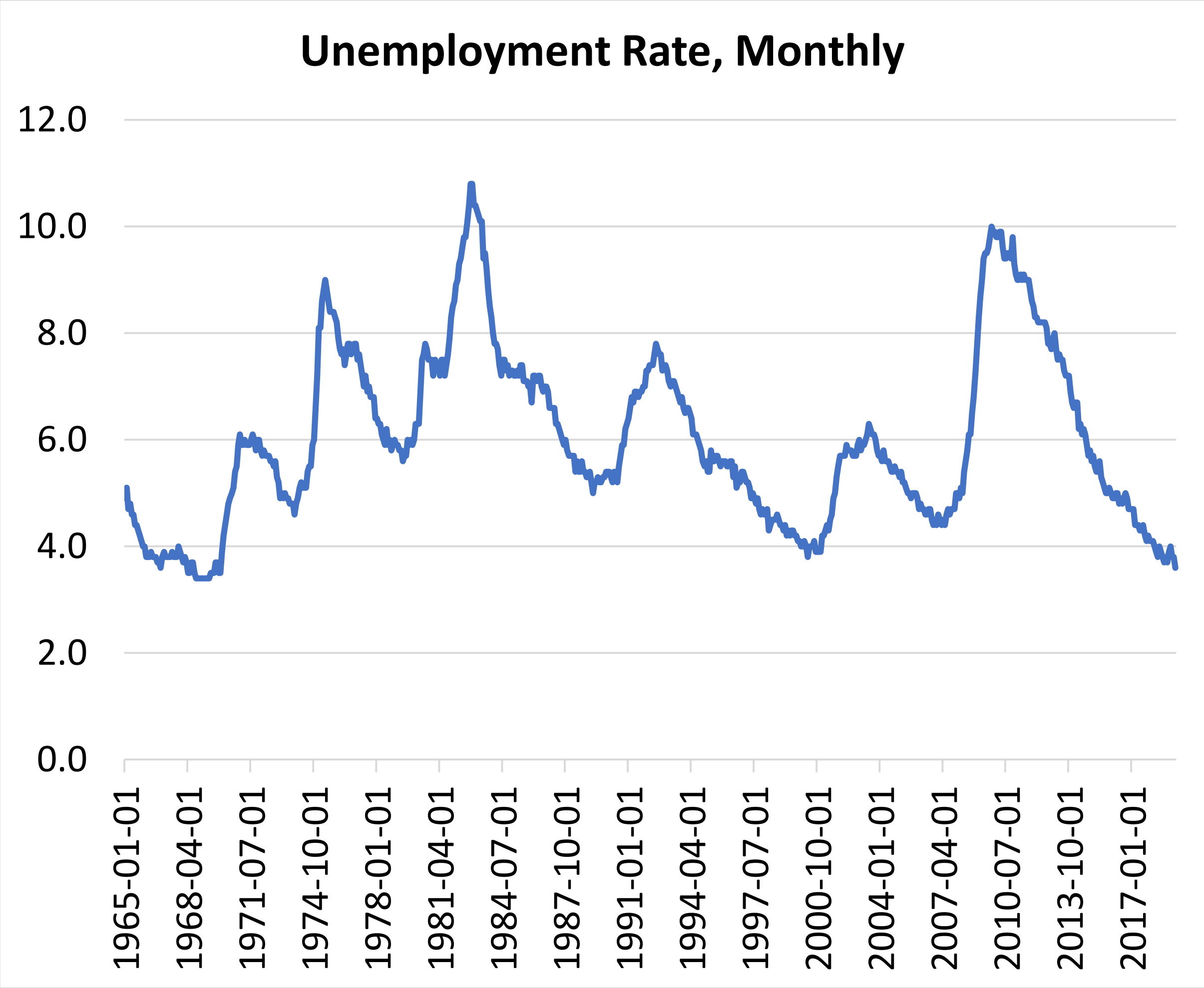
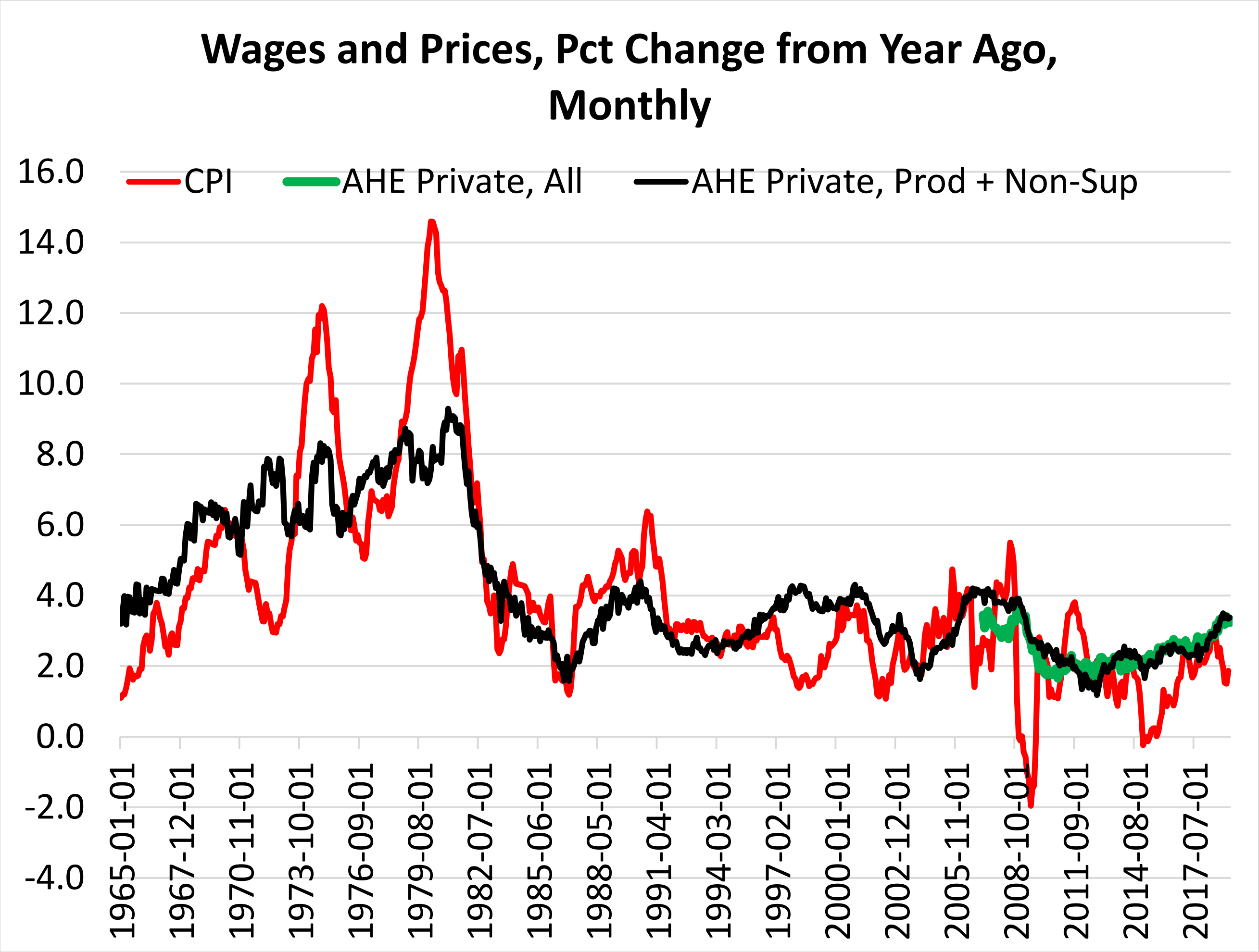
Productivity, Growth, Job Creation and Entrepreneurship

By John Haltiwanger, University of Maryland*

*This talk without implication draws on collaborative work with many colleagues

Key Indicators Suggest U.S. Economy is a Robust Period of Low Unemployment and Moderate Pressure on Inflation

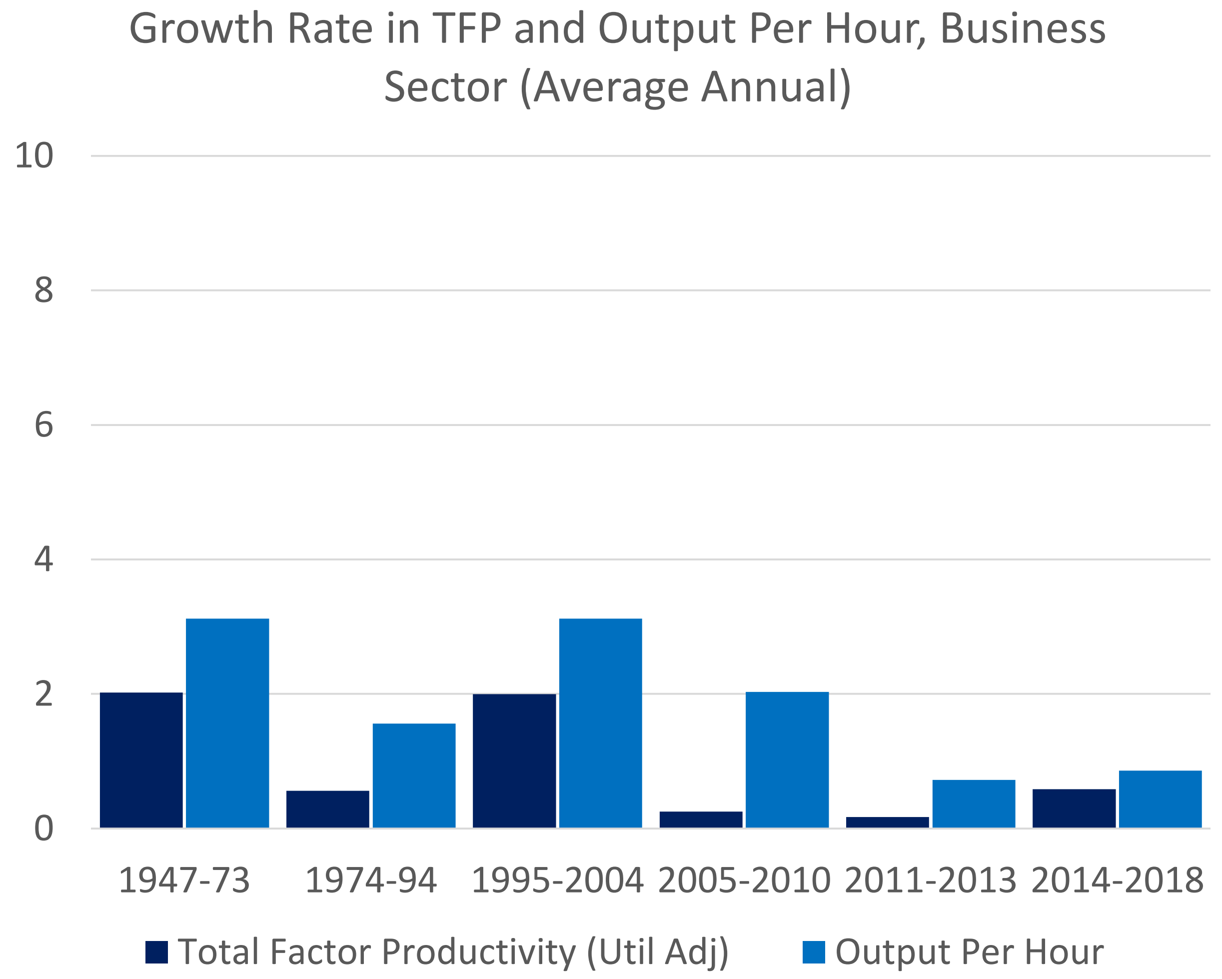


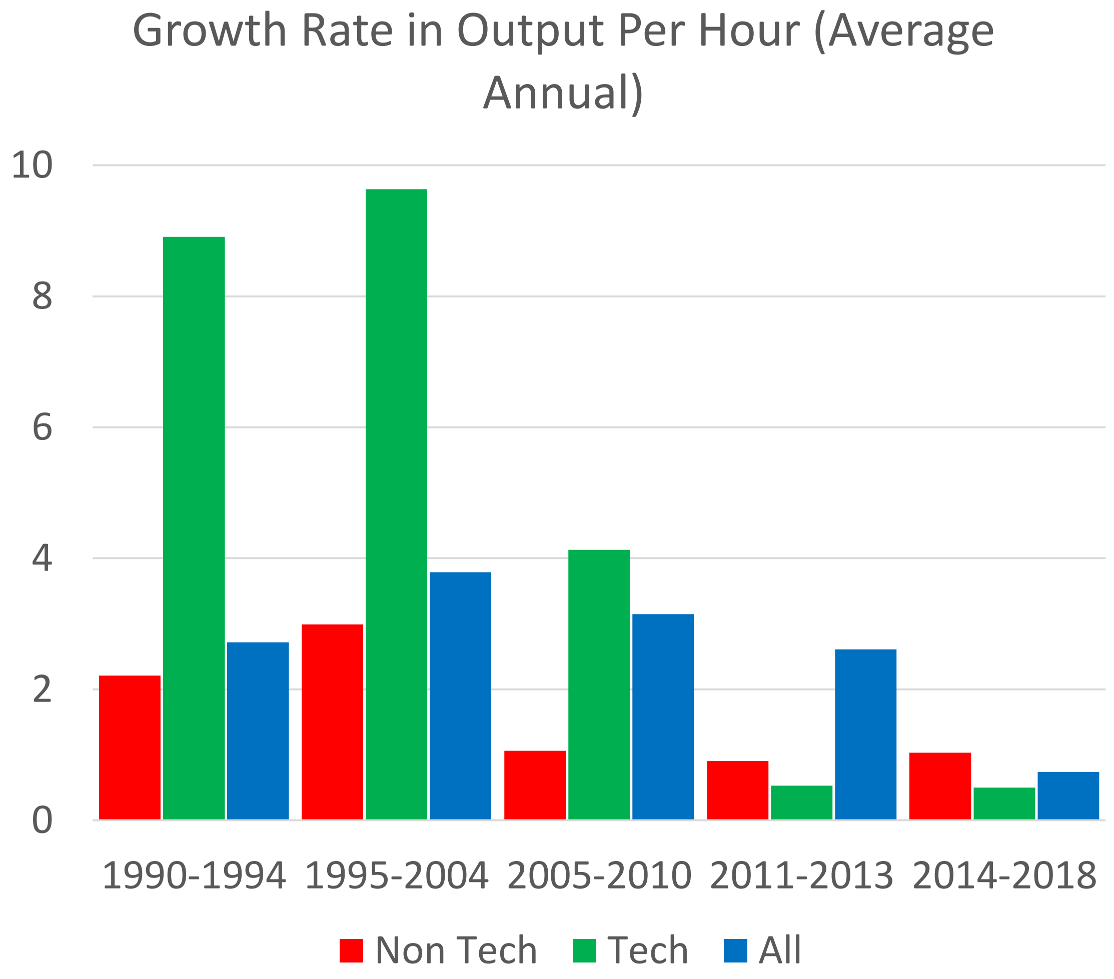


Source: BLS, through April 2019

Productivity Growth Has Been Very Low Since Early 2000s. Including in High Tech (STEM intensive industries).

