
[81%]</td><td rowspan="2">larger buyers
[19%]</td></tr>
<tr><td>more buyers
[35%]</td><td>larger share of buyers' costs
[46%]</td></tr>
</table>

Individual buyers' input sourcing decisions → # buyers, share of buyers' costs

Towards the Model

Endogenous Network Margin

<table>
<tr><td colspan="2">higher intensity of use
[81%]</td><td rowspan="2">larger buyers
[19%]</td></tr>
<tr><td>more buyers
[35%]</td><td>larger share of buyers' costs
[46%]</td></tr>
</table>

$$\text{intensity of use}(s) = \#\ \text{buyers}(s) \times \text{average intensity}(s)$$

Towards the Model

Low production cost firms end up larger because

— find **more buyers**

— **used more intensively** by their buyers

— buyers **use cheaper inputs intensively → lower production costs**

— lower production costs → **buyers become larger** themselves

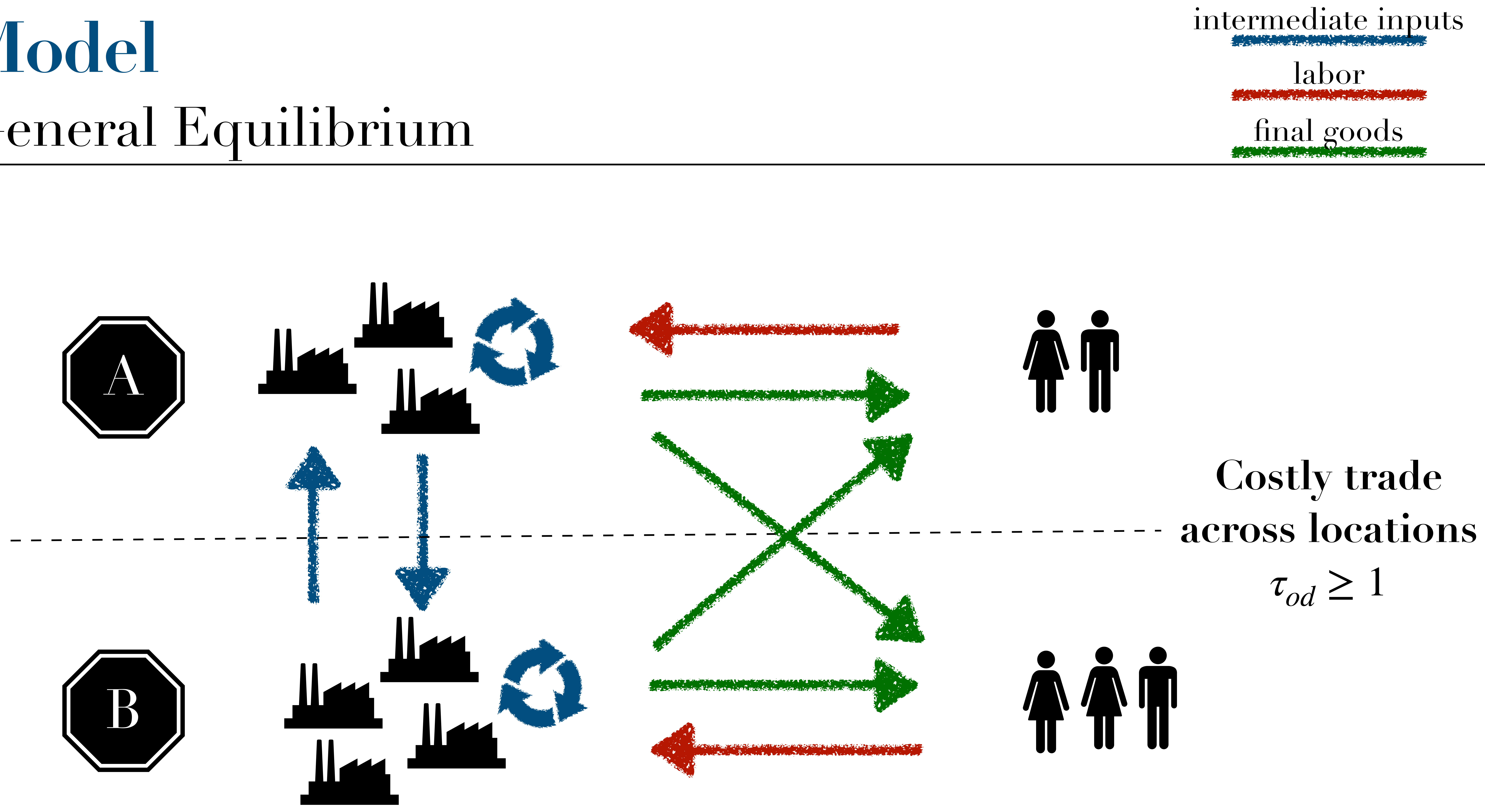
Towards the Model

In the cross-section, larger firms

- tend to have **more buyers**
- tend to be **used more intensively** by buyers
- tend to have **larger buyers**

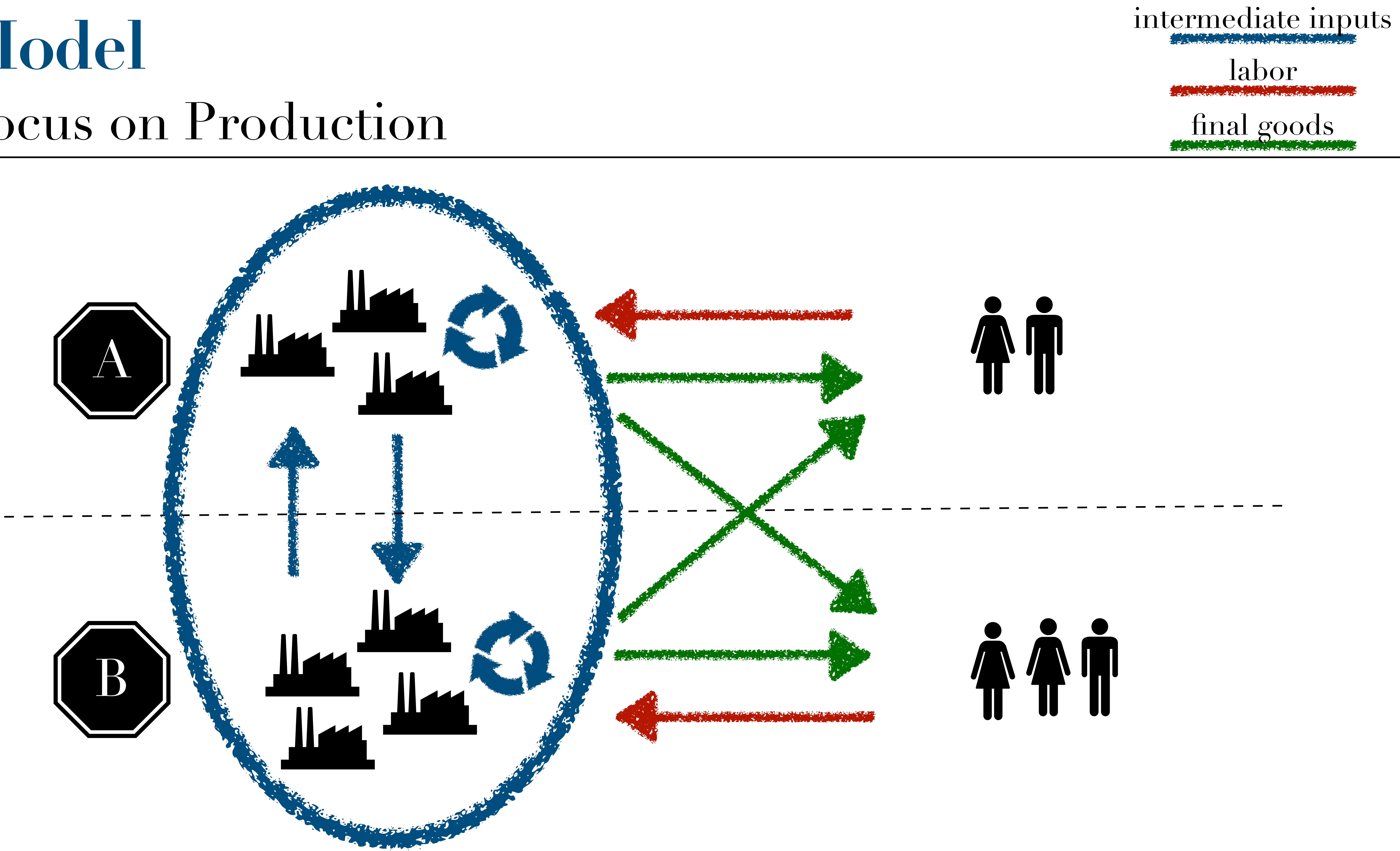
Model

General Equilibrium



Model

Focus on Production



Model

Production Function

$$y(b) = z(b) \times \underbrace{\left(l(b)\right)^{1-\alpha_d}}_{\text{labor}} \times \underbrace{\left(\prod_{k=1}^{K} m(b,k)^{\frac{1}{K}}\right)^{\alpha_d}}_{\text{materials}}$$

Model

Production Function

materials share

tasks

productivity

$$y(b) = z(b) \times \underbrace{\left(l(b)\right)^{1-\alpha_d}}_{\text{labor}} \times \underbrace{\left(\prod_{k=1}^{K} m(b,k)^{\frac{1}{K}}\right)^{\alpha_d}}_{\text{materials}}$$

technology consists of
multiple input requirements

Model

Production Function

tasks enter **symmetrically**

$$y(b) = z(b) \times \underbrace{\left(l(b)\right)^{1-\alpha_d}}_{\text{labor}} \times \underbrace{\left(\prod_{k=1}^{K} m(b,k)^{\frac{1}{K}}\right)^{\alpha_d}}_{\text{materials}}$$

$$m(b,k) = \sum_{s} m(s,b,k)$$

output of potential suppliers
are **substitutes**

Model

Cost Function

$$c(b) = \frac{w_d^{1-\alpha_d} \times \prod_{k=1}^{K} \left(p(b,k)\right)^{\frac{\alpha_d}{K}}}{z(b)}$$

marginal cost

Model

Cost Function

wage

effective price of task

$$c(b) = \frac{w_d^{1-\alpha_d} \times \prod_{k=1}^{K} \left(p(b,k)\right)^{\frac{\alpha_d}{K}}}{z(b)}$$