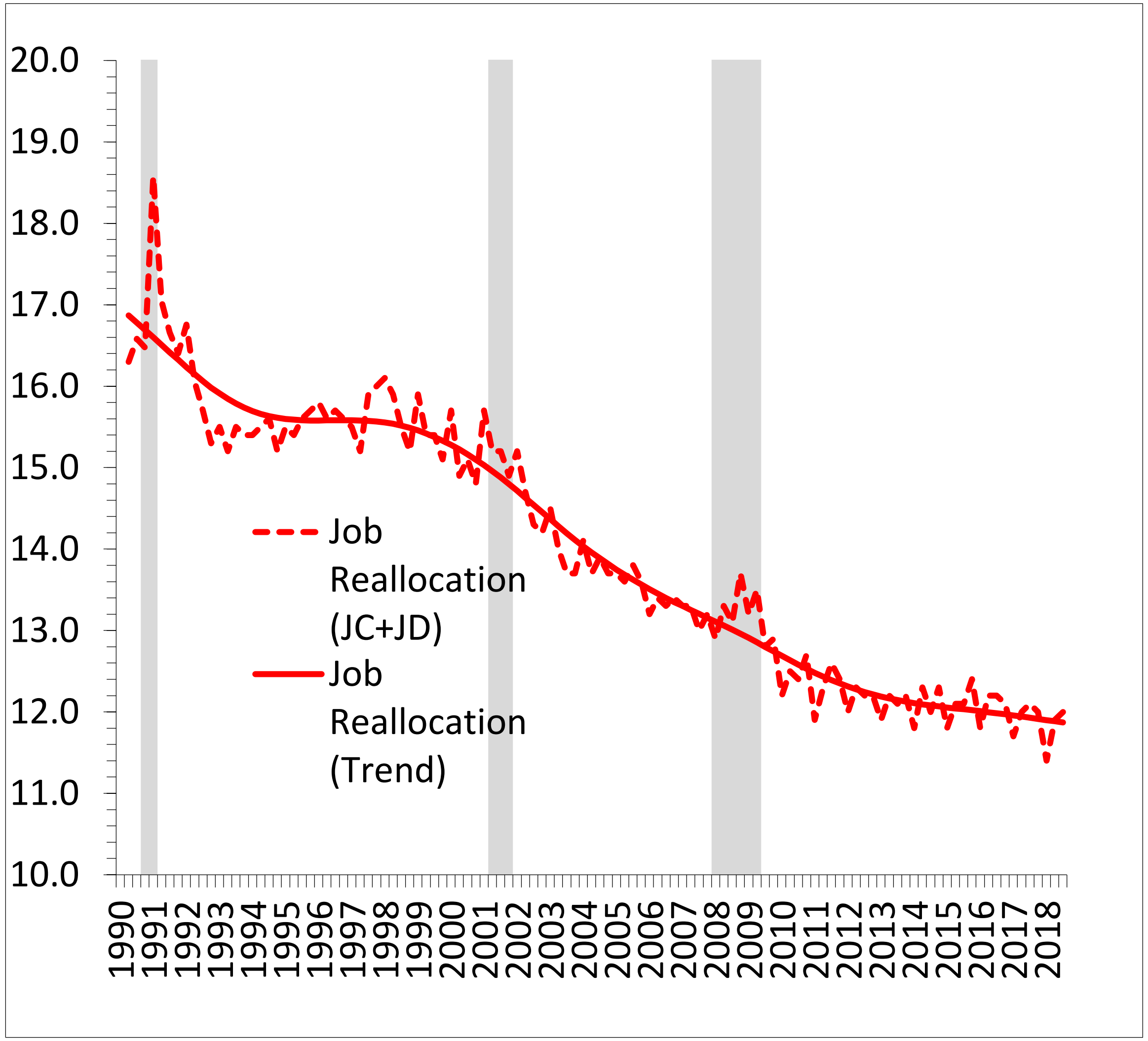
Some modest signs of recent upturn (last 4 quarters).

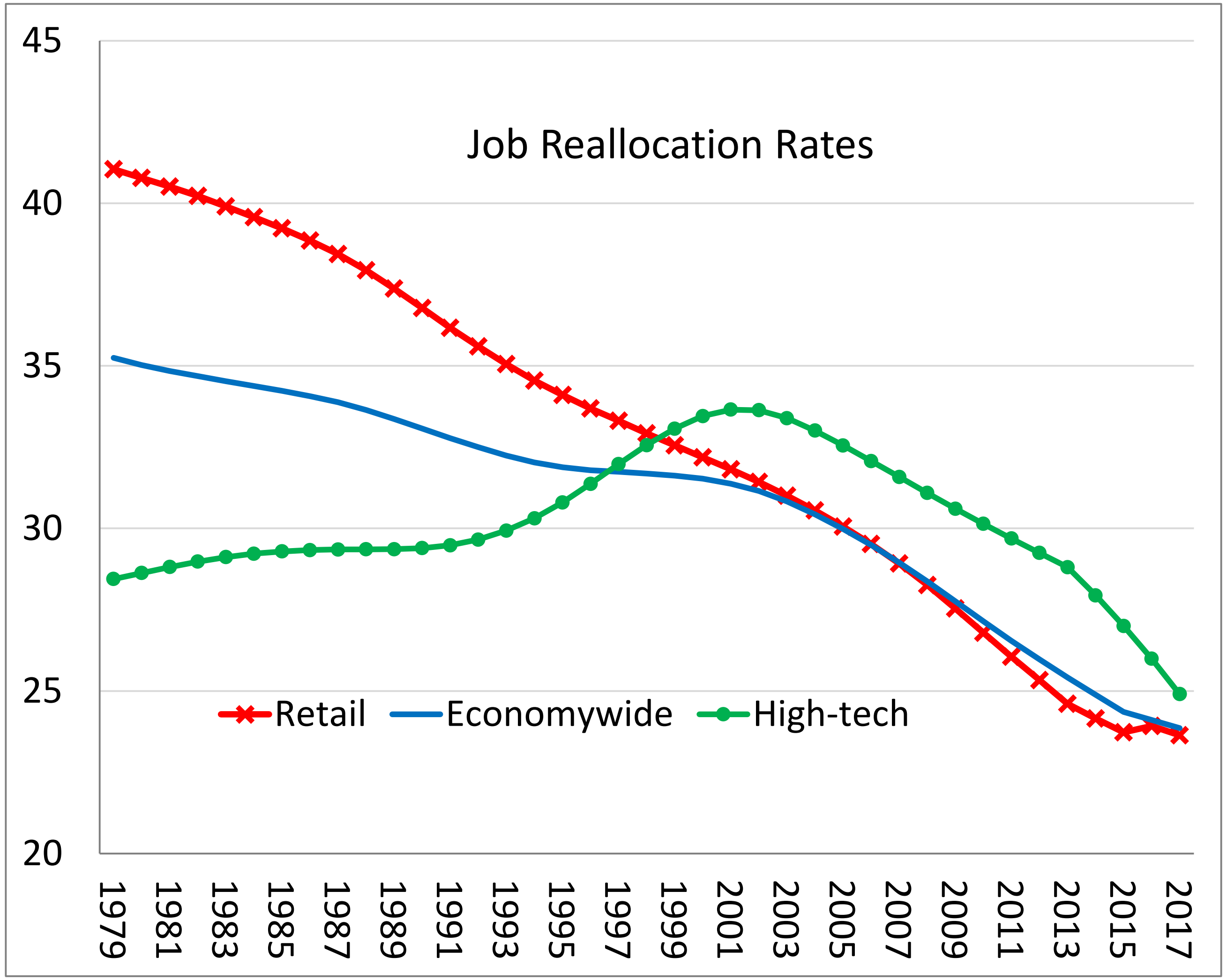




Source: Left Panel from Fernald, SF Fed. Right Panel from Aggregated 4-digit industries from BLS

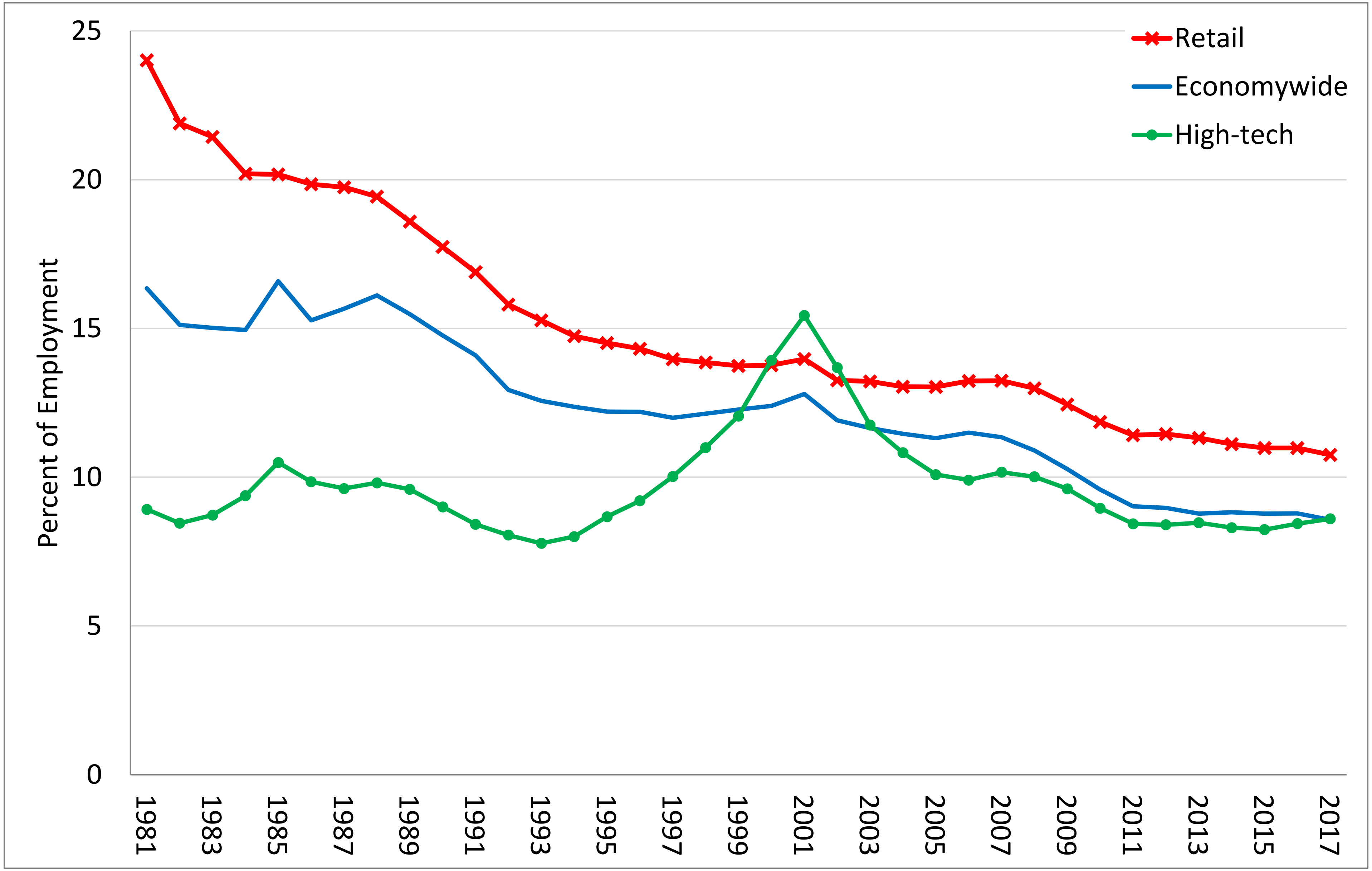
Post 2000 Decline in Productivity Growth Accompanies by Decline in Business Dynamism. (Dynamism Declining Even in High Tech in Post 2000 Period).





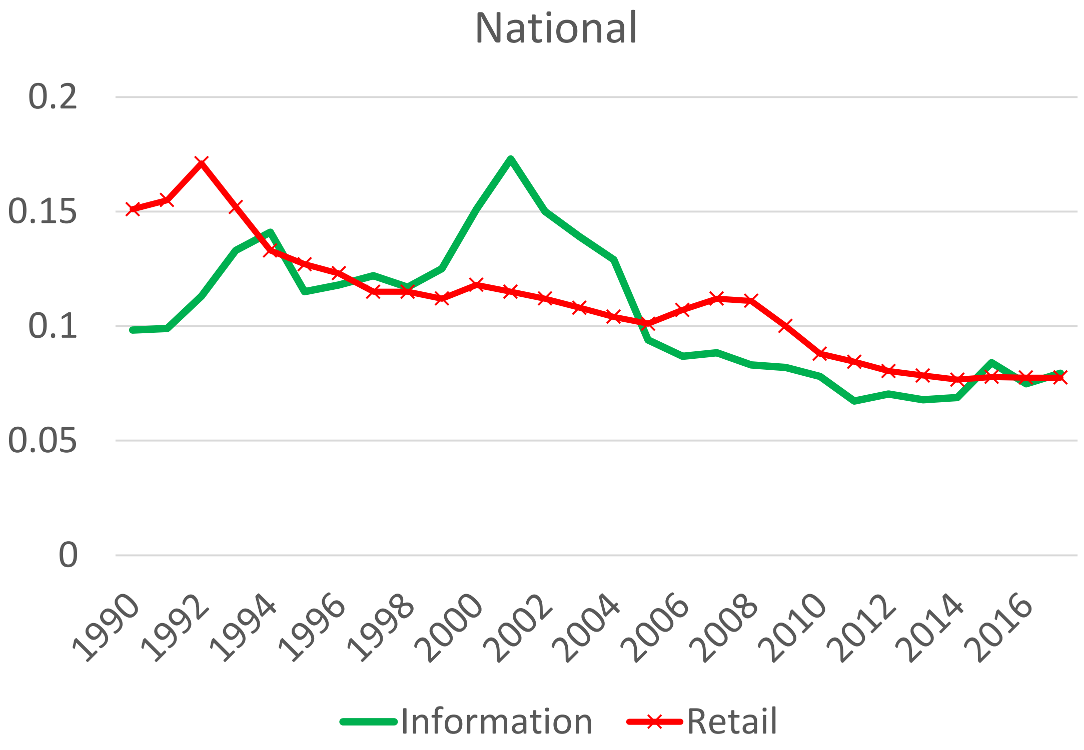
Source: Left Panel (BED, BLS). Right Panel: Spliced LBD tabulations from Decker et. al. (2017) and BED (Hodrick Prescott Trends)

Share of Activity at Young (Less than 5 years Old) Firms, U.S. Private Sector, High-Tech and Retail Sectors

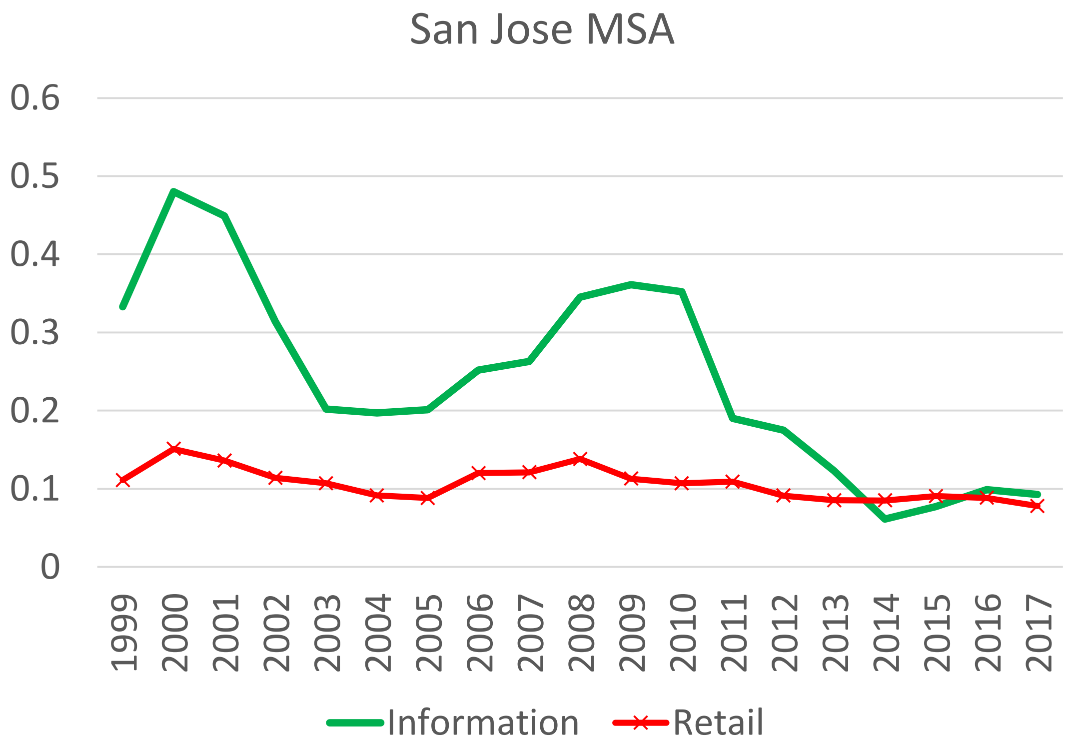


Source: Tabulations from LBD (Census) by Decker et. al. (2017) spliced with Business Employment Dynamics (BLS)

Share of Employment at Young (Age<6)

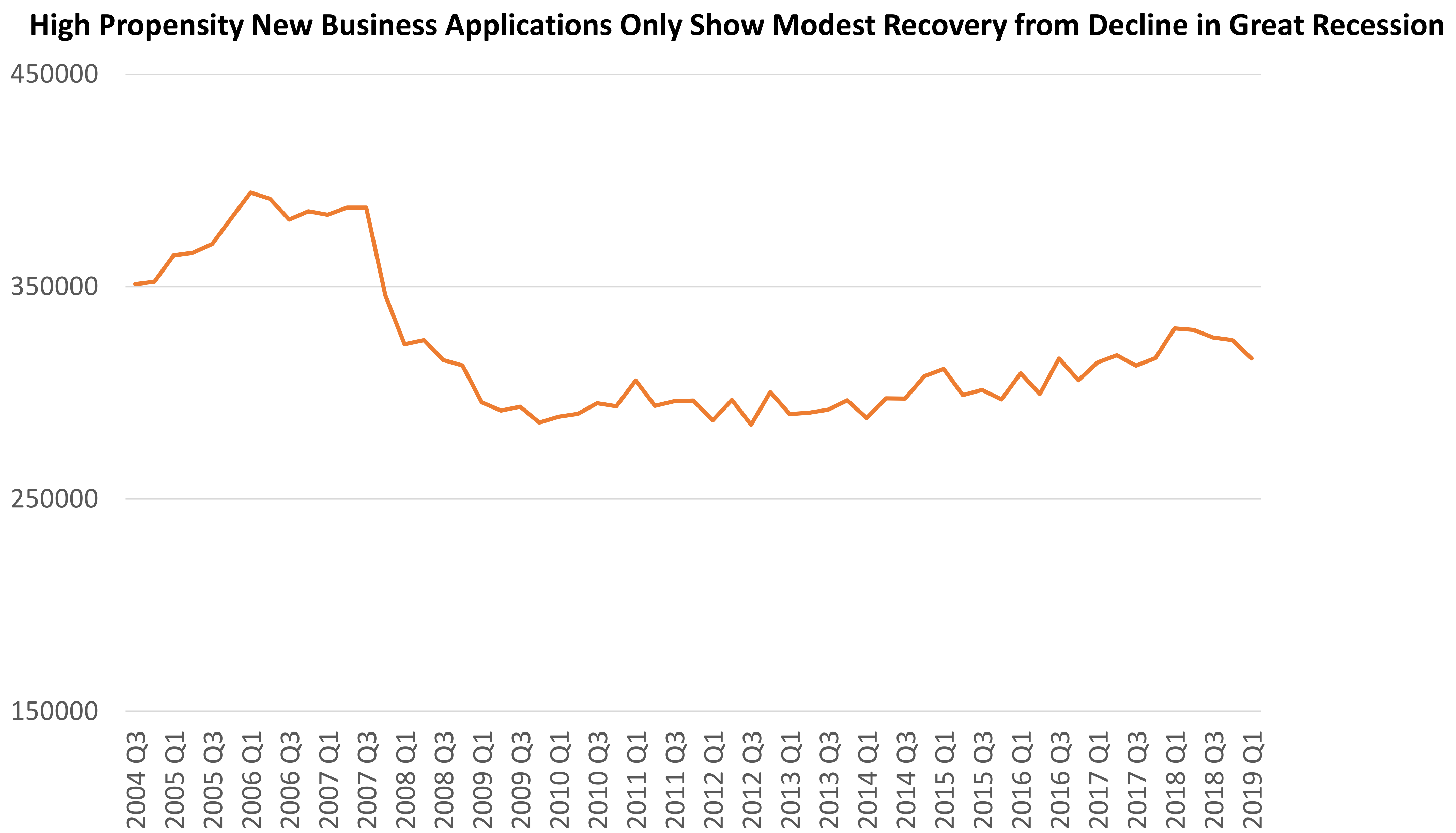


In 2000, about 50 percent of employment in in the information sector in San Jose MSA (including Silicon valley) was in firms < 6 years old. Now it is about 10 percent.



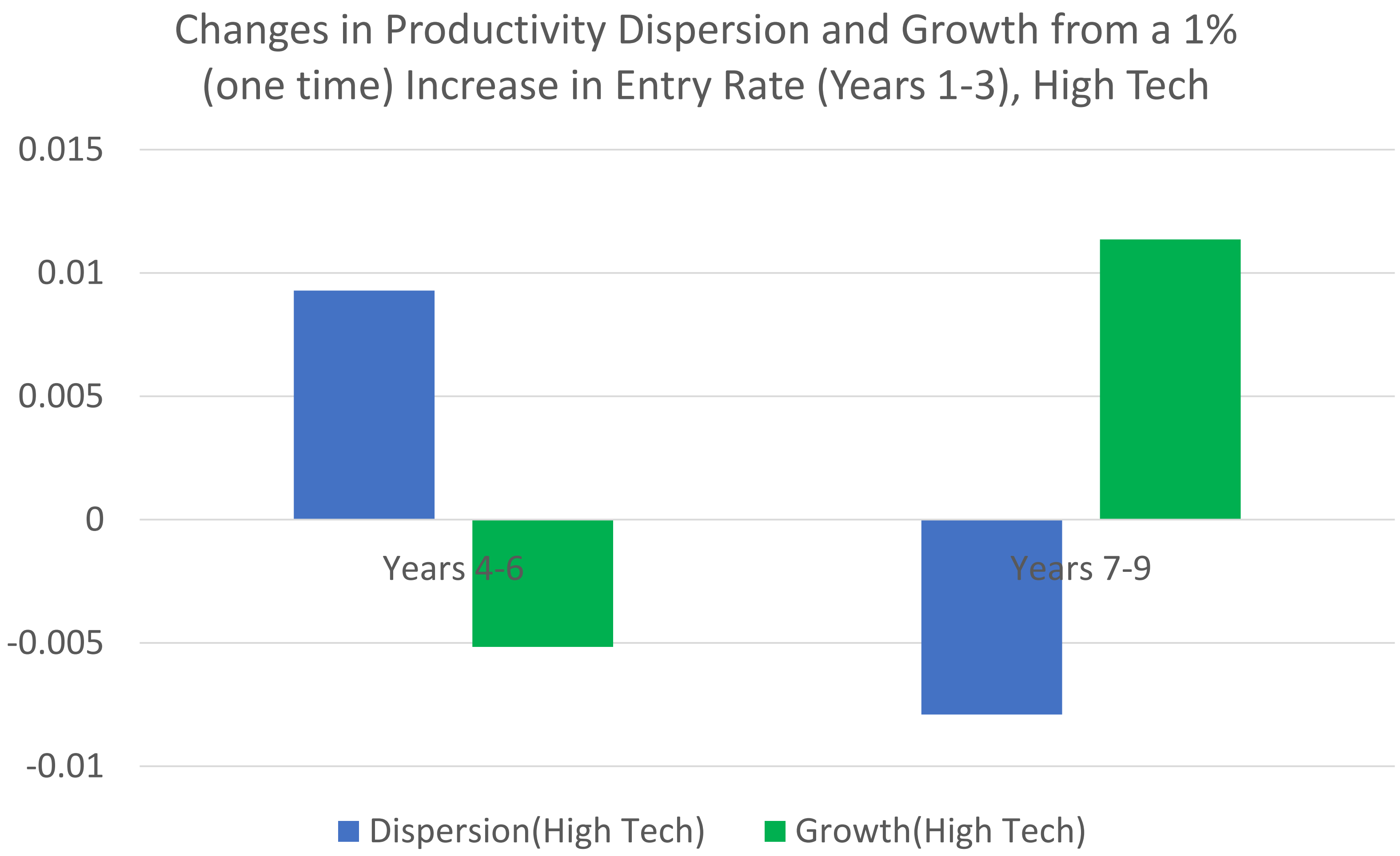
QWI national trends broadly match BDS

Source: Quarterly Workforce Indicators (QWI)



Source: Business Formation Statistics

Dynamics of Entry, Productivity dispersion and Productivity growth



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- Rise in within industry productivity dispersion and decline in industry productivity growth in next 3-year Period
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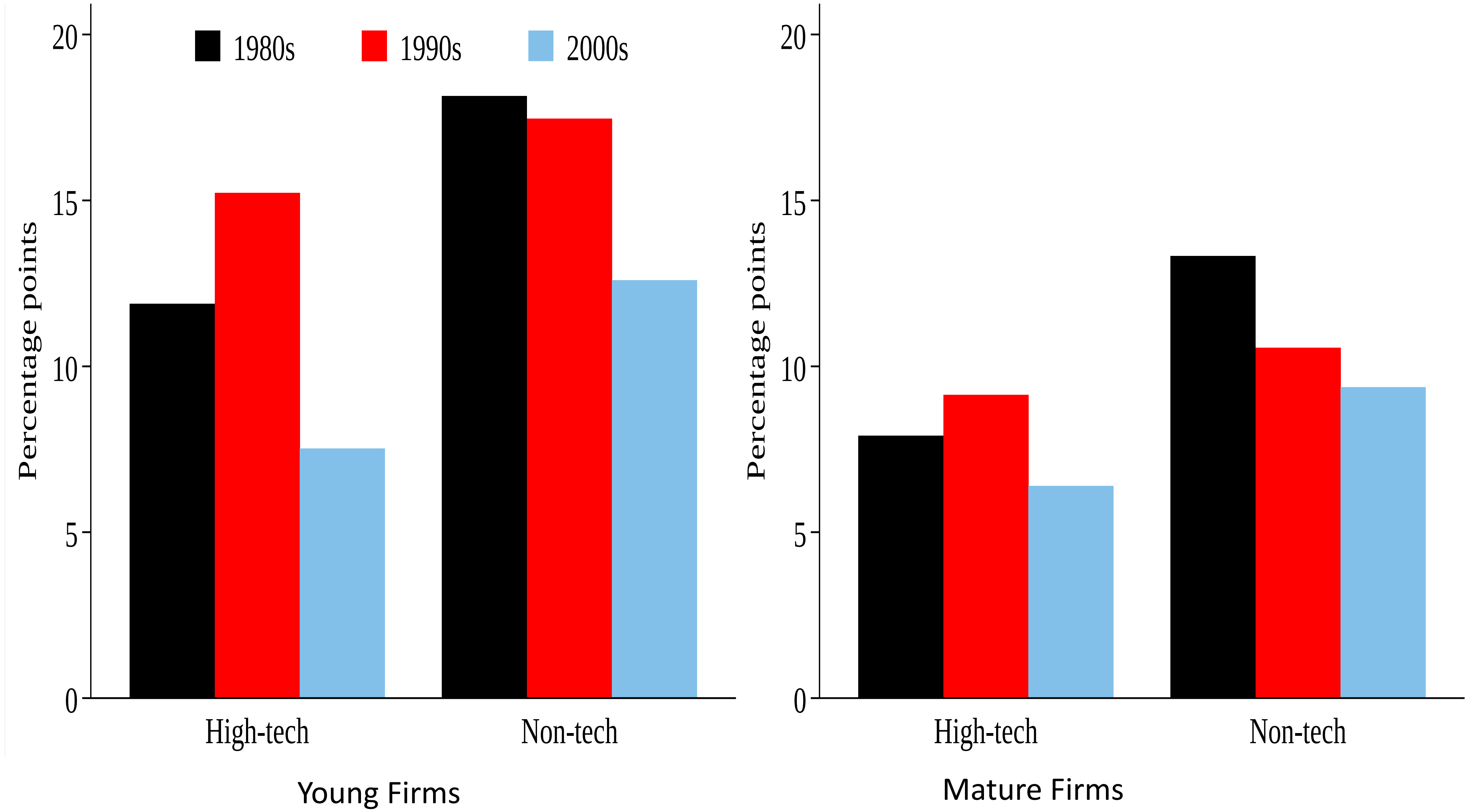
- Surge in reallocation following surge in entry as well (not depicted).
- Similar, dampened patterns for Non-Tech

Using 4-digit NAICS data for High Tech sectors (ICT in mfg and non-mfg plus sectors such as Bio Tech)

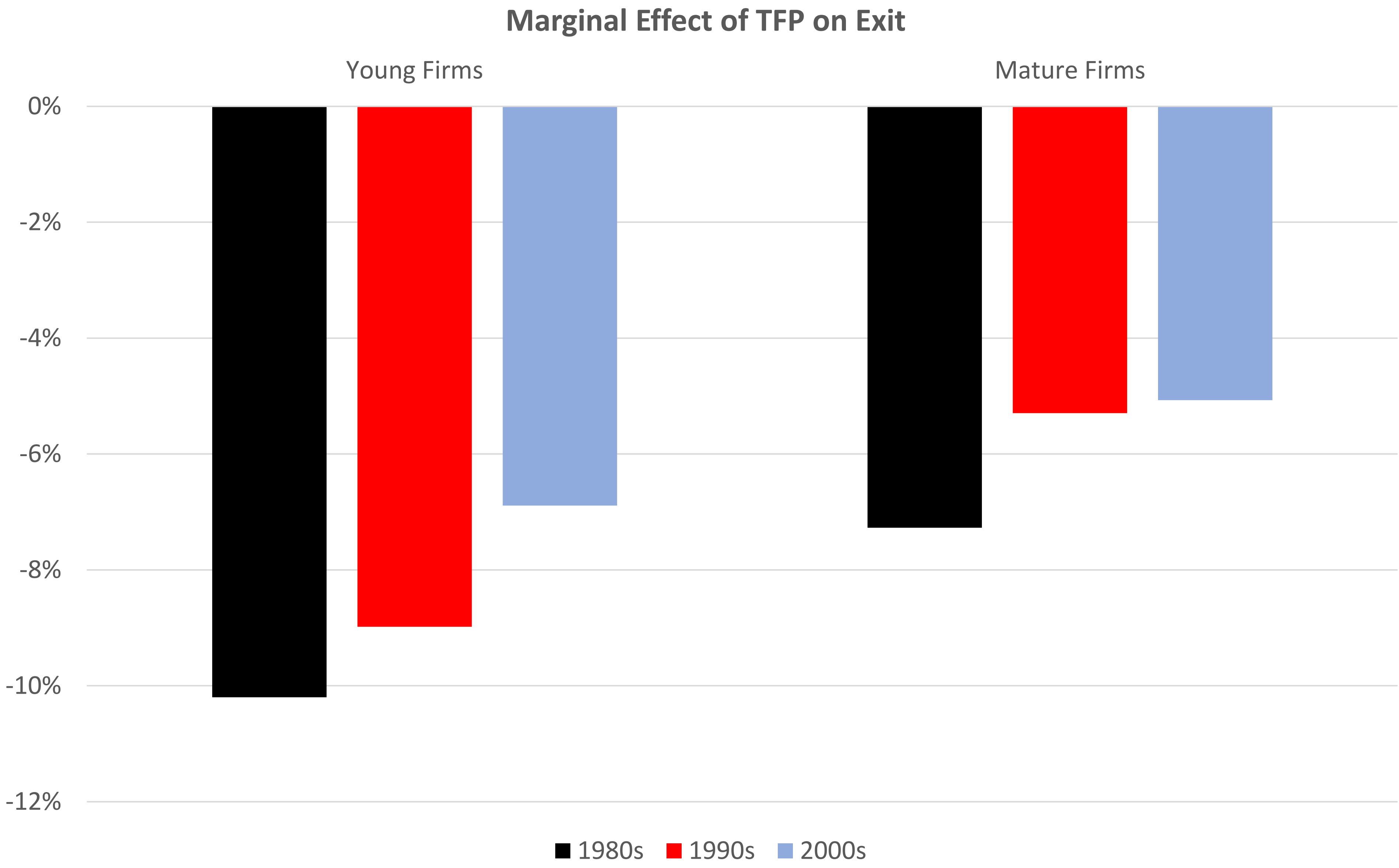
Source: Foster et. al. (2018)

Responsiveness to TFP Shocks has Declined in Post 2000 in Manufacturing. Similar results for Labor Productivity Shocks For Entire Private Sector



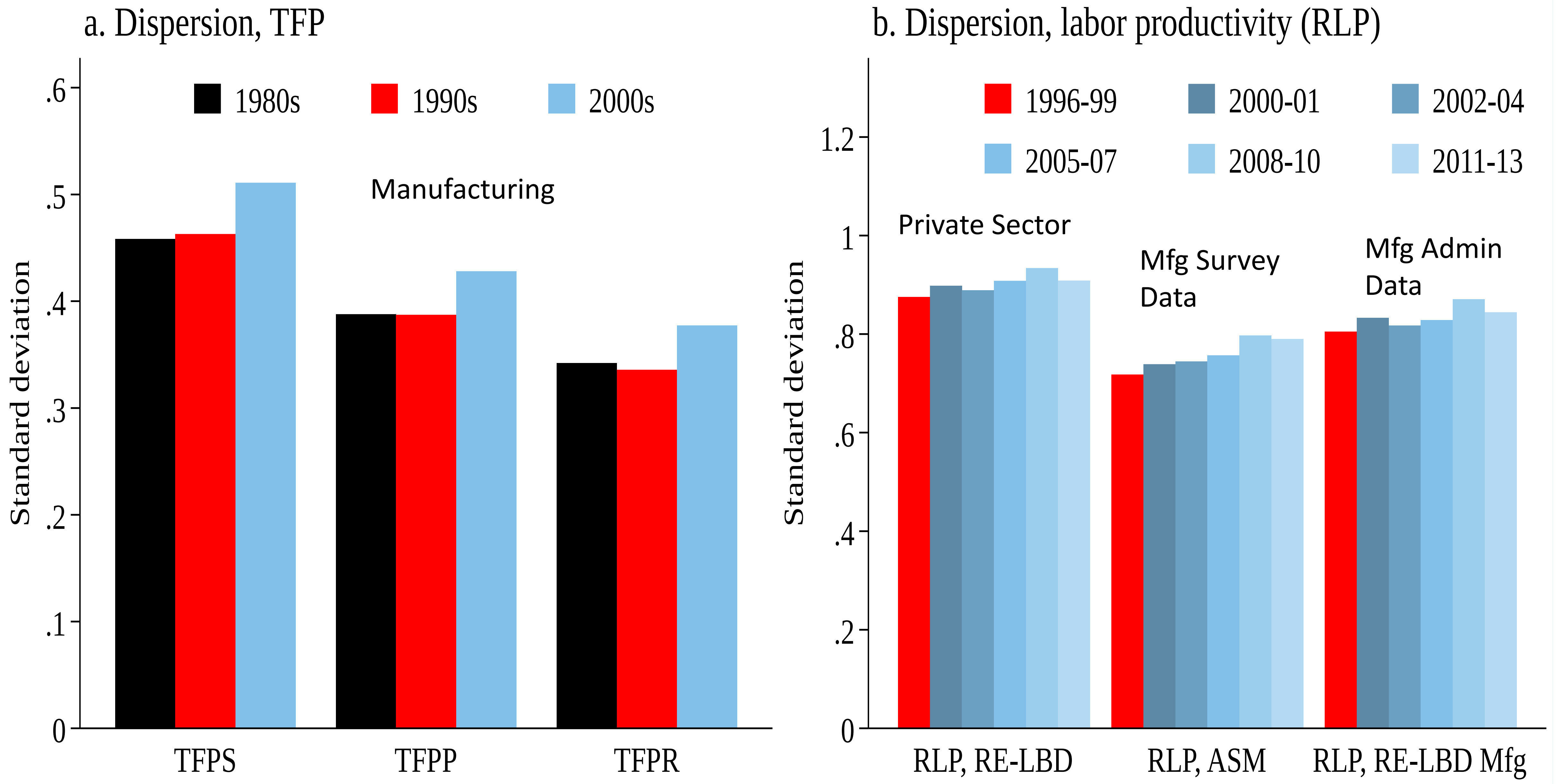
Source: Decker et. al. (2019) using tabulations from LBD/ASM/CM