Model

Cost Function

effective price of task

$$p(b,k) = \min_{s} \left(\frac{\bar{m}(s,b,k) \times c(s) \times \tau_{od}}{a(s,b,k)} \right)$$

Model

Cost Function

seller's marginal cost

markups [Bertrand competition]

trade cost

$$p(b,k) = \min_s \left(\frac{\bar{m}(s,b,k) \times c(s) \times \tau_{od}}{a(s,b,k)} \right)$$

match-specific productivity

Model

Cost Function

$$c(b) = \frac{w_d^{1-\alpha_d} \times \prod_{k=1}^{K} \left(p(b,k)\right)^{\frac{\alpha_d}{K}}}{z(b)}$$

$$p(b,k) = \min_s \left(\frac{\bar{m}(s,b,k) \times c(s) \times \tau_{od}}{a(s,b,k)} \right)$$

Taking Model to Data

$$c(b) = \frac{w_d^{1-\alpha_d}}{z(b)} \times \prod_{k=1}^{K} \min_s \left(\frac{\bar{m}(s,b,k) \times \tau_{od}}{a(s,b,k)} \times c(s) \right)^{\frac{\alpha_d}{K}}$$

marginal cost function has recursive formulation

Taking Model to Data

Network Formation → Quasi-Dynamic Programming

cost share ↦ discount factor

$$c(b) = \frac{w_d^{1-\alpha_d}}{z(b)} \times \prod_{k=1}^{K} \min_s \left(\frac{\bar{m}(s,b,k) \times \tau_{od}}{a(s,b,k)} \times c(s) \right)^{\frac{\alpha_d}{K}}$$

buyer MC ↦ current period value function

seller MC ↦ next period value function

Taking Model to Data

Network Formation → Quasi-Dynamic Programming

exogenous
estimands

$$c(b) = \frac{w_d^{1-\alpha_d}}{z(b)} \times \prod_{k=1}^{K} \min_s \left(\frac{\bar{m}(s,b,k) \times \tau_{od}}{a(s,b,k)} \times c(s) \right)^{\frac{\alpha_d}{K}}$$

endogenous
estimands

Taking Model to Data

Network Formation → Quasi-Dynamic Programming

exogenous estimands

$$c(b) = \frac{w_d^{1-\alpha_d}}{z(b)} \times \prod_{k=1}^{K} \min_s \left(\frac{\bar{m}(s,b,k) \times \tau_{od}}{a(s,b,k)} \times c(s) \right)^{\frac{\alpha_d}{K}}$$

endogenous estimands

— very-high dimensional → full solution methods infeasible

— interdependence in link formation → simulation burdensome

[Rust (1987), Anderson & van Wincoop (2003), Antras & de Gortari (2020)]

Taking Model to Data

Quasi-Dynamic Programming → Conditional Choice Probabilities

Conditional Choice Probabilities

[conditional on marginal cost (endogenous state), probability of getting chosen]

have closed-form solution

Taking Model to Data

Quasi-Dynamic Programming → Conditional Choice Probabilities

Conditional Choice Probabilities [CCPs]

For sufficiently large economies, given productivities and trade costs, conditional on marginal cost being $c(s)$, the probability with which b selects s for any given task is:

$$\pi_{od}(s,b) = \frac{c(s)^{-\zeta} \times \tau_{od}^{-\zeta}}{\sum_{s'} c(s')^{-\zeta} \times \tau_{o'd}^{-\zeta}}$$

— CCPs which depend on endogenous state ↦ sample analogs

[Hotz & Miller (1993)]

Estimating Equation

Conditional Choice Probabilities → Multinomial Logit

$$\mathbb{E}[\text{share}(s, b)] = \frac{c(s)^{-\zeta} \times \tau_{od}^{-\zeta}}{\sum_{s'} c(s')^{-\zeta} \times \tau_{o'd}^{-\zeta}}$$

CCPs

Estimating Equation

Conditional Choice Probabilities → Multinomial Logit

$$\mathbb{E}[\text{share}(s,b)] = \frac{c(s)^{-\zeta} \times \tau_{od}^{-\zeta}}{\sum_{s'} c(s')^{-\zeta} \times \tau_{o'd}^{-\zeta}}$$

Estimands:

— marginal cost $c(s)$ estimated as seller fixed effects

— $\tau_{od}^{-\zeta} = \exp\left(X'_{od}\beta\right)$ $[X_{od} \equiv$ distance, borders etc.$]$

Estimating Equation

Conditional Choice Probabilities → Multinomial Logit

$$\mathbb{E}[\text{share}(s, b)] = \frac{c(s)^{-\zeta} \times \tau_{od}^{-\zeta}}{\sum_{s'} c(s')^{-\zeta} \times \tau_{o'd}^{-\zeta}}$$

Estimands:

— marginal cost $c(s)$ estimated as seller fixed effects

— $\tau_{od}^{-\zeta} = \exp\left(X'_{od}\beta\right)$ [$X_{od} \equiv$ distance, borders etc.]

Natural choice since probability of sourcing adds to unity

[Gourieroux, Monfort & Trognon (1984), Eaton, Kortum & Sotelo (2013)]

Counterfactual Analysis

Large Networks & Granularity

Aggregate Trade Models + Exact Hat Algebra

model degeneracy $\Longrightarrow$ model prediction = observed data

Counterfactual Analysis

Large Networks & Granularity

Aggregate Trade Models + Exact Hat Algebra

model degeneracy $\Longrightarrow$ model prediction = observed data

Models with Large Networks & Granularity

model non-degeneracy $\Longrightarrow$ model prediction(s) $\neq$ observed data

— observed data $\rightarrow$ estimated model $\rightarrow$ $\mathbb{E}[\text{model predictions} \mid \text{initial state}]$

— counterfactual evaluation:

$$\mathbb{E}[\widehat{\text{model predictions}}] = \frac{\mathbb{E}[\text{model predictions} \mid \text{counterfactual state}]}{\mathbb{E}[\text{model predictions} \mid \text{initial state}]}$$

India’s 2017 Goods & Services Tax Reform

Background

Prior to 2017 in India, each state had its own VAT tax system

— when sourcing inputs outside own state, firms paid sales tax (no input tax credit)

— entry taxes, border inspections made it even more expensive

— large border frictions & regional segregation of production

India’s 2017 Goods & Services Tax Reform

Background

Prior to 2017 in India, each state had its own VAT tax system

— when sourcing inputs outside own state, firms paid sales tax
(no input tax credit)

— entry taxes, border inspections made it even more expensive

— large border frictions & regional segregation of production

2017 Goods & Services Tax (GST) Reform

— harmonized VAT system

— input tax credits irrespective of source of inputs

— mitigate border frictions across states

India’s 2017 Goods & Services Tax Reform

Quantitative Analysis: Market Integration

For district pairs that cross state borders:

— border frictions account for $\sim 90\%$ of estimated trade frictions

— in the counterfactual exercise, trade frictions reduced by $\sim 90\%$

In the counterfactual equilibrium:

— production network reorganizes across space

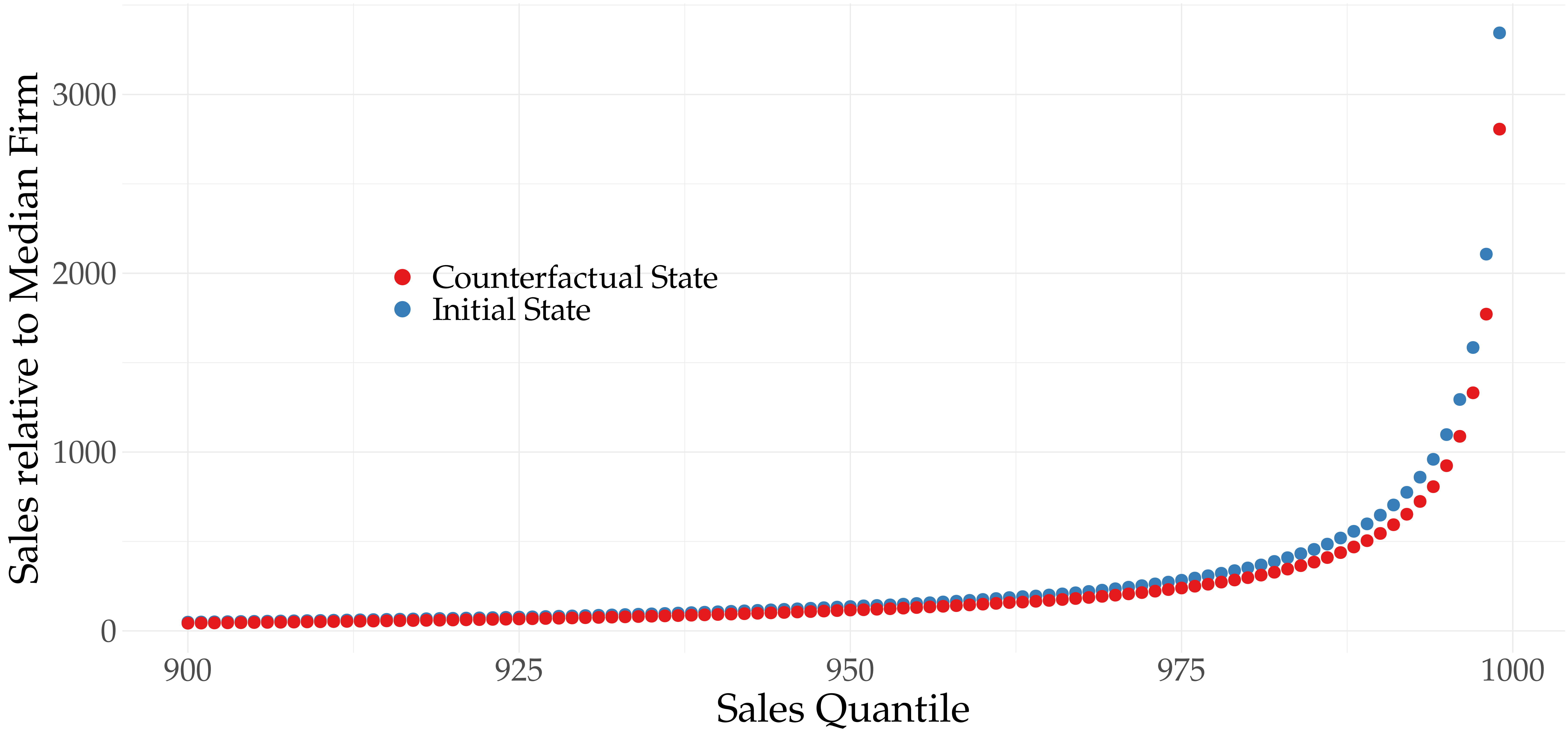
— dispersion in network connectivity across firms $\uparrow$