An Important Component of Declining Responsiveness is that Low Productivity Firms Less Likely to Exit



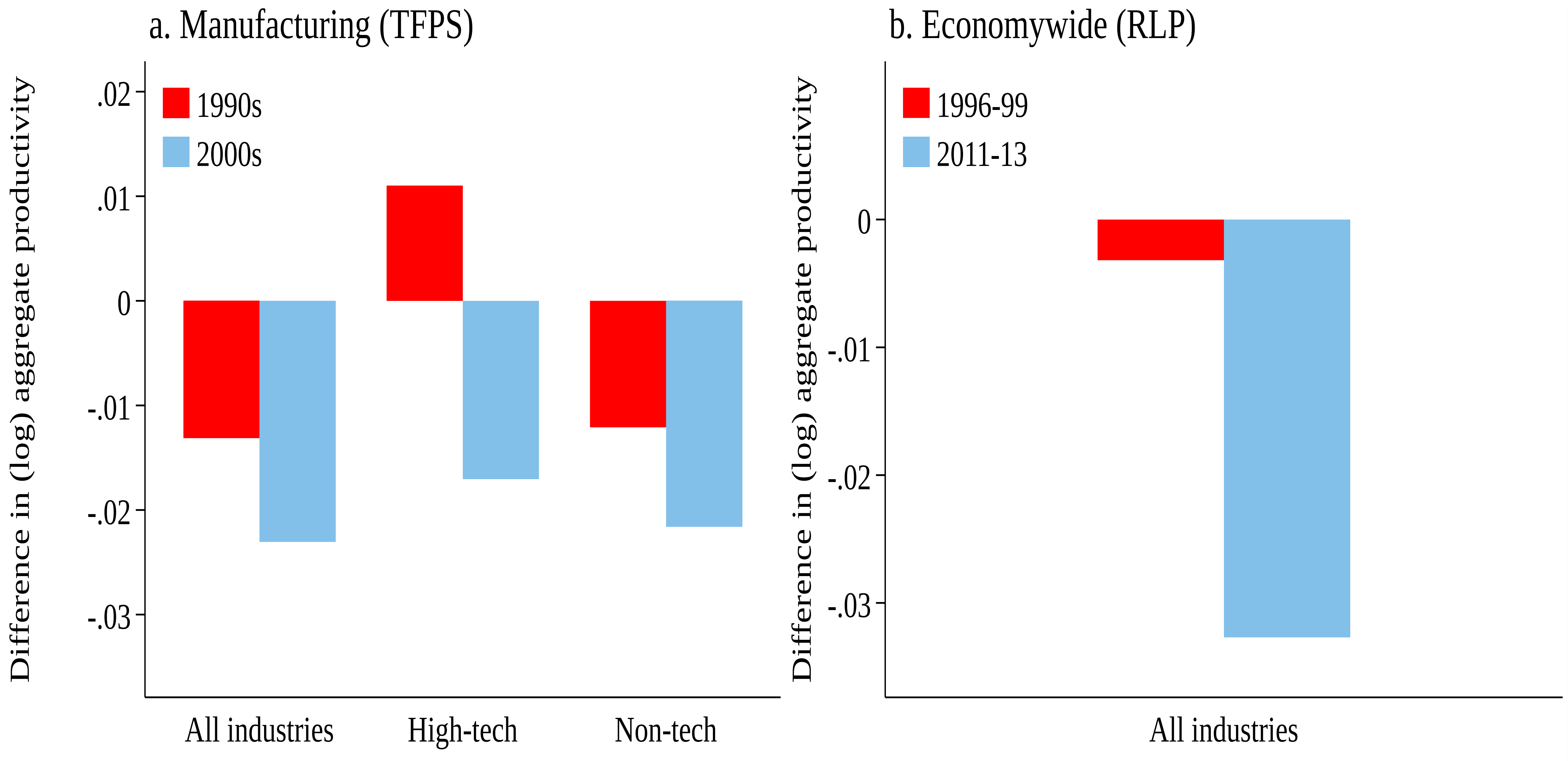
Source: Decker et. al. (2019) using tabulations from LBD/ASM/CM

TPF Shock Dispersion has Risen. Revenue Productivity (TFPR and Labor Productivity (RLP)) Dispersion Has Also Risen.



Source: Decker et. al. (2019) using tabulations from LBD/ASM/CM

Annual Drag on Productivity from Declining Responsiveness is Substantial



Source: Decker et. al (2019)

Open Questions

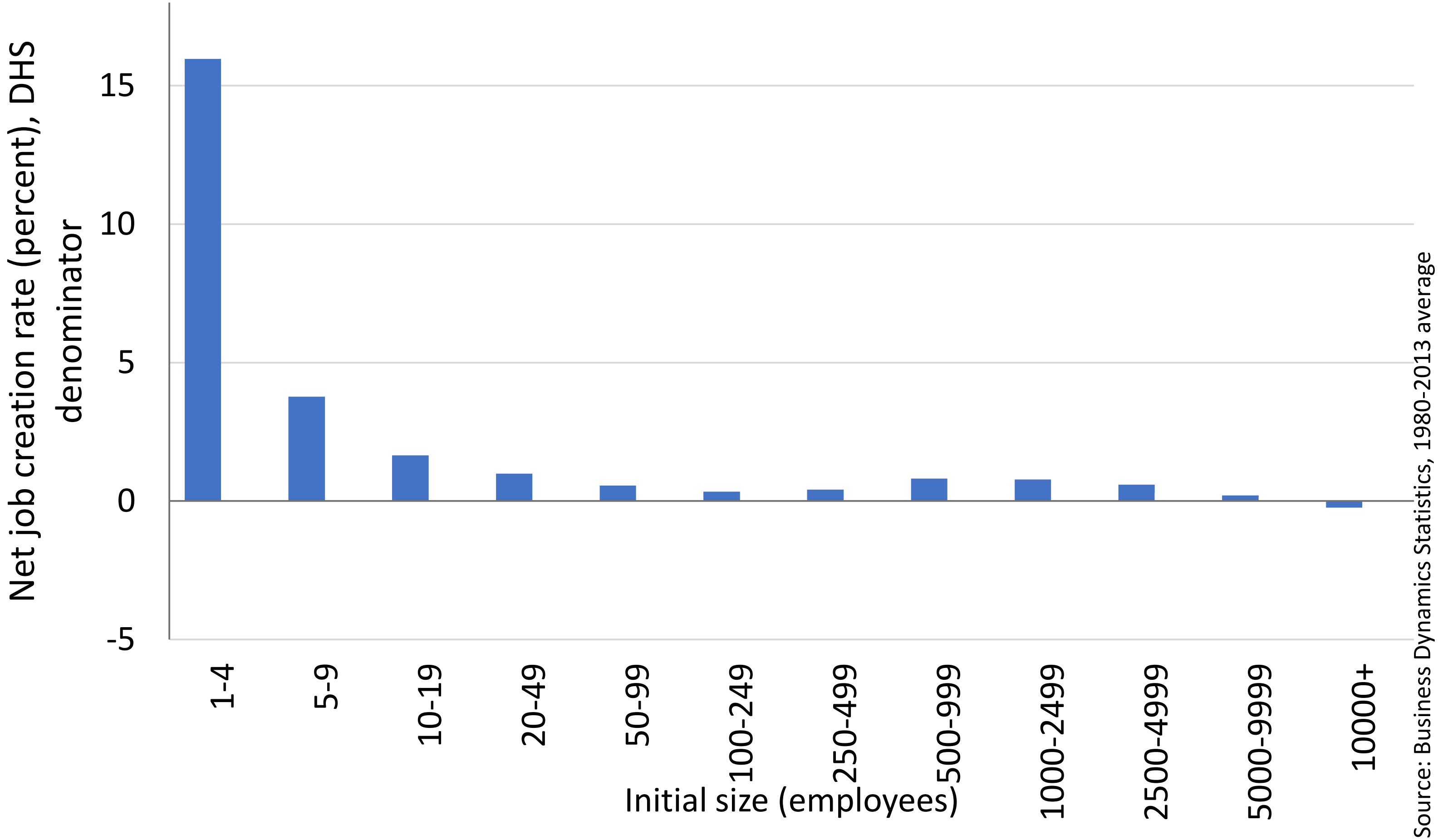
- What is the role of dynamism and startups for growth?
  - Do the declines reflect adverse changes in the business climate with increasing impediments to entry and post entry growth?
    - Occupational licensing, zoning restrictions, decline in employment at will?
    - What is the role of rising concentration and markups? (DeLoecker, Eeckhout and Unger (2018))
  - Does the decline in startups (in all sectors) reflect reductions in the pace of major innovations? (Gordon + Gort/Klepper/Jovanovic?)
  - Has there been a change in the nature of the experimentation role of startups?
    - Is the objective increasingly to be acquired rather than grow?
  - Is the rise in revenue productivity dispersion (during this period of anemic young firm activity) an indicator of rising frictions and distortions or slower diffusion? Might the latter be just an implication of the former?

Taking a Step Back: Six Facts about Entrepreneurship

Six facts about entrepreneurship

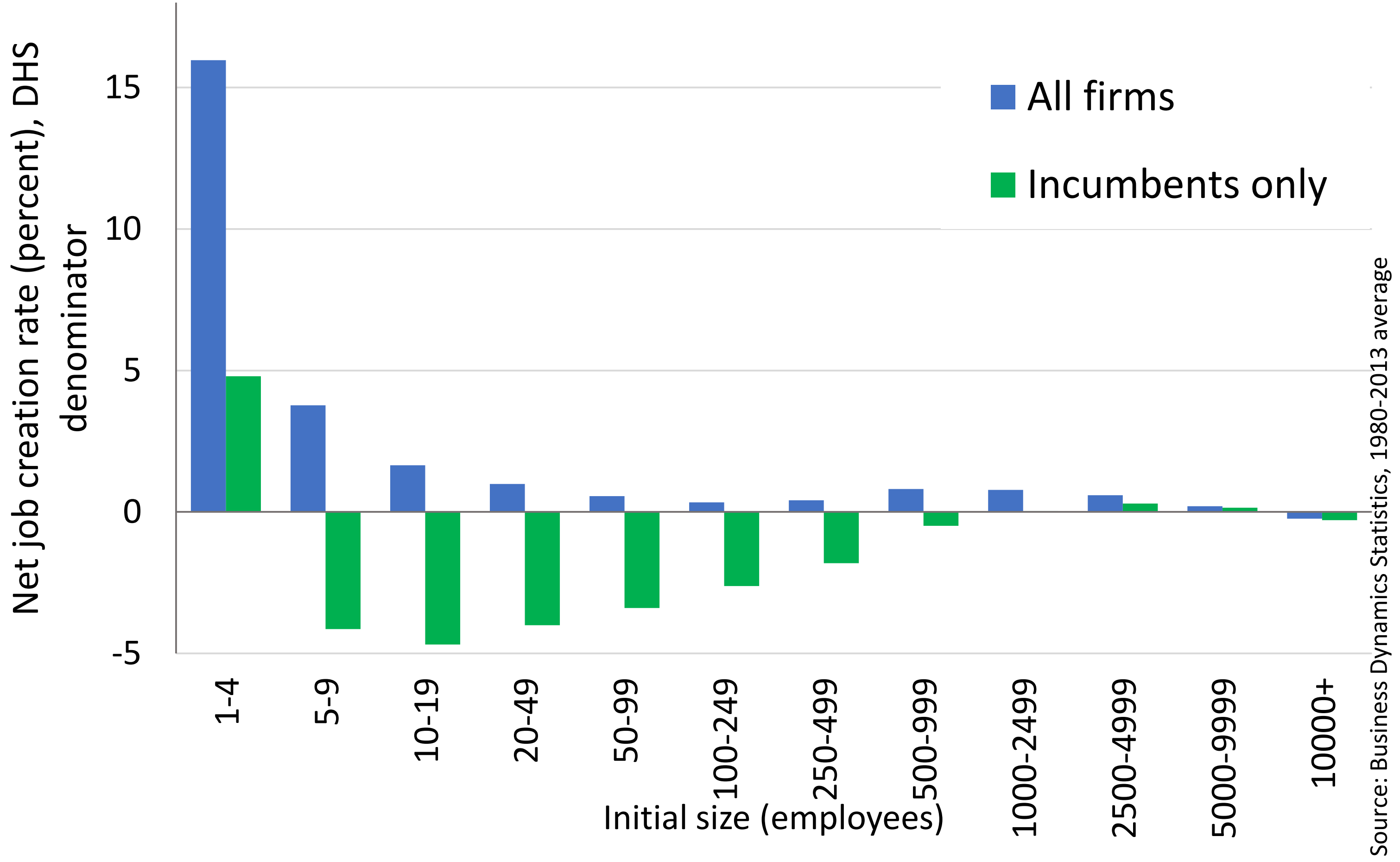
1. ***Young* firms, not *small* firms, are the key to job (and productivity) growth**
2. **Many young firms fail, yet each cohort makes long-lasting contributions to U.S. employment**
3. A small fraction of high growth young firms play an outsized role
4. Young firms face intense *selection* and are more responsive to their environment
5. Periods of innovation and subsequent productivity growth have following dynamics: entry leads to dispersion which leads to shakeout which leads to productivity growth.
6. Young-firm activity—particularly *high-growth* young firm activity—has been declining in the U.S.

Net Job creation by Firm Size

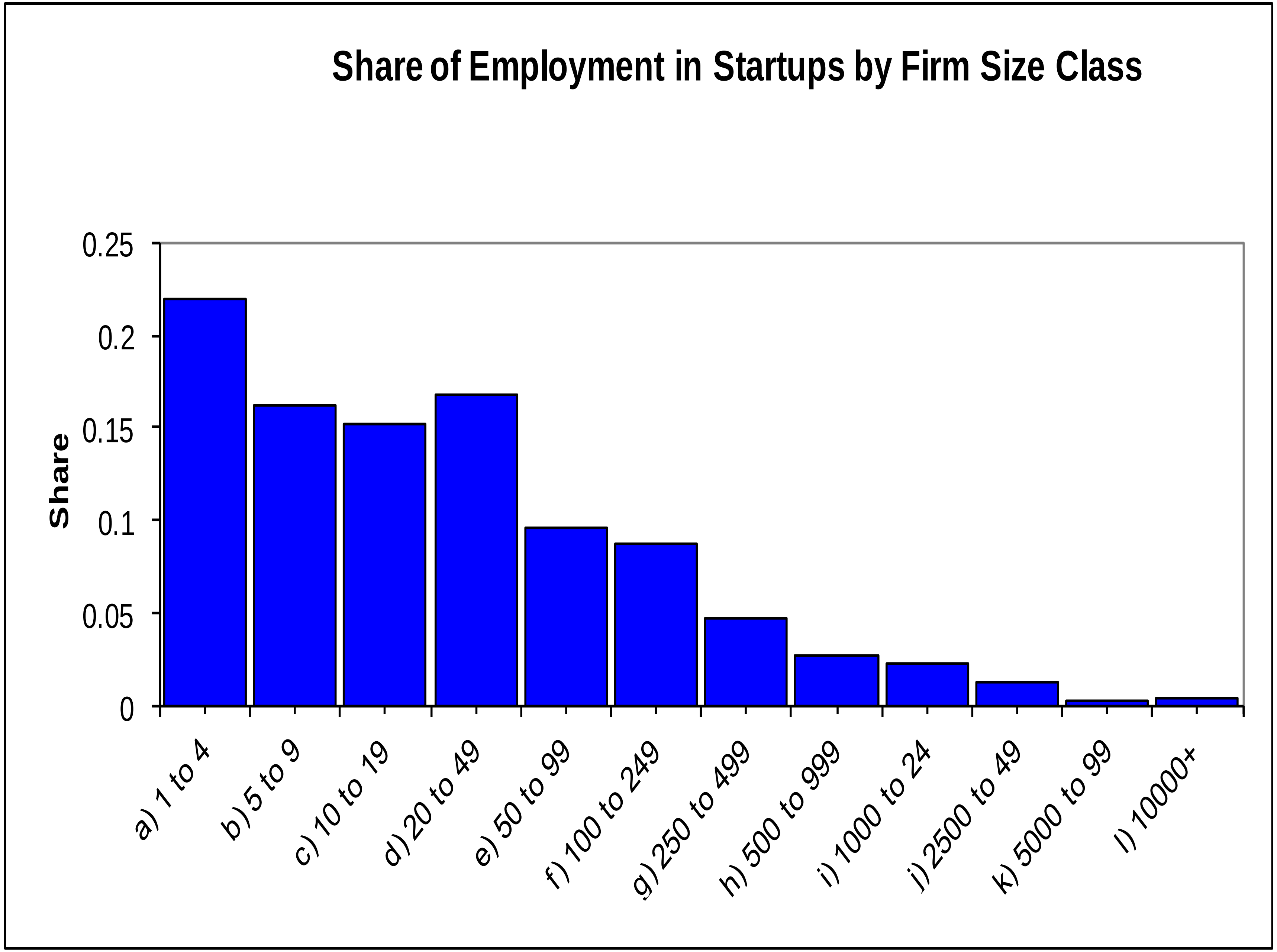


Using Longitudinal Business Database (BDS), Only Organic Growth, Firm Size Based on Enterprise Control. Inclusive of firm births and deaths

Net Job creation



Source: Haltiwanger, Jarmin and Miranda (2013)

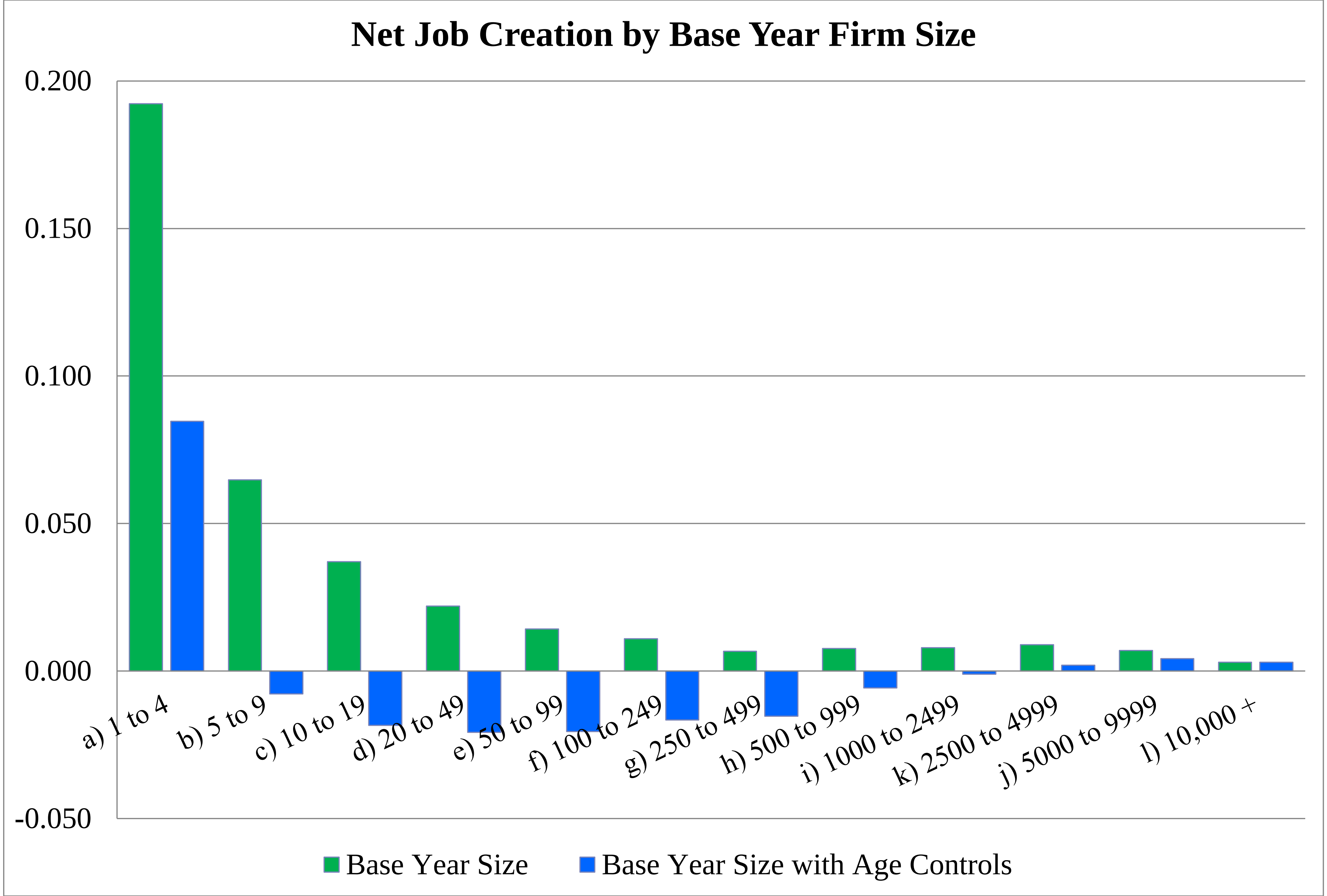


Startups are small
Much less skewed size distribution of startups than overall

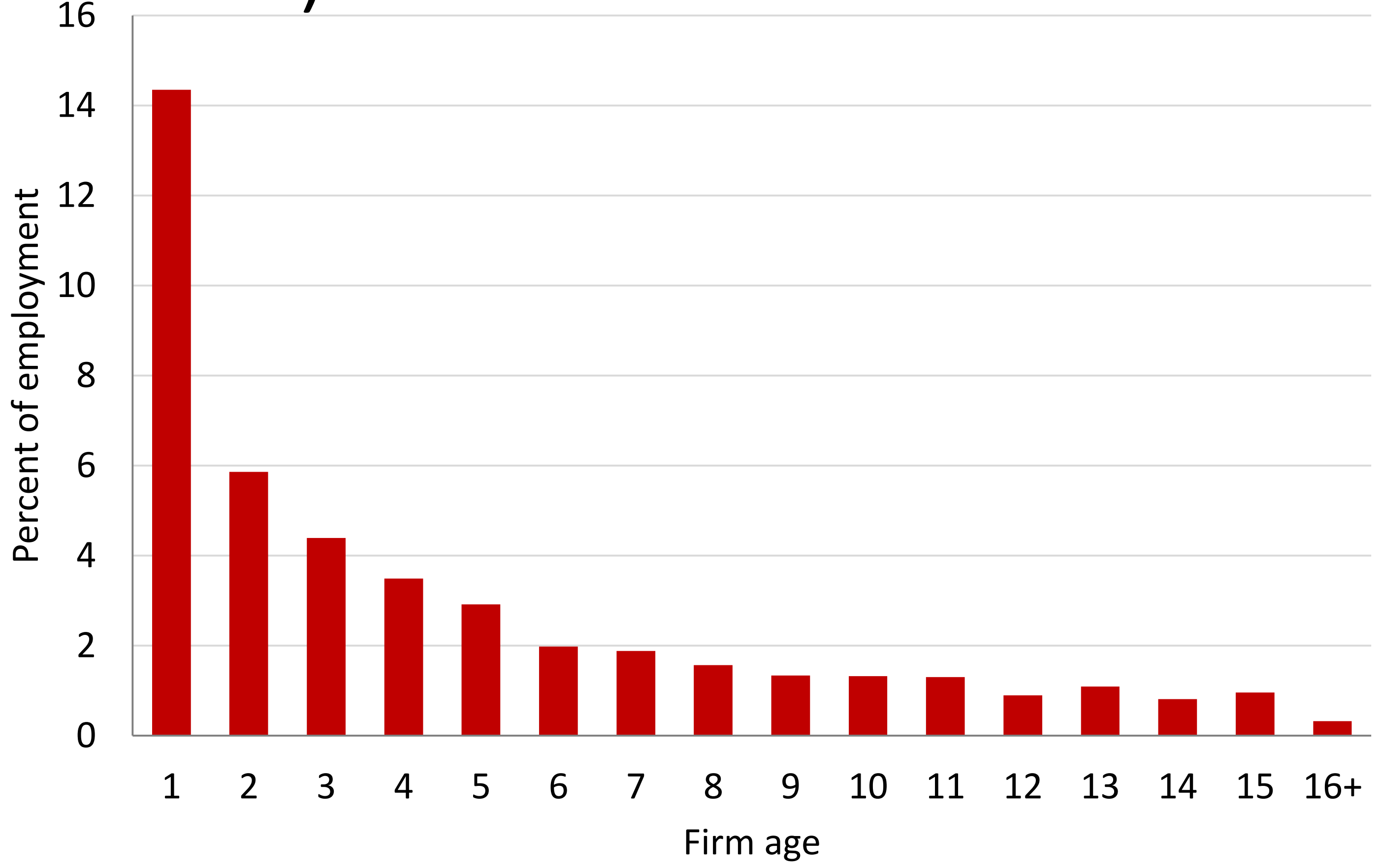
70 percent of employment Of startups Firm Size < 50

25 percent of employment Of all firms firm size<50

Startups are new legal entities with ALL new Establishments.
(Not due to ownership change, change in LFO, M&A, etc.)

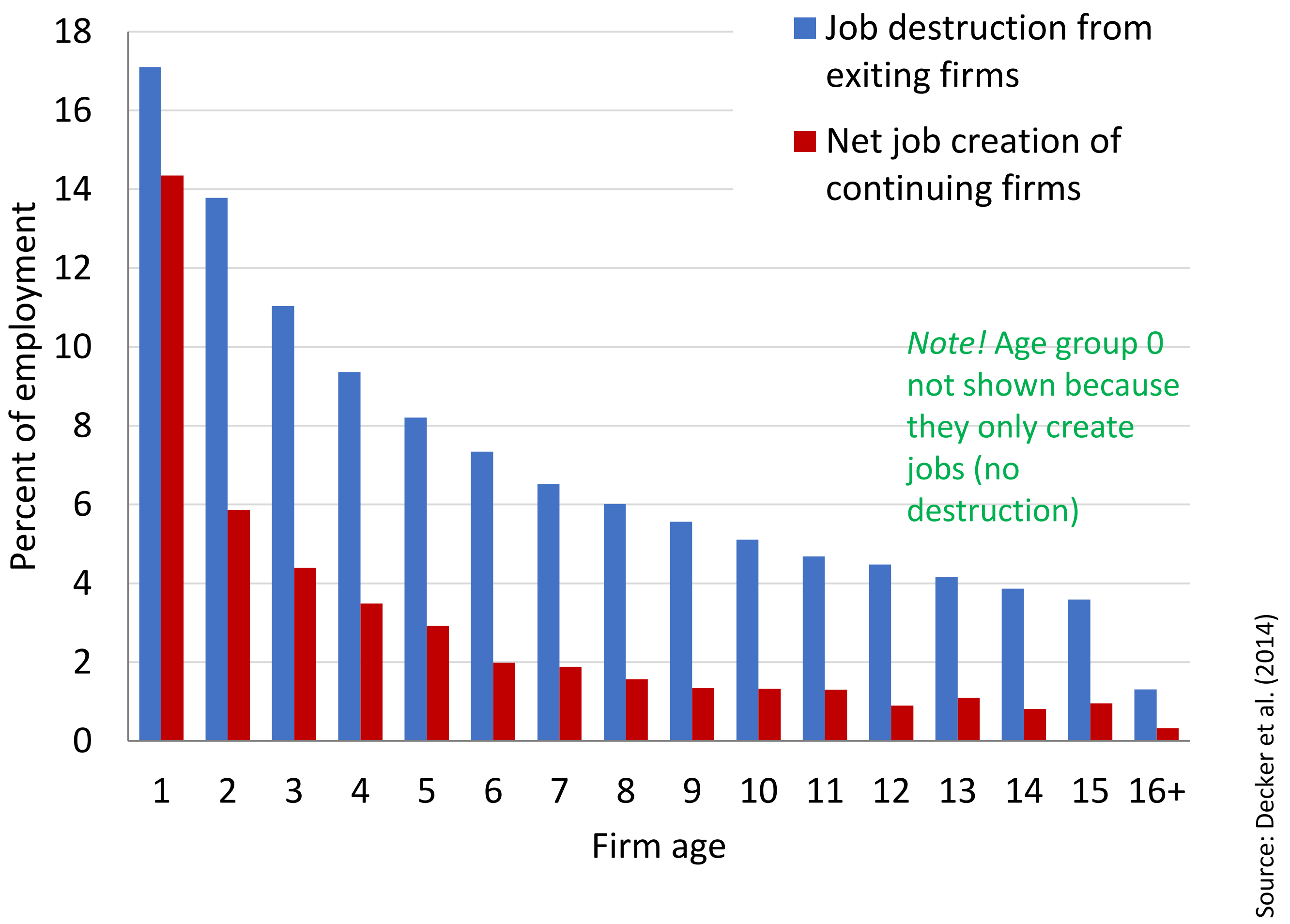

Net Job Creation by Base Year Firm Size
0.200
0.150
0.100
0.050
0.000
-0.050
a) 1 to 4
b) 5 to 9
c) 10 to 19
d) 20 to 49
e) 50 to 99
f) 100 to 249
g) 250 to 499
h) 500 to 999
i) 1000 to 2499
k) 2500 to 4999
j) 5000 to 9999
l) 10,000 +
Base Year Size
Base Year Size with Age Controls

Net Job Creation of Continuing Firms (Post-entry Growth)



Source: Decker et al. (2014)

Up or out!