— dispersion in intermediate input sales across firms $\downarrow$

— over half of the variation explain by endogenous changes

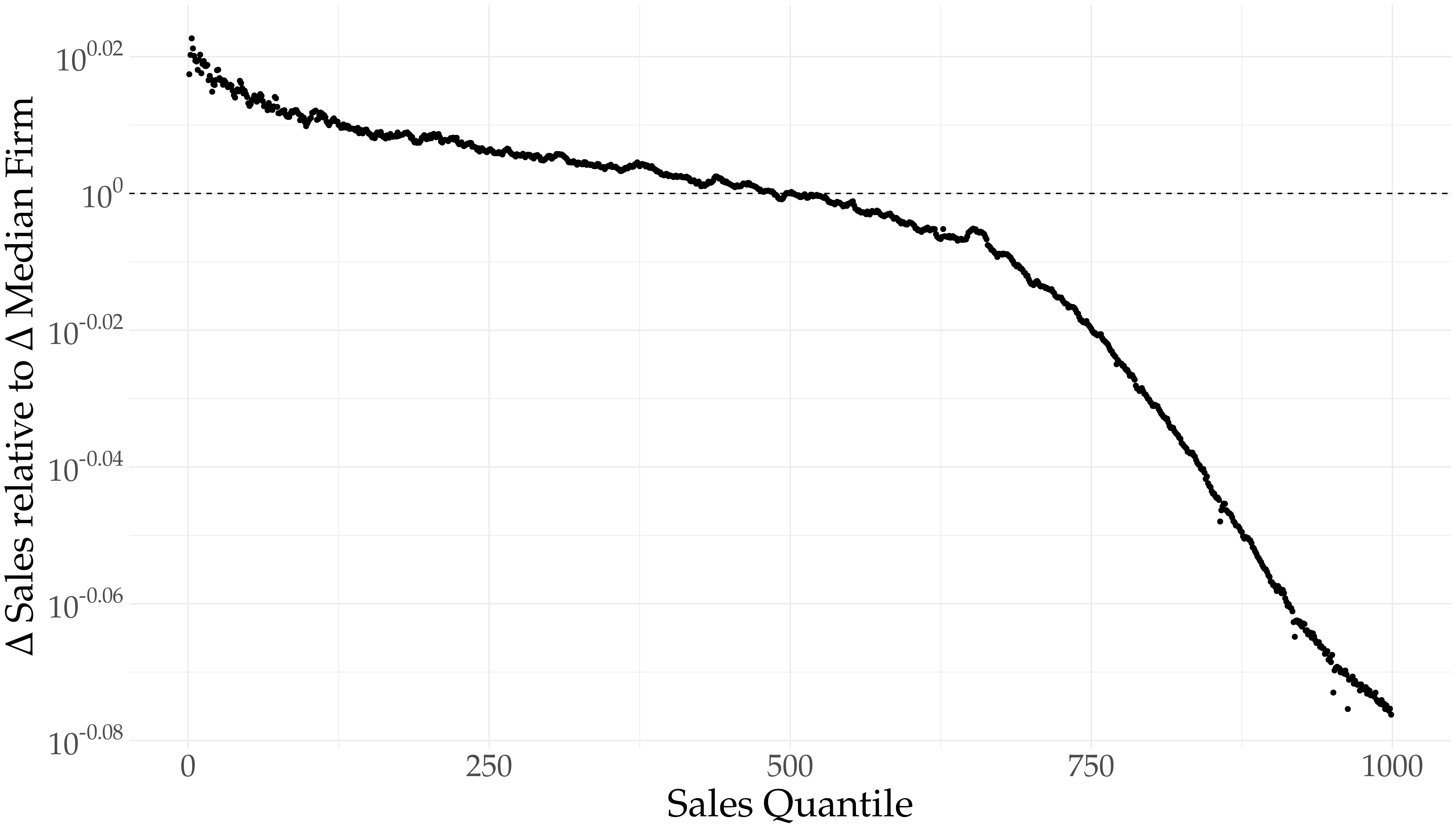
India’s 2017 Goods & Services Tax Reform

Dispersion in Intermediate Input Sales



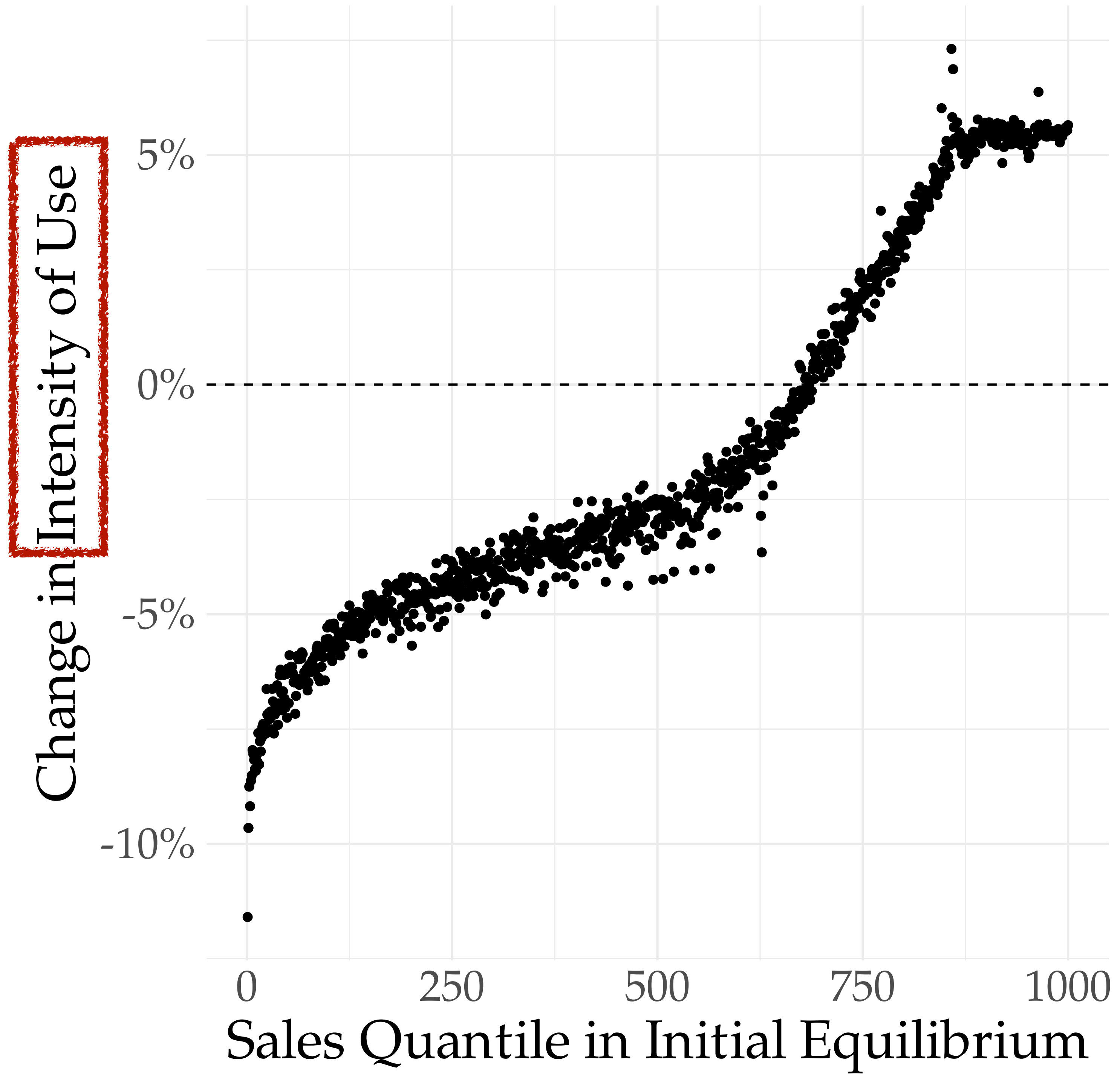
India's 2017 Goods & Services Tax Reform

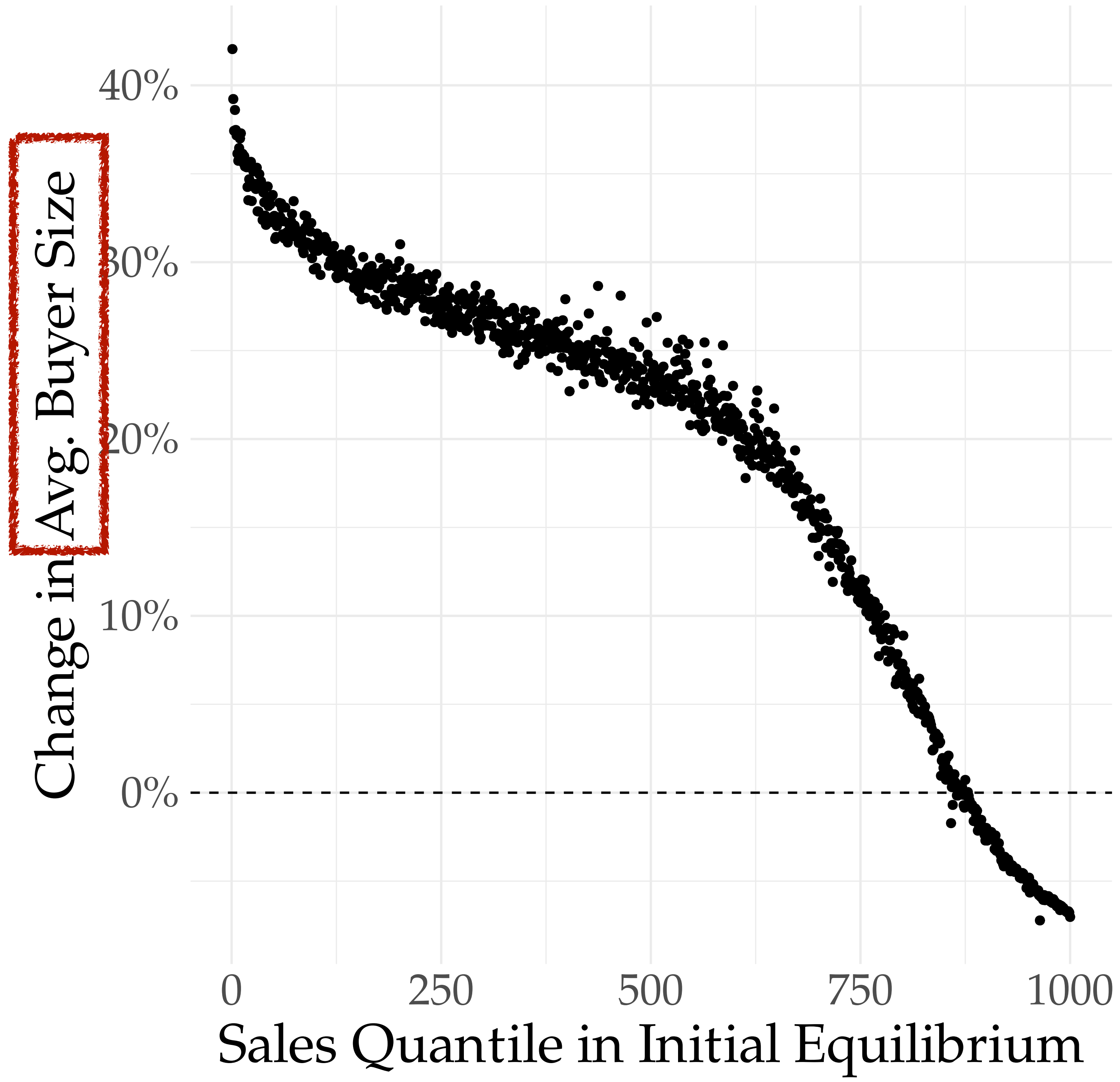
Dispersion in Intermediate Input Sales

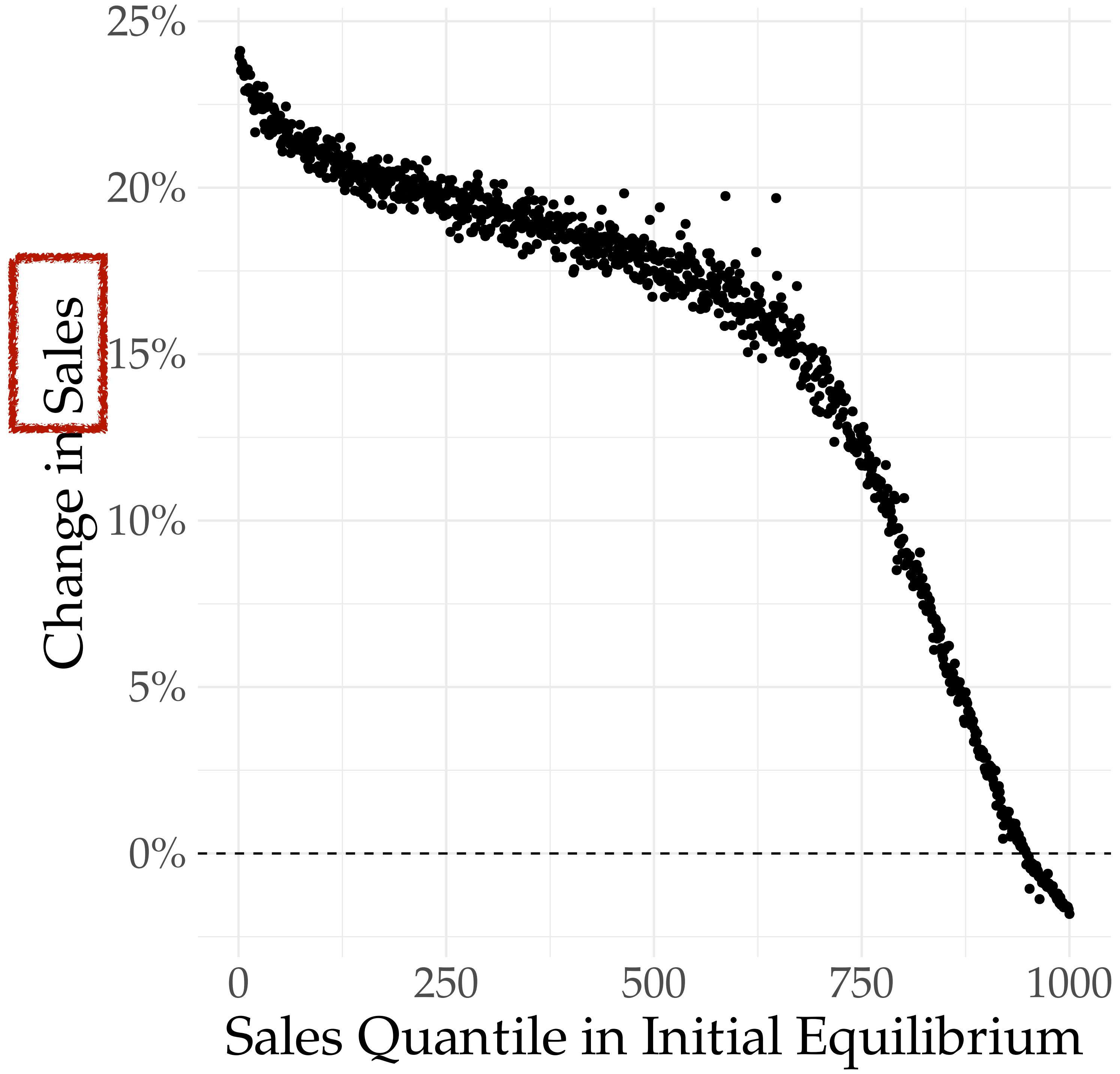


India’s 2017 Goods & Services Tax Reform