Job destruction from exiting firms
Net job creation of continuing firms
Note! Age group 0 not shown because they only create jobs (no destruction)
Percent of employment
18
16
14
12
10
8
6
4
2
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16+
Firm age
Source: Decker et al. (2014)

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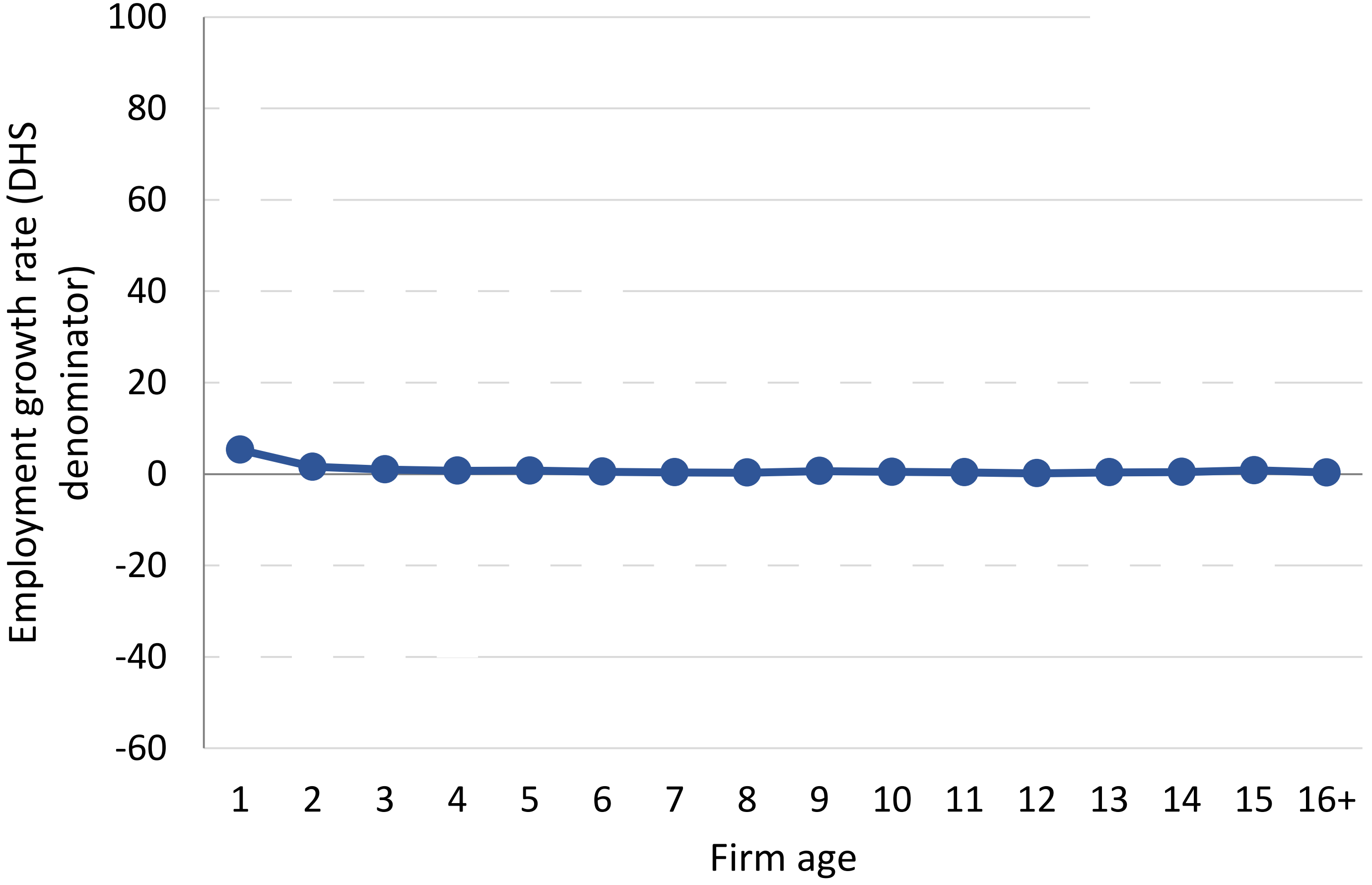
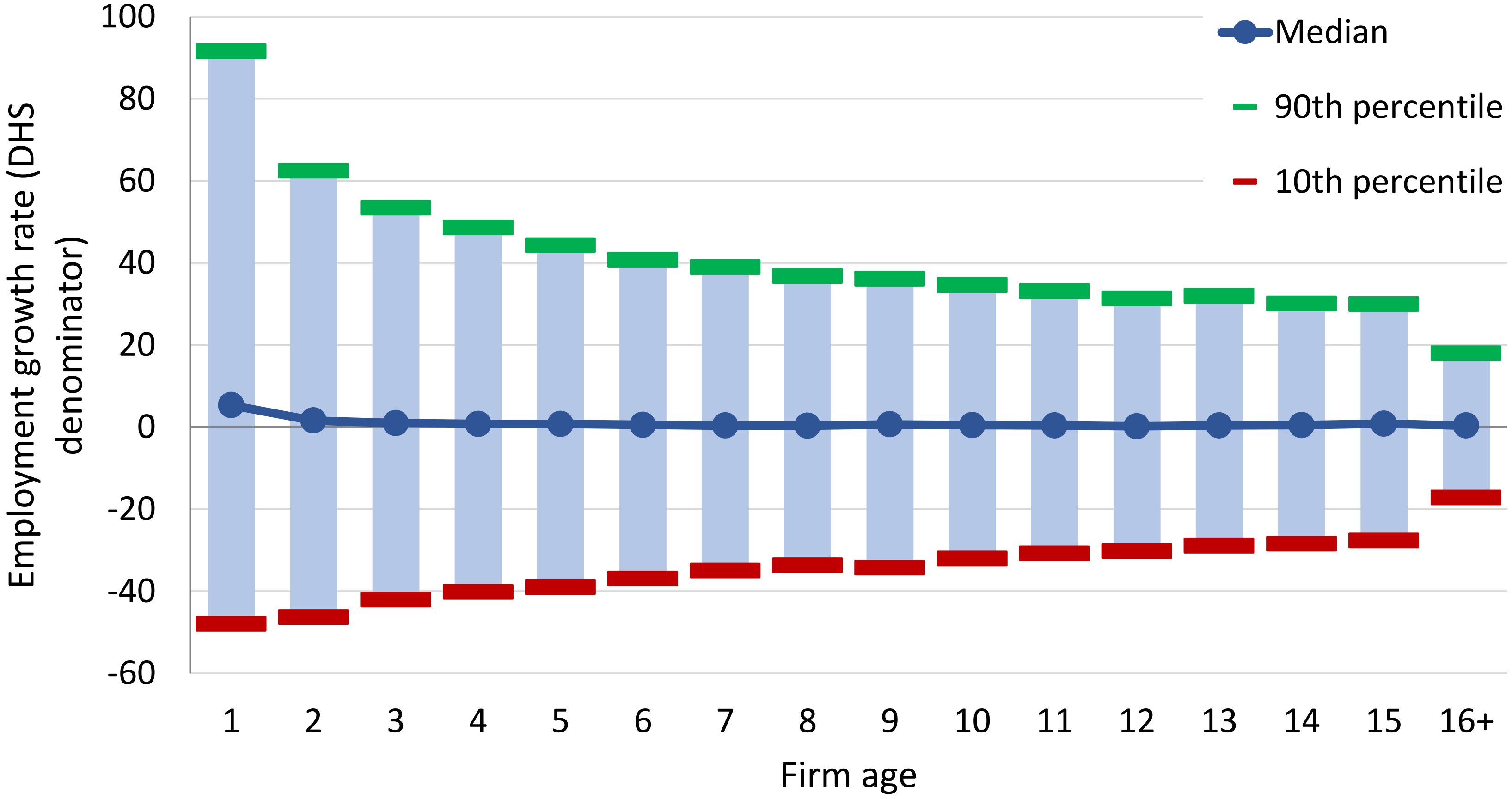
A view of the skew



Source: Decker et al. (2014). Employment-weighted distributions.

Median Growth of Young (all) Firms is zero

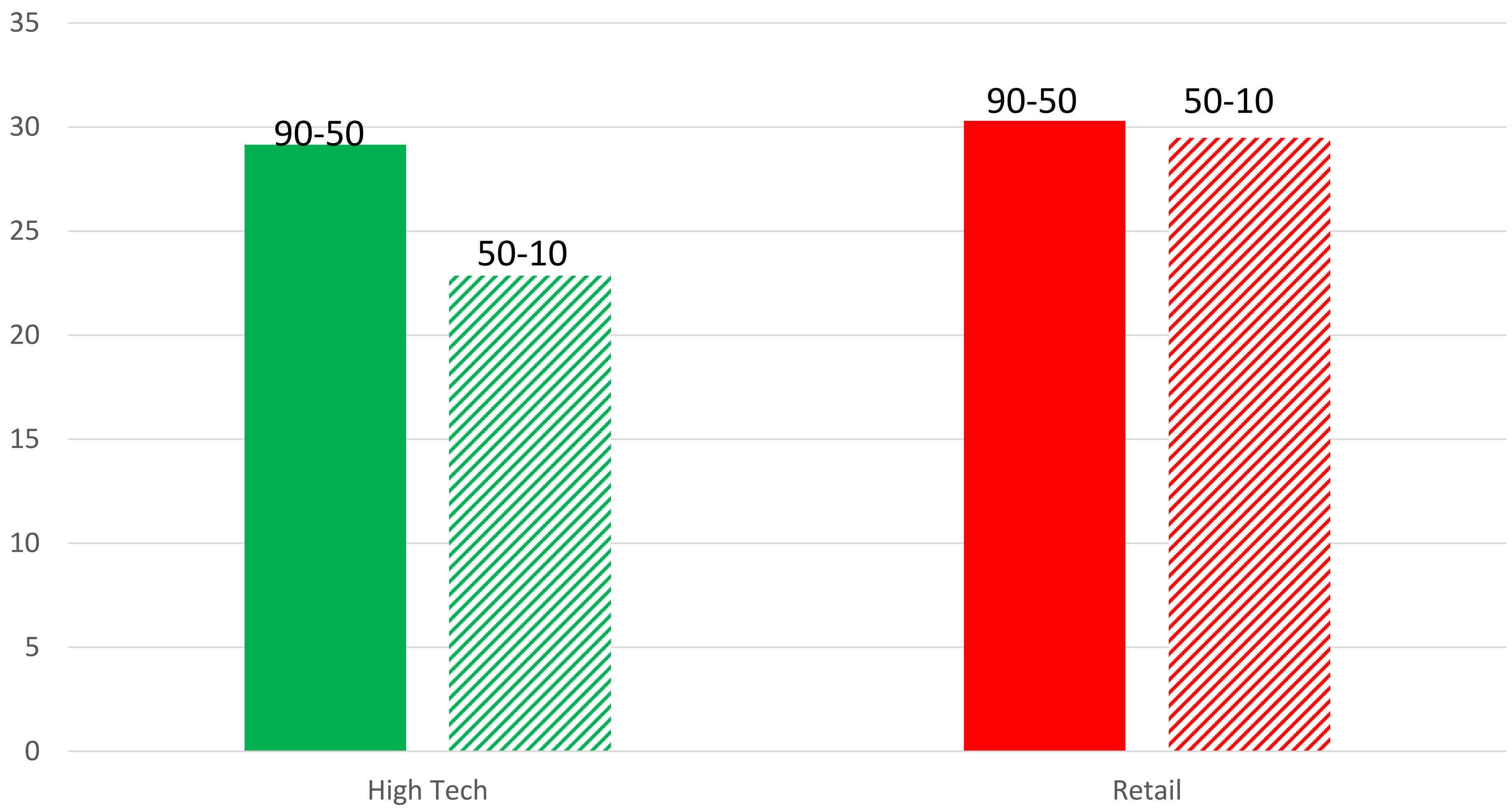
A view of the skew



These patterns Also hold for Output growth distributions

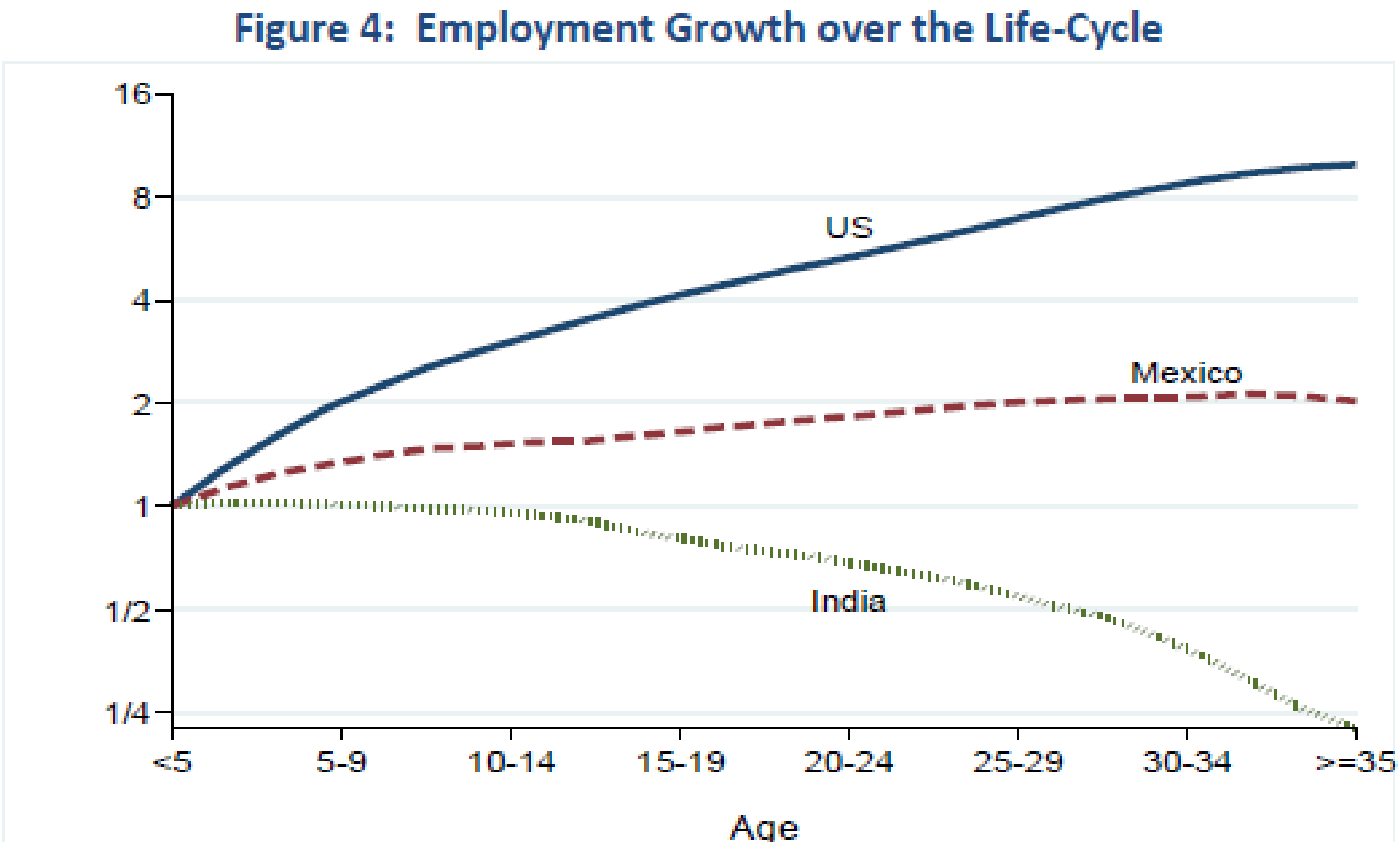
Source: Decker et al. (2014). Employment-weighted distributions.

Large Differences in Skewness Across Sectors – High 90-50 in High Tech Driven by Young Firms



Source: Decker et. al. (2016). HT are STEM intensive sectors (includes ICT)

For comparison: Hsieh-Klenow (2014) – Post-entry *mean* growth patterns across countries



Is this due to lack of up or out dynamics in emerging economies? Is it differences in the skewness?

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Selection and growth

- In well-functioning market economies:
  - Productive businesses should grow
  - Unproductive businesses should downsize or exit
  - This is dynamic equivalent of the determination of the size distribution via productivity.
  - Standard predictions of canonical firm dynamics models like Hopenhayn (1992) and Hopenhayn and Rogerson (1993)
- This is the theory; what is the empirical evidence?
  - Measure productivity (TFP) of individual firms relative to their industry
  - Compare (employment) growth rates and exit rates across (relative) productivity realizations (holding constant initial employment). Estimates of decision rules (as functions of key state variables.
  - Do productive firms grow? Do unproductive firms downsize or exit?

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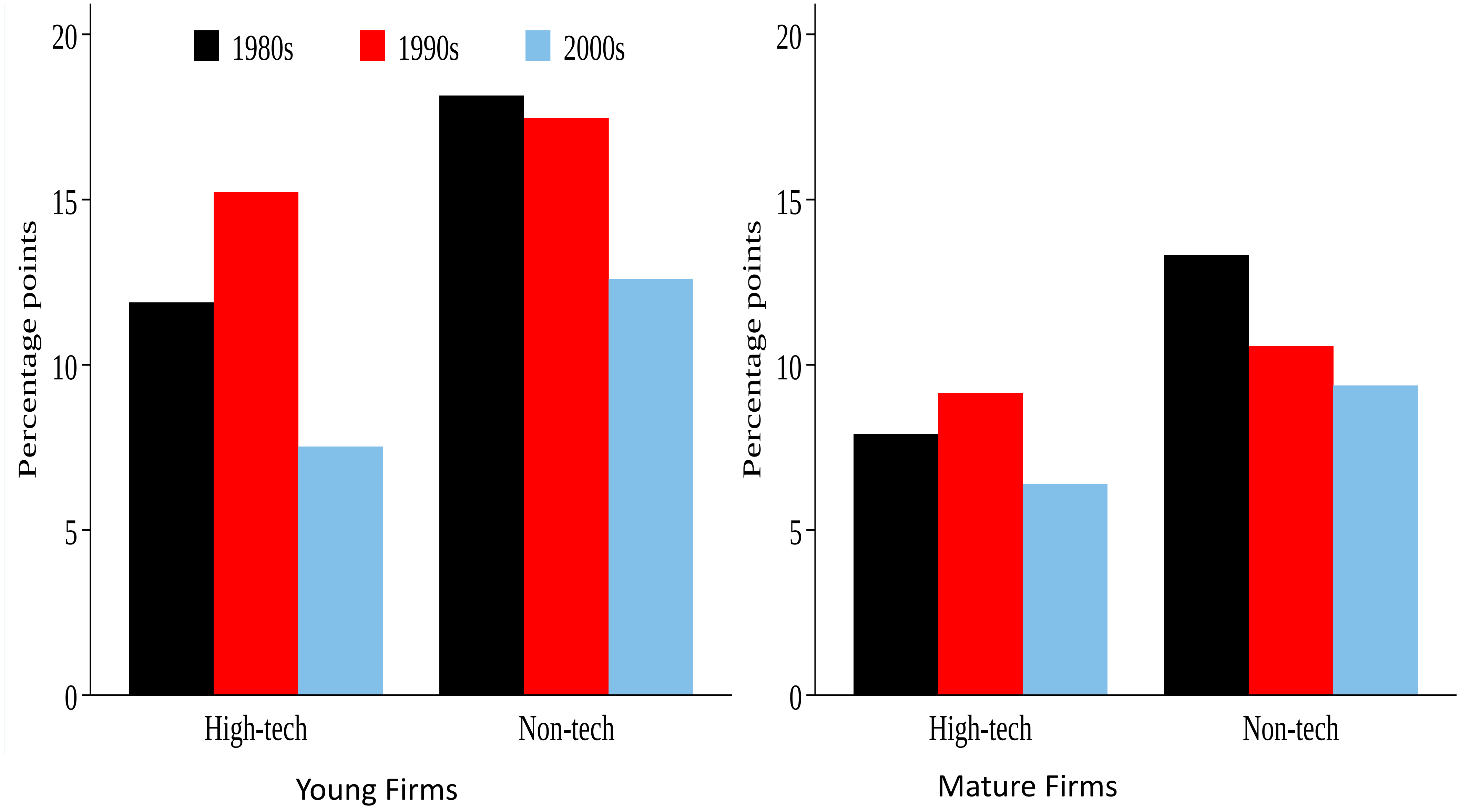

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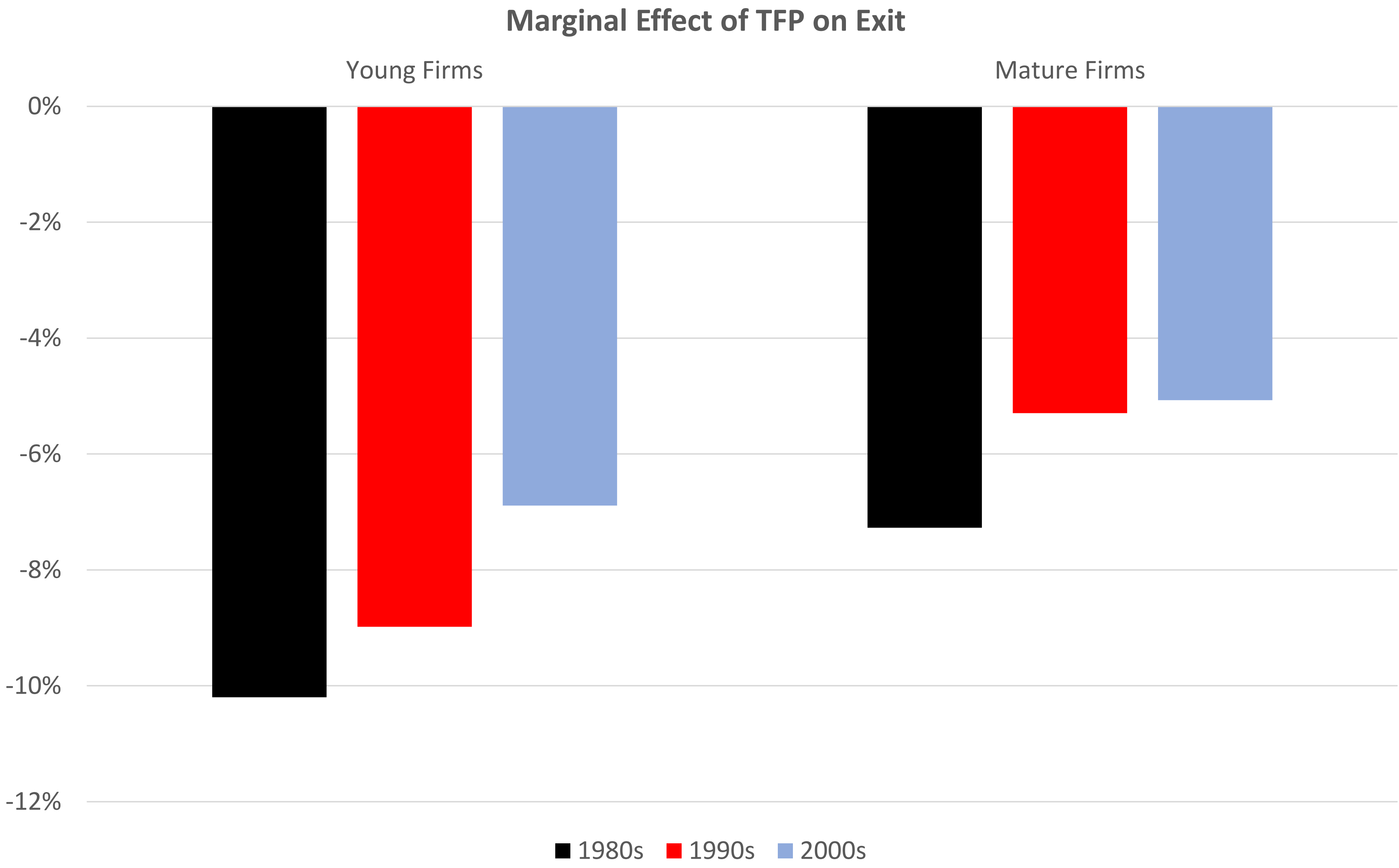

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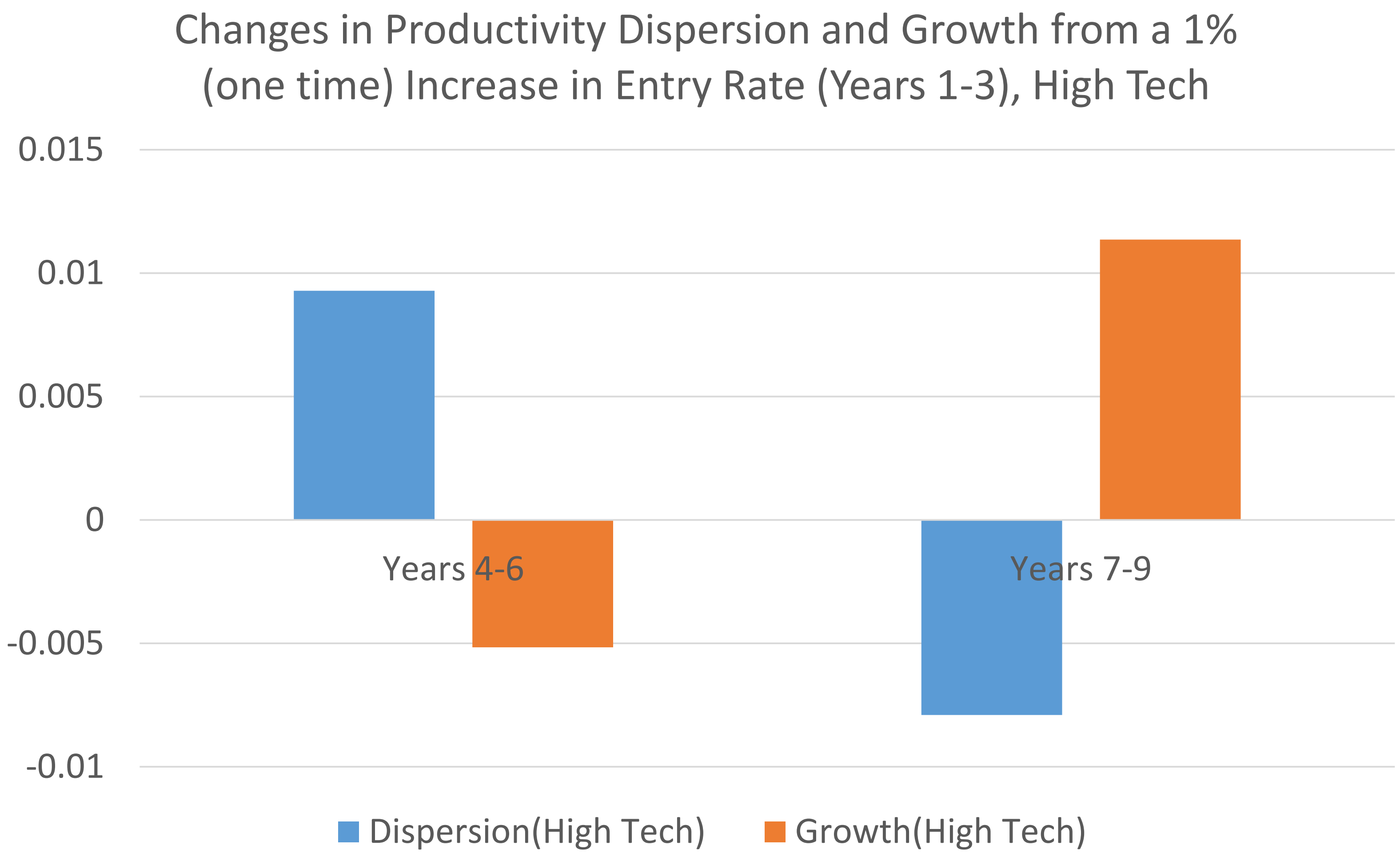
Creative Destruction – Role of Young Firms

- Two related perspectives:
  - Gort and Klepper (1982)
    - Innovation in industry accompanied by surge in entry and experimentation
    - During experimentation phase, high dispersion of productivity and perhaps decline in productivity.
    - Then shakeout/consolidation phase. Productivity growth emerges as successful innovators expand and unsuccessful entrants contract and exit.
    - Their evidence shows business formation and evolution of firm counts with specific innovations (e.g., TVs vs. Tires vs. Lasers)
  - Acemoglu et. al. (2017) and Ackcigit and Kerr (2017):
    - Evidence and model that young firms make major innovations, mature firms minor (defensive) innovations.
- Both perspectives suggest that innovation closely linked to entry/young firm activity.

Dynamics of Entry, Productivity dispersion and Productivity growth



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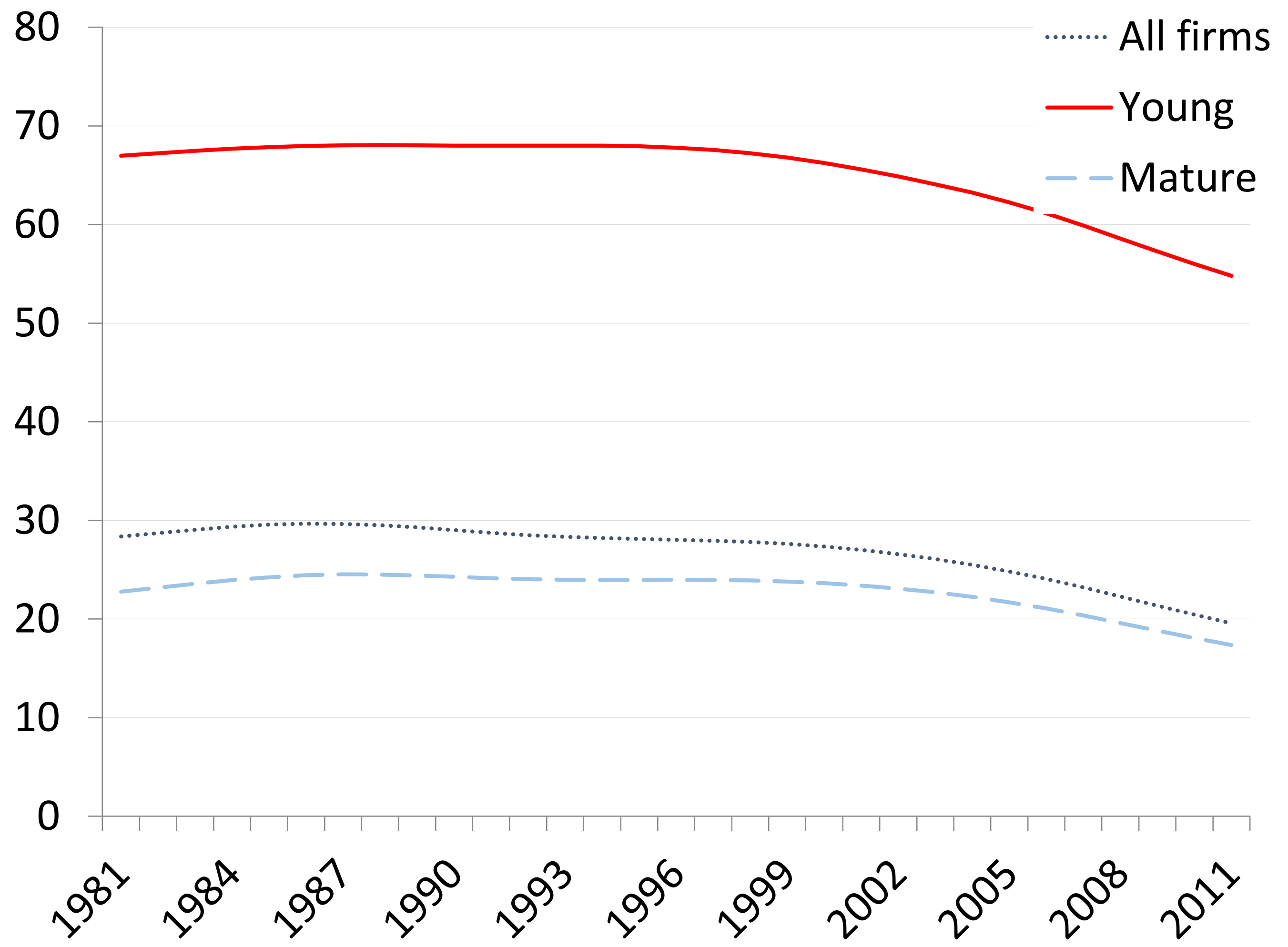
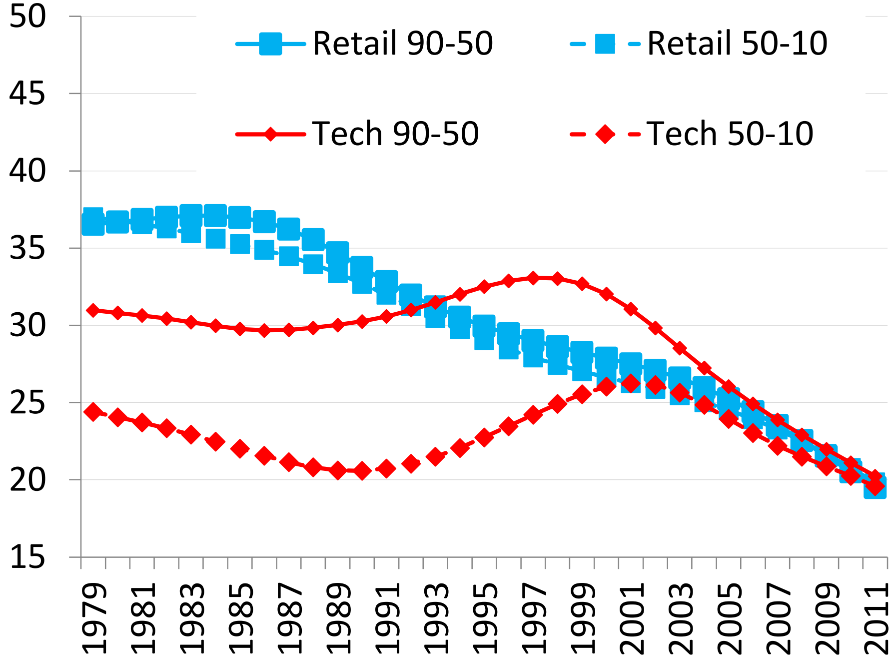
   Post 2000 IPOs are down and post 2000 cohort has not grown as fast

High-growth young firms

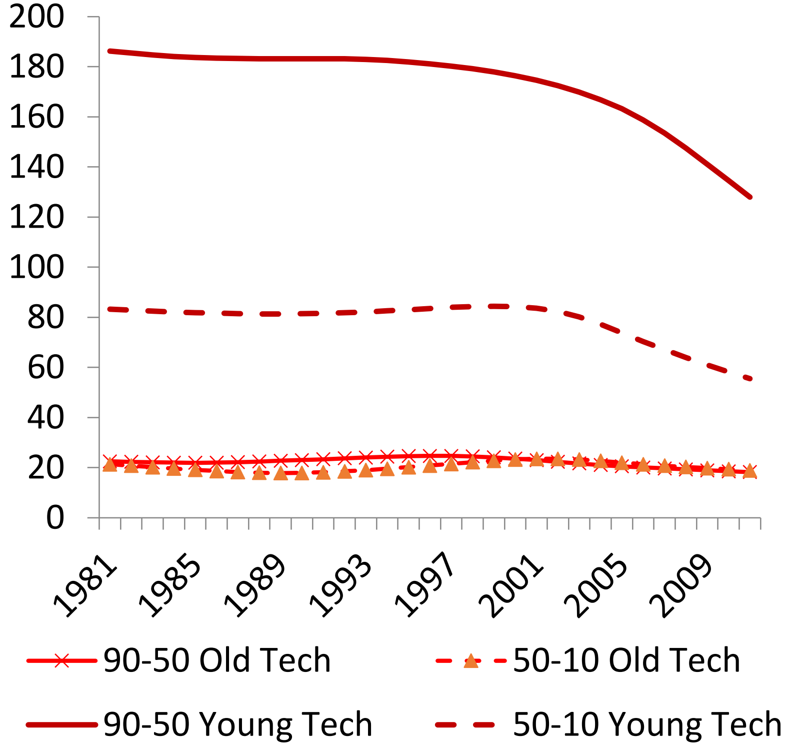


Source: Decker e al. (2016b)