Changes in Margins of Intermediate Input Sales



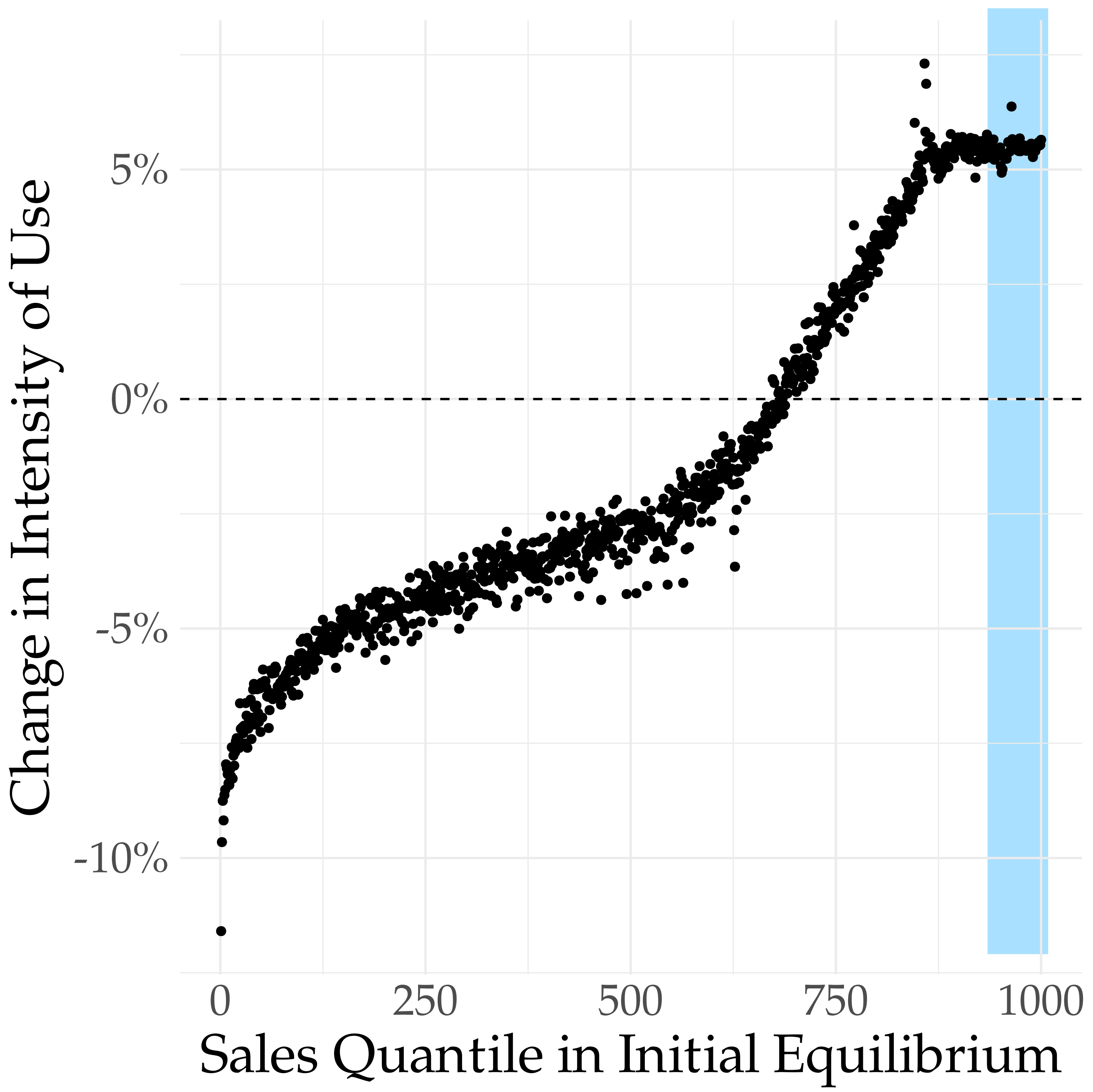




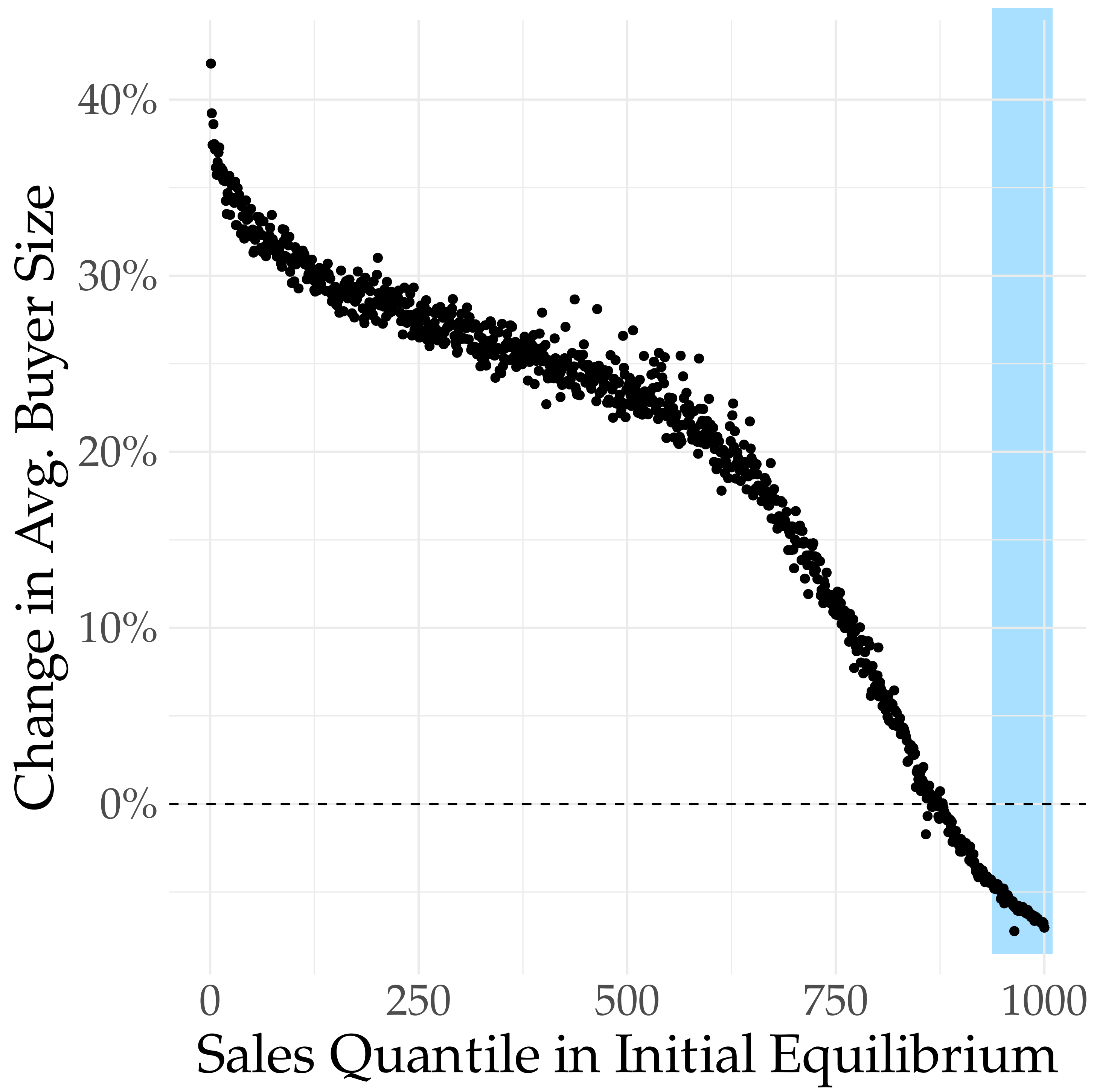
India's 2017 Goods & Services Tax Reform

Changes in Margins of Intermediate Input Sales

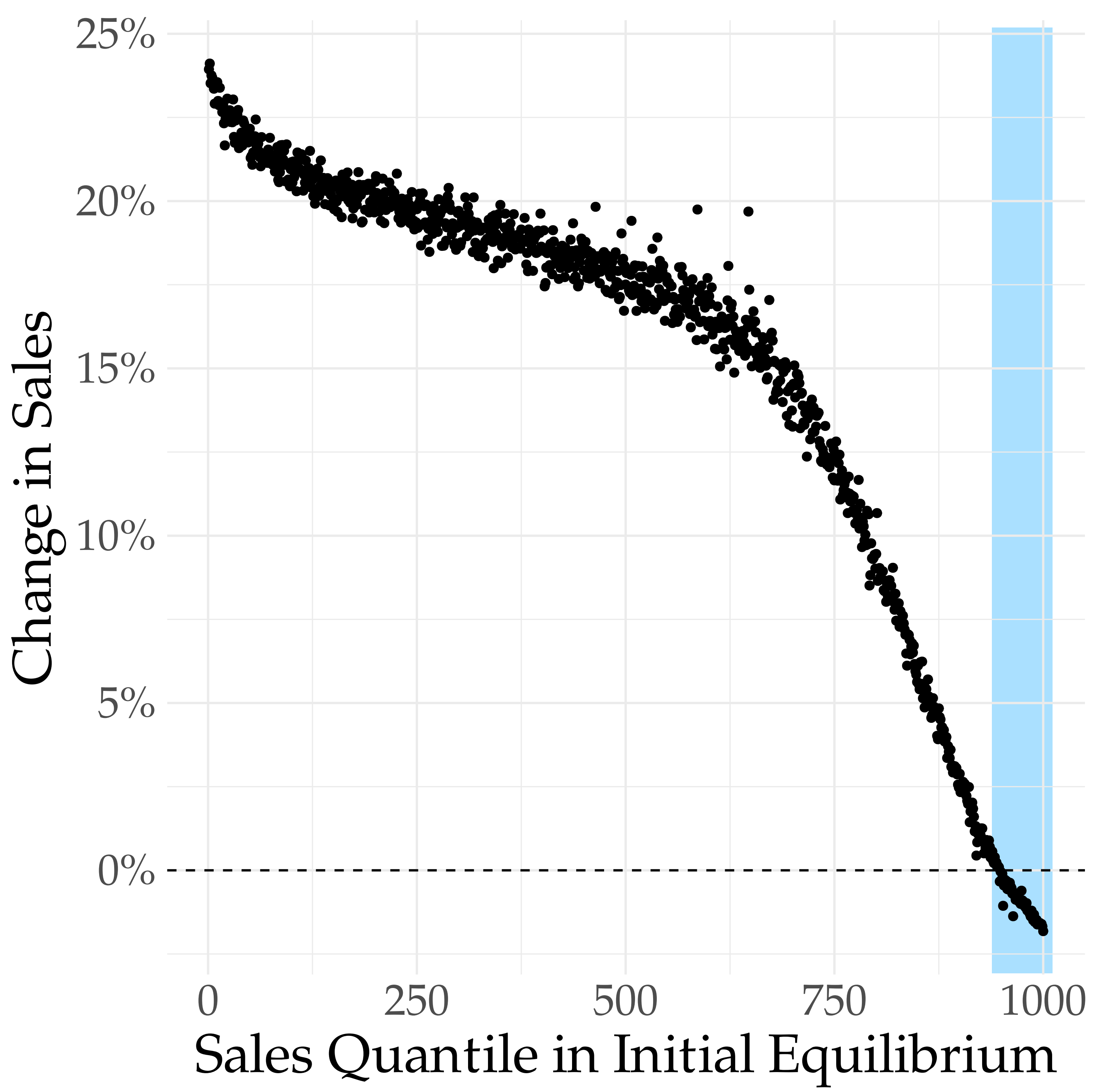
Intensity of Use ↑



Average Buyer Size ↓



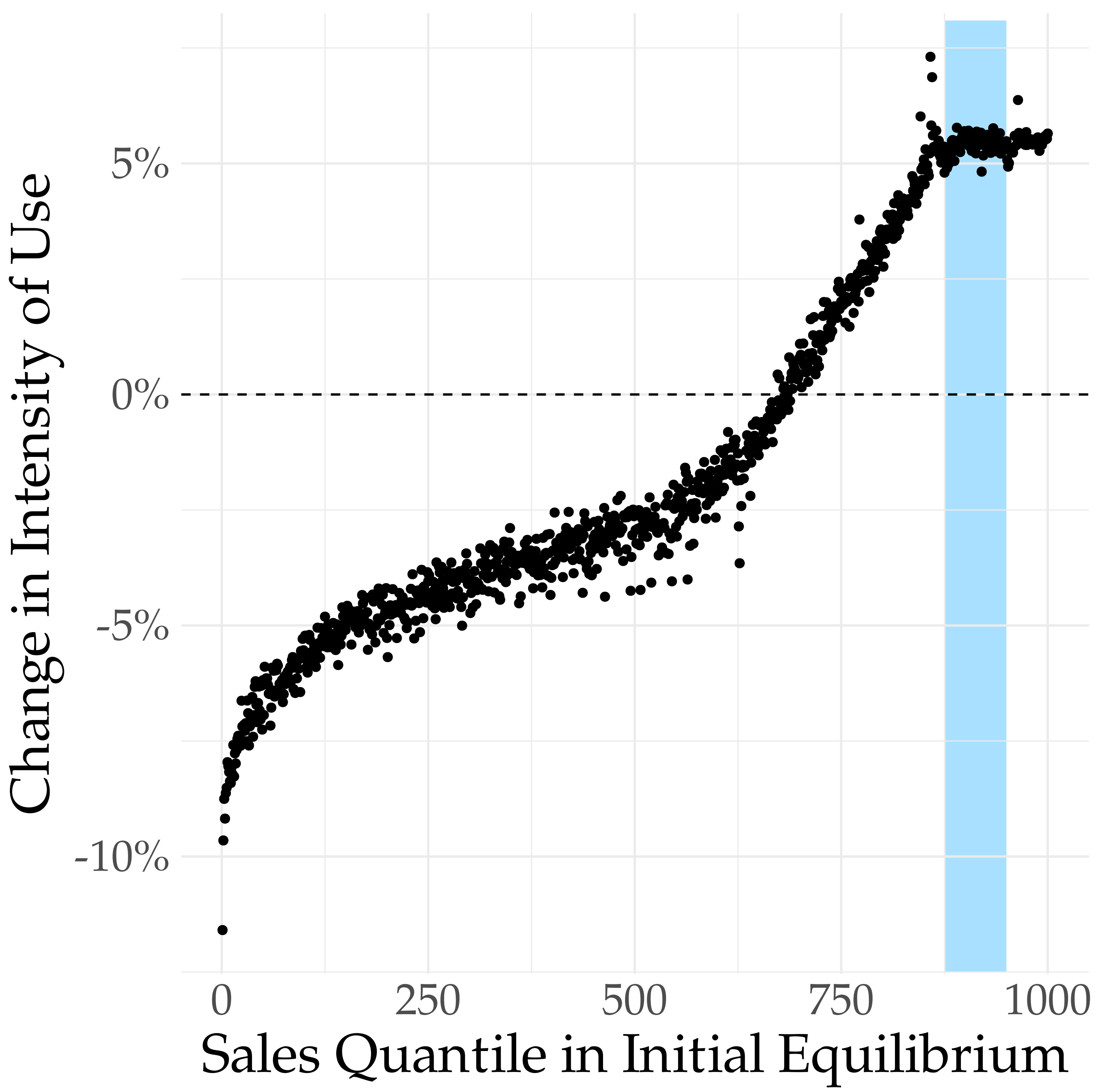
Sales ↓



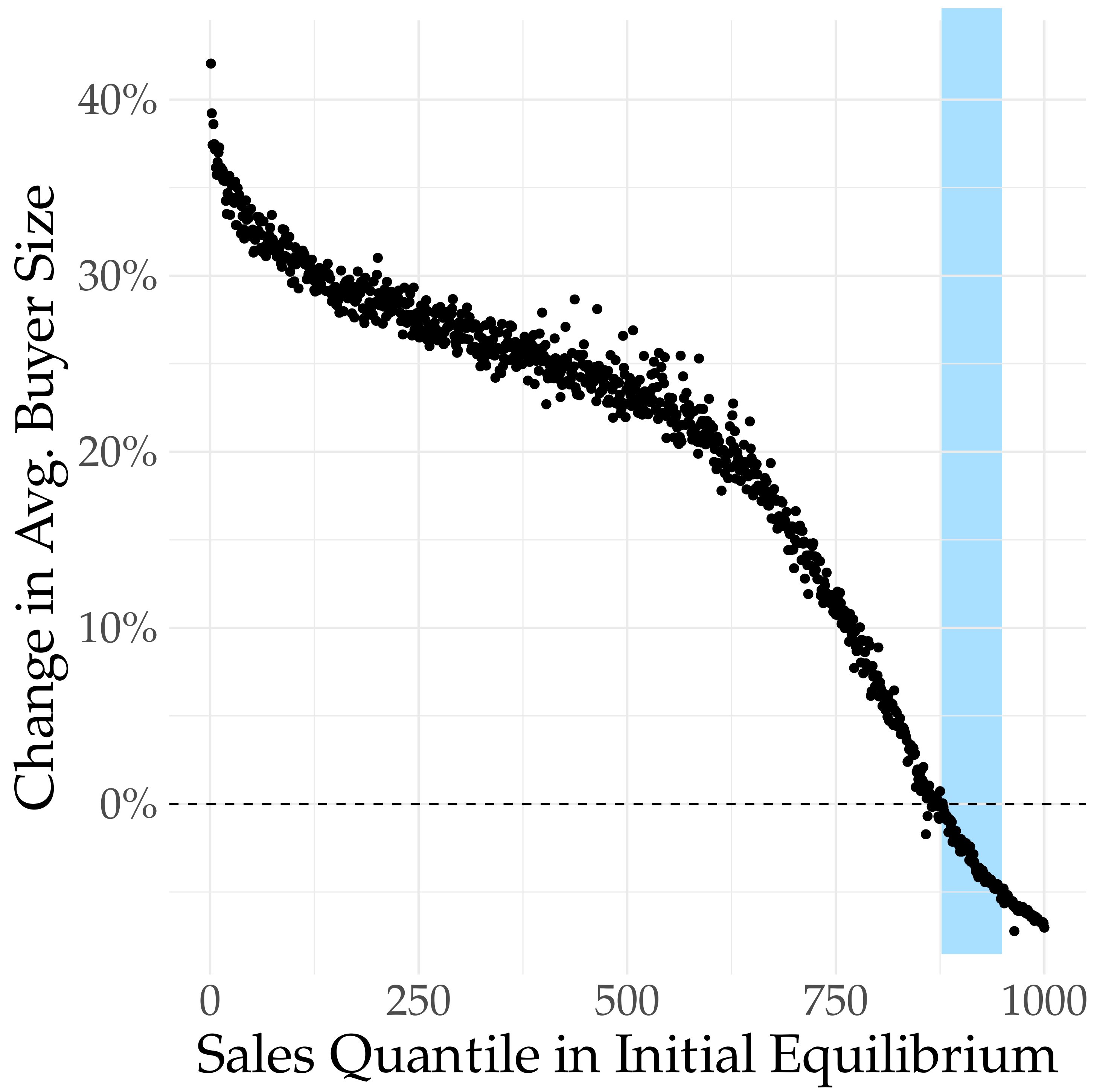
India's 2017 Goods & Services Tax Reform

Changes in Margins of Intermediate Input Sales

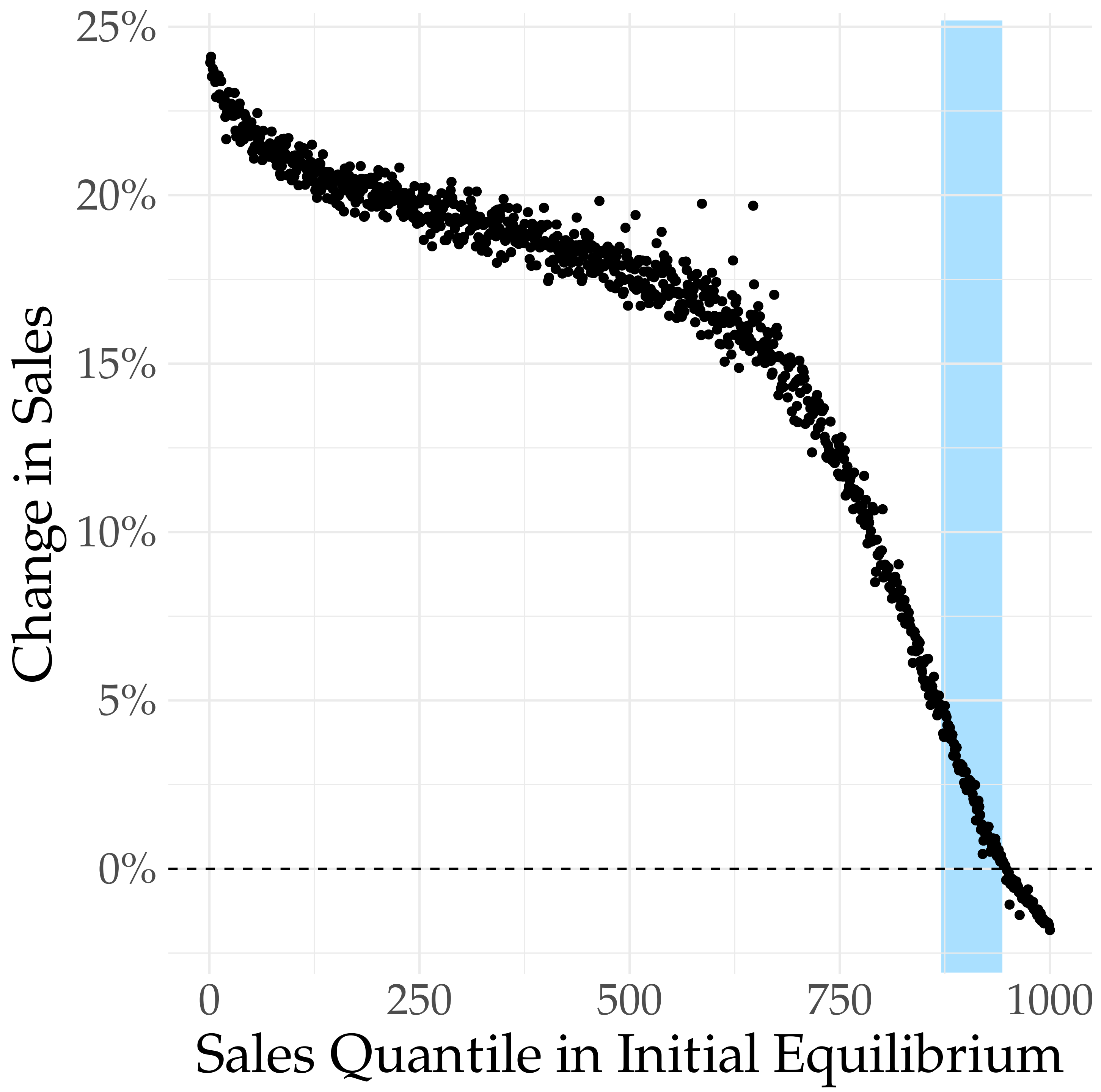
Intensity of Use ↑



Average Buyer Size ↓



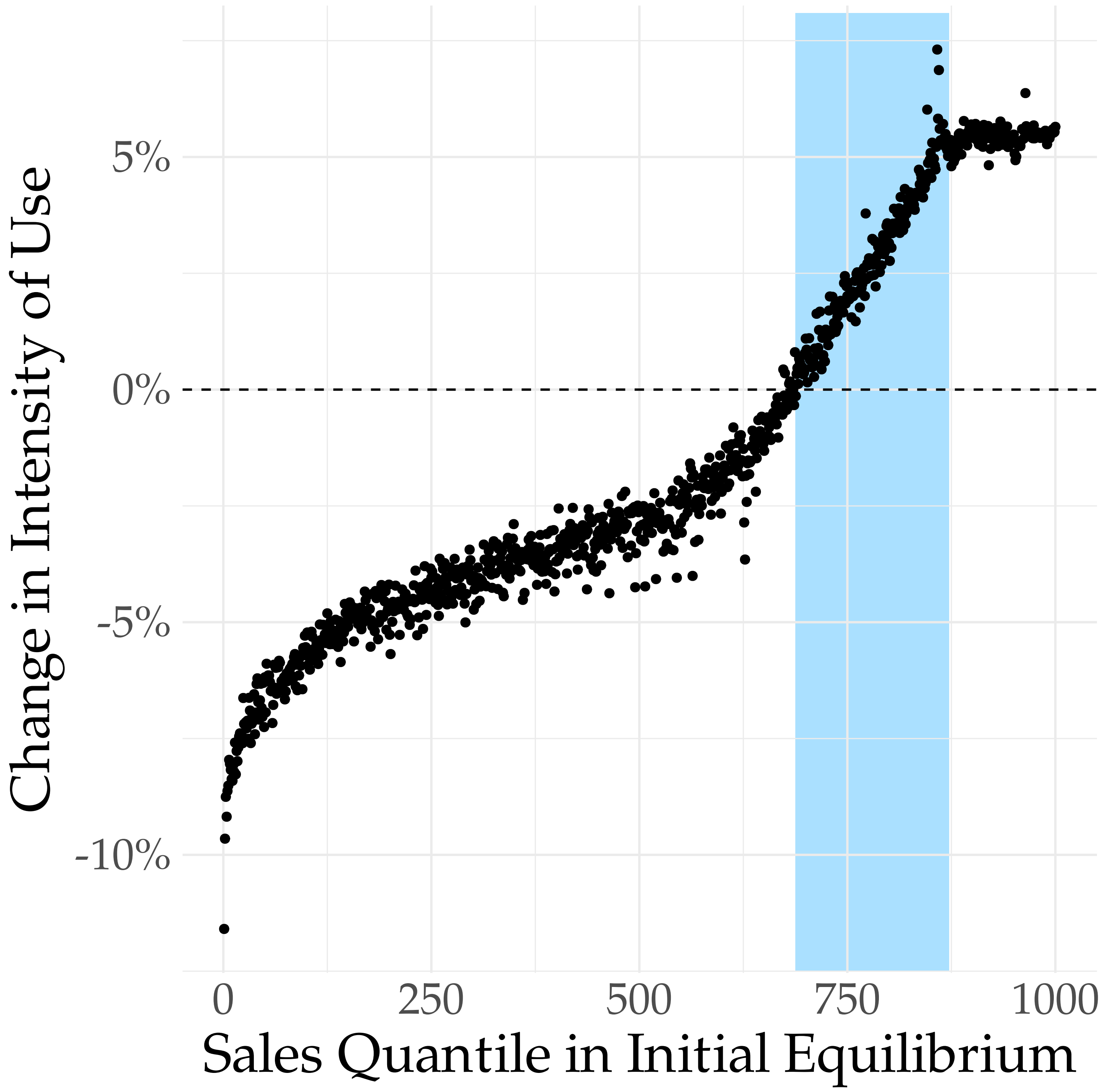
Sales ↑



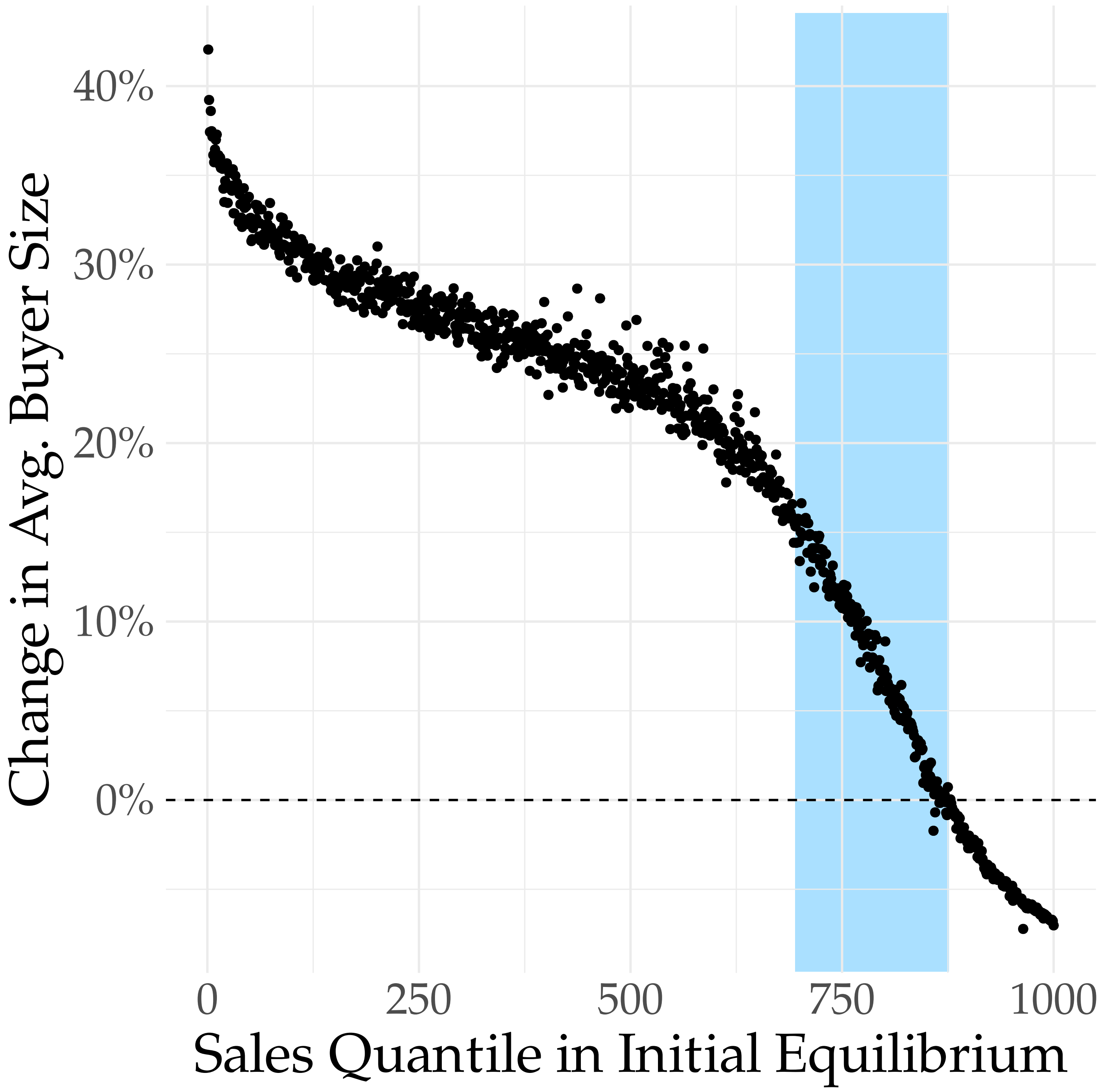
India’s 2017 Goods & Services Tax Reform

Changes in Margins of Intermediate Input Sales

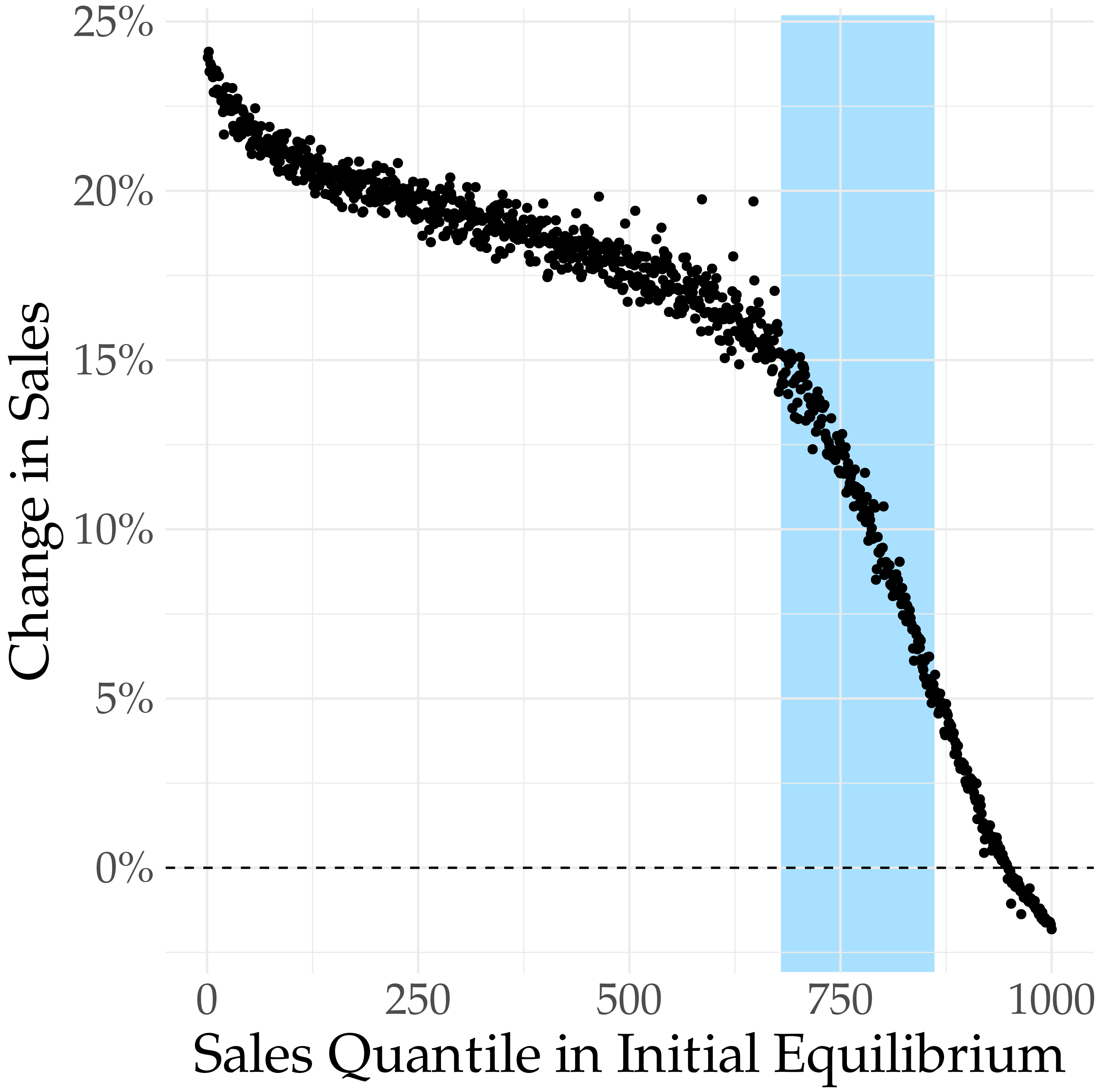
Intensity of Use ↑



Average Buyer Size ↑

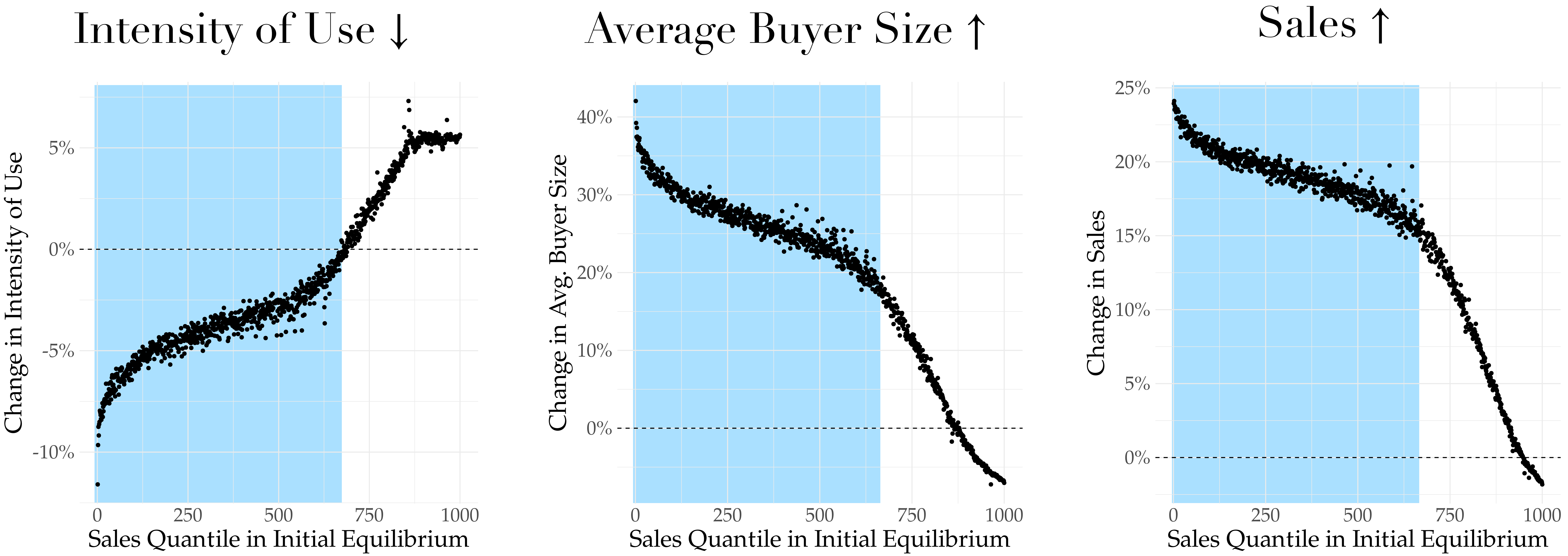


Sales ↑



India's 2017 Goods & Services Tax Reform

Changes in Margins of Intermediate Input Sales



India's 2017 Goods & Services Tax Reform

Contribution of Margins of Intermediate Input Sales

$$\text{Sales} = \text{Intensity of Use} \times \text{Average Buyer Size}$$

$$\frac{\Delta\text{Sales}}{\text{Sales}} = \frac{\Delta\text{Intensity of Use}}{\text{Intensity of Use}} + \frac{\Delta\text{Avg. Buyer Size}}{\text{Avg. Buyer Size}} + \frac{\Delta\text{Intensity of Use}}{\text{Intensity of Use}} \times \frac{\Delta\text{Avg. Buyer Size}}{\text{Avg. Buyer Size}}$$

India's 2017 Goods & Services Tax Reform

Contribution of Margins of Intermediate Input Sales

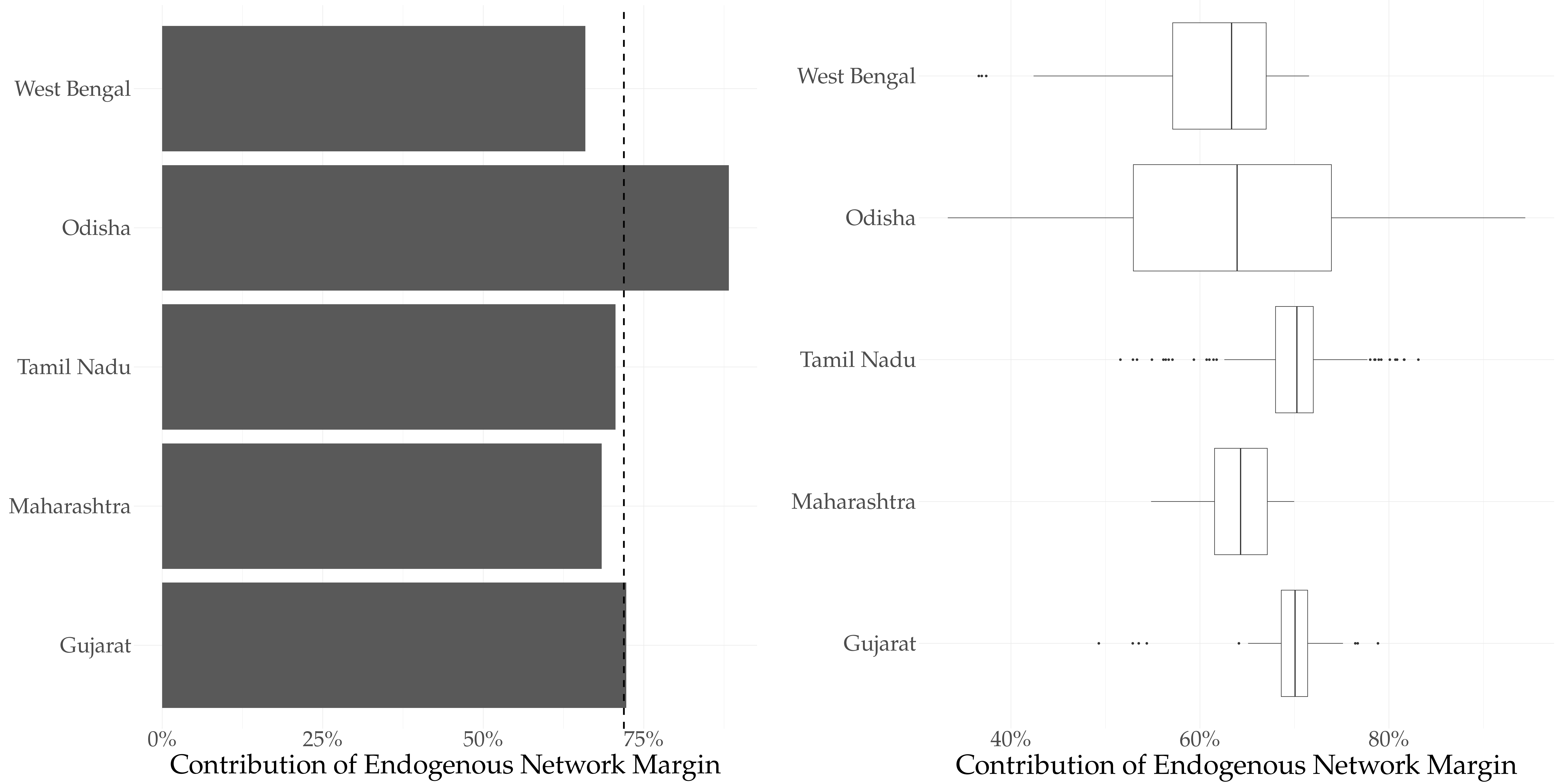
$$\text{Sales} = \text{Intensity of Use} \times \text{Average Buyer Size}$$

$$\frac{\Delta\text{Sales}}{\text{Sales}} = \frac{\Delta\text{Intensity of Use}}{\text{Intensity of Use}} + \frac{\Delta\text{Avg. Buyer Size}}{\text{Avg. Buyer Size}} + \frac{\Delta\text{Intensity of Use}}{\text{Intensity of Use}} \times \frac{\Delta\text{Avg. Buyer Size}}{\text{Avg. Buyer Size}}$$

contribution of
endogenous network margin

India's 2017 Goods & Services Tax Reform

Contribution of Margins: Shapley Decomposition



Δ % Sales to Destination = $\boxed{\Delta \text{ \% Intensity of Use}}$ + Δ % Avg. Buyer Size + Second Order Term

Conclusion

— Documented **importance** of endogenous networks **towards firm heterogeneity**

— Developed **tractable model** of endogenous spatial production networks

— Proposed **scalable framework for estimation** + **counterfactual analysis**

— Studied **market integration** following India's GST reform

- significant spatial reorganization of production networks
- reduced dispersion across firms, mostly due to endogenous network changes

Conclusion

- Documented **importance** of endogenous networks **towards firm heterogeneity**
- Developed **tractable model** of endogenous spatial production networks
- Proposed **scalable framework for estimation** + **counterfactual analysis**
- Studied **market integration** following India's GST reform
    - significant spatial reorganization of production networks
    - reduced dispersion across firms, mostly due to endogenous network changes

fertile baseline model for studying impact of

micro- and macro- shocks on the spatial network economy

thank you!

piyushp@berkeley.edu | piyush.panigrahi@jhu.edu