Skewness (high growth) patterns vary dramatically across sectors



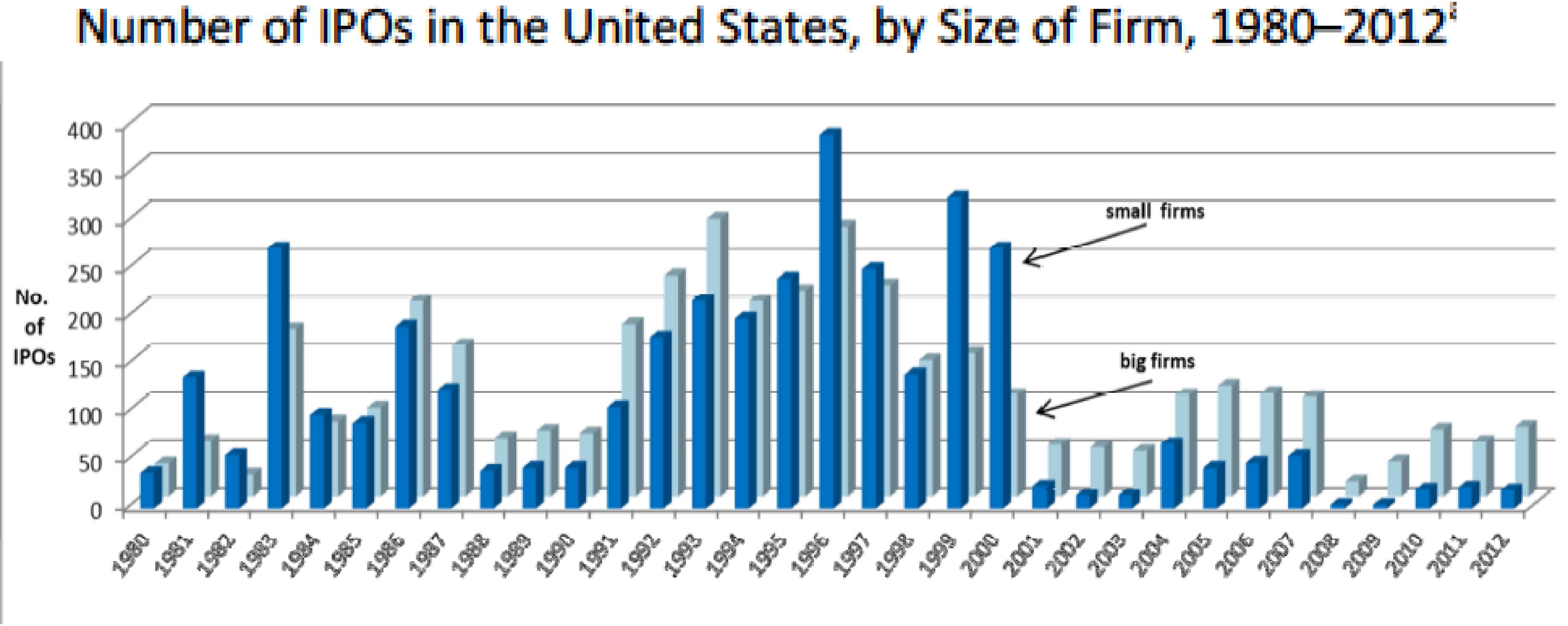
Skewness primarily accounted for by Young Firms. In High Tech, Decline in young firms and decline In High Growth Firms in High Tech



Retail: dispersion decline equal parts 90-50, 50-10
High Tech: Growing Skewness in 1990s, sharp Decline post 2000

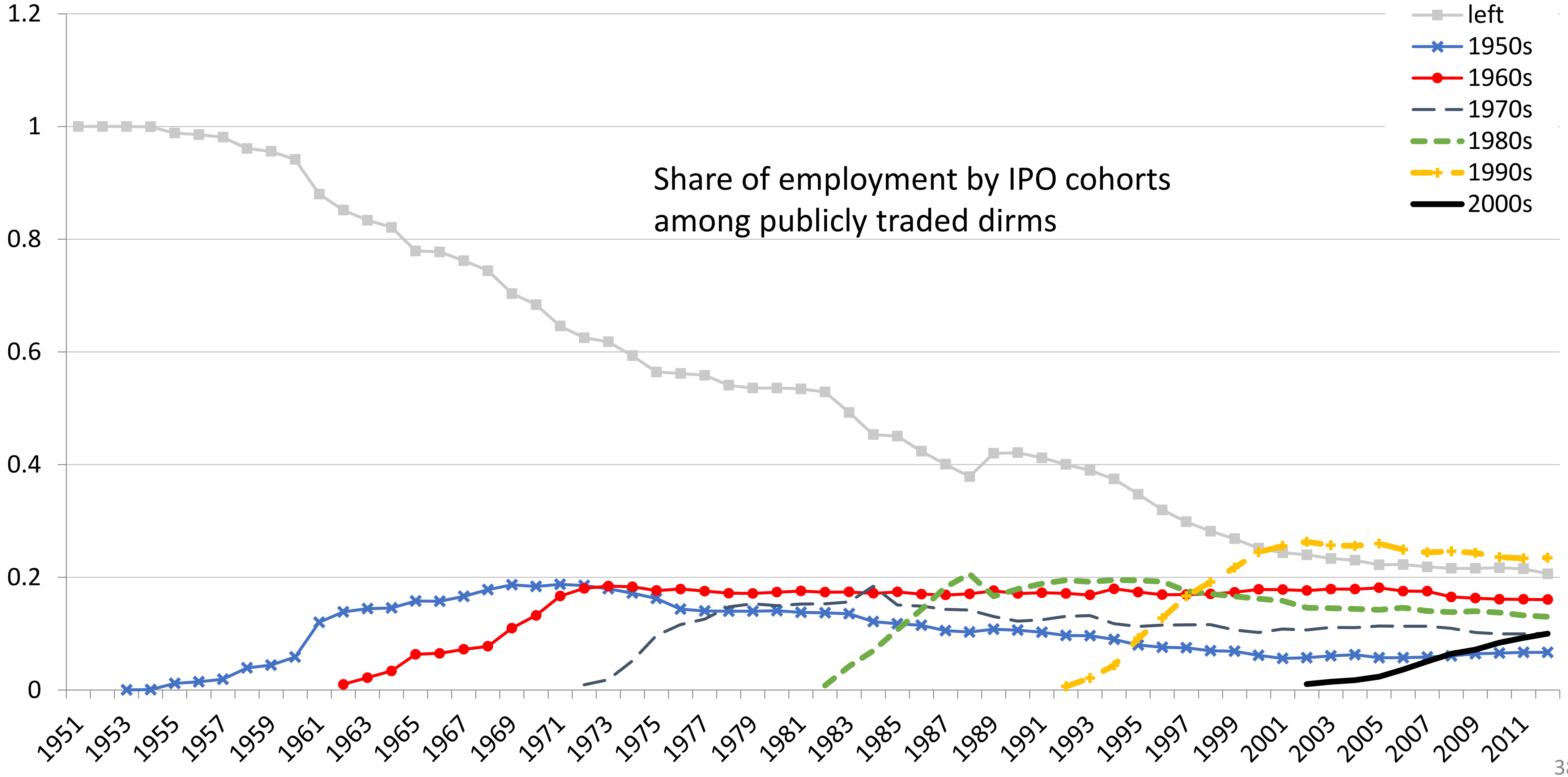
High Tech includes (most of) Information but also High Tech Mfg and Services. Source: Decker et. al. (2016)

Initial Public Offerings (IPOs) Declined after 2000



Reproduced from Xiaohui Gao, Jay R. Ritter and Zhongyan Zhu, 2013. "Where Have All the IPOs Gone?" working paper, University of Florida.

1990s cohort of IPOs large and rapidly growing contribution, post 2000s cohort small and anemic contribution.



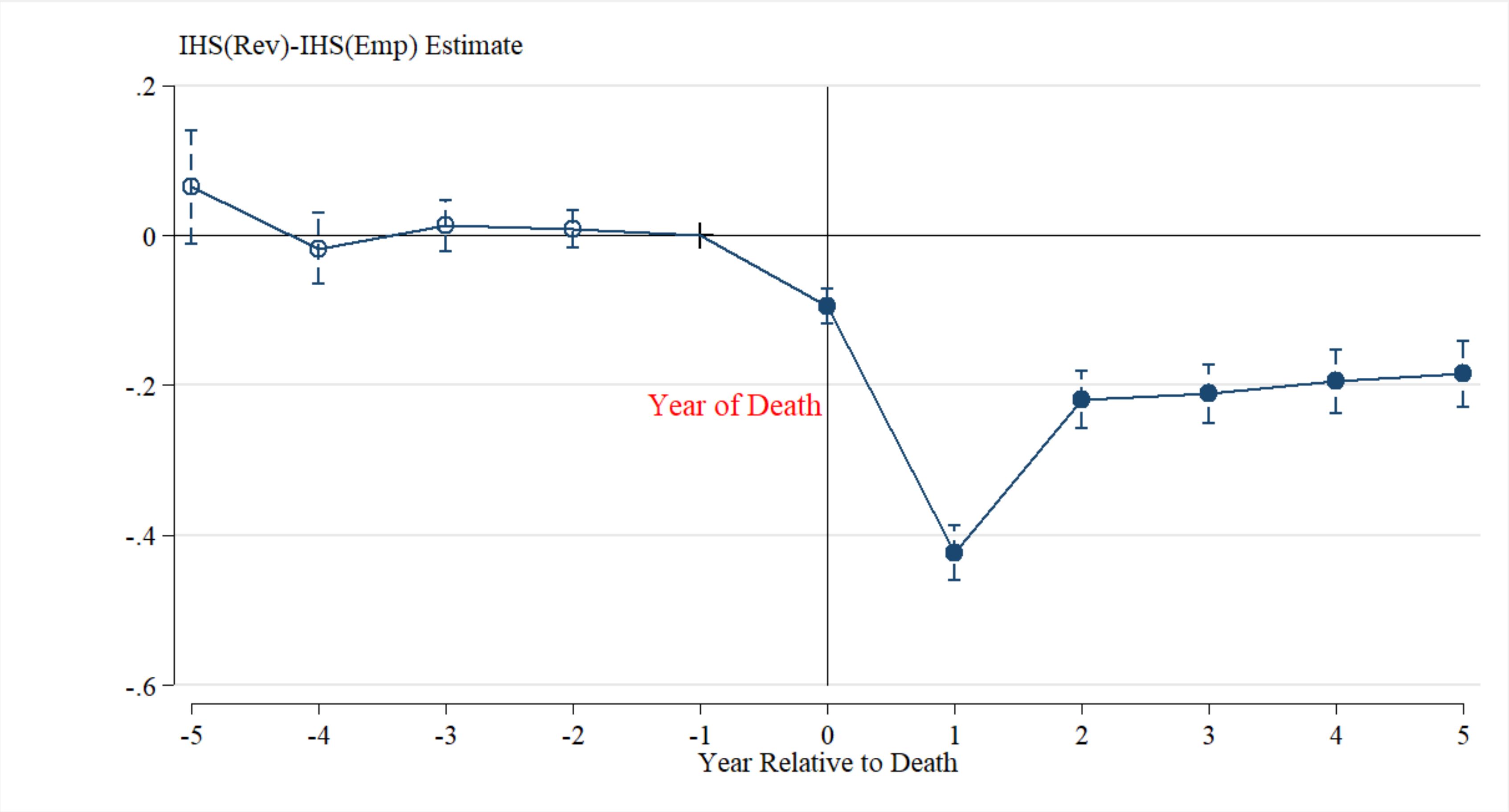
Highlights so far

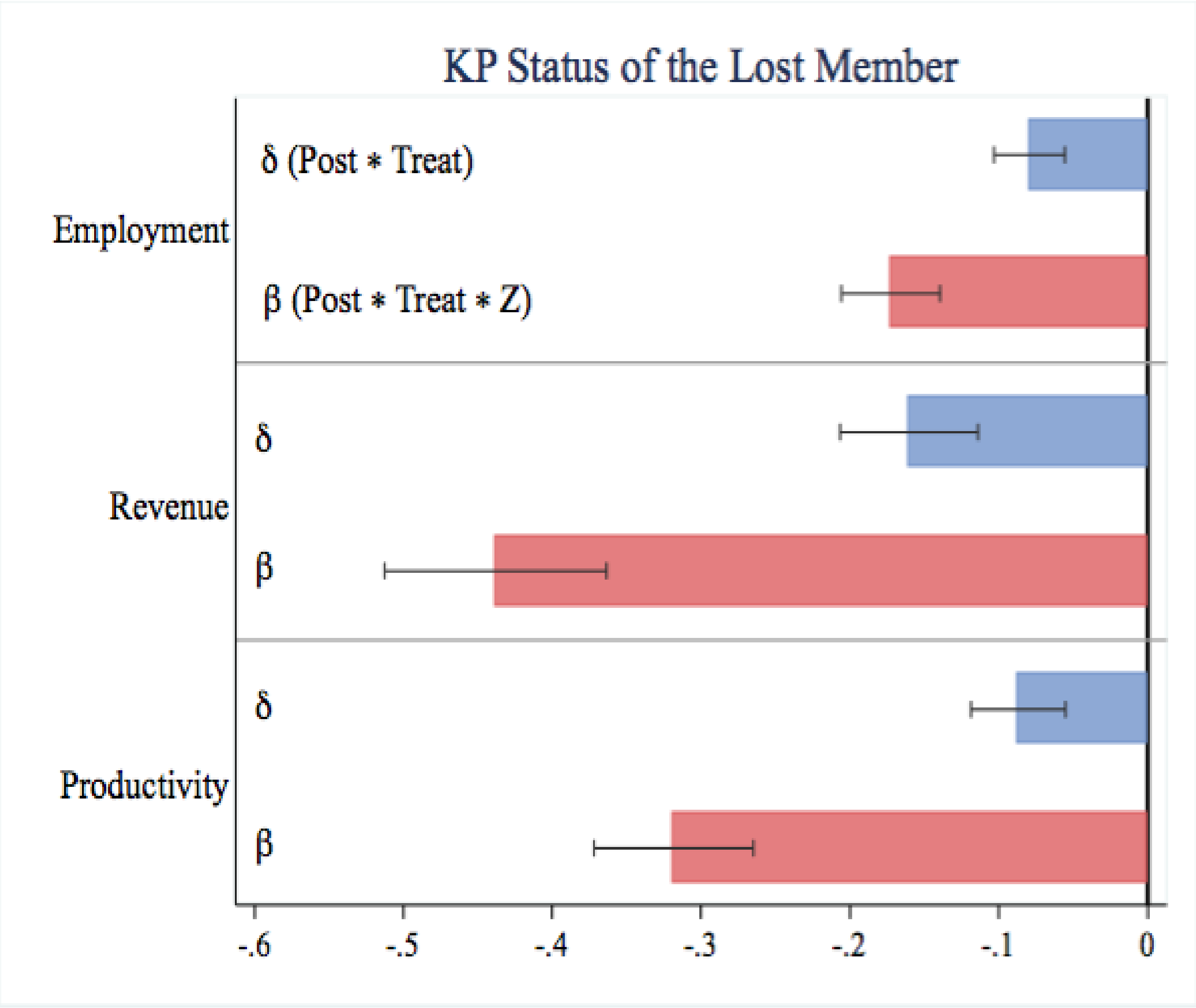
- Startups are small.
  - About 70% of employment at startups are size<50. This compares to 25% of employment at size<50 amongs all firms.
  - Important for the accounting finding that small businesses create most net new jobs.
- Most startups fail or don't grow (median growth is zero).
- Relative to more mature businesses, young firms employment and output growth rate distribution conditional on survival has:
  - Much higher mean, dispersion and right skewness.
- High productivity young firms grow rapidly and low productivity young firms likely to exit. Responsiveness greater for young firms.
- Surges in entry at industry level yield initially rise in dispersion of productivity and decline in productivity. After shakeout rise in productivity and decline in productivity dispersion.
- The outsized role of high growth young firms (e.g. the skewness) is more pronounced in High Tech (innovative intensive sectors).
- Startups and young firm activity have declined over last 30 years but nature of decline has changed over time:
  - Pre 2000, no decline in high growth young firms (e.g., no decline in skewness). Pre-2000 dominated by retail trade with change in business model favoring large firms.
  - Post 2000, decline in high growth firms and skewness in High Tech sectors of the economy. IPOs in economy and HT collapsed post 2000.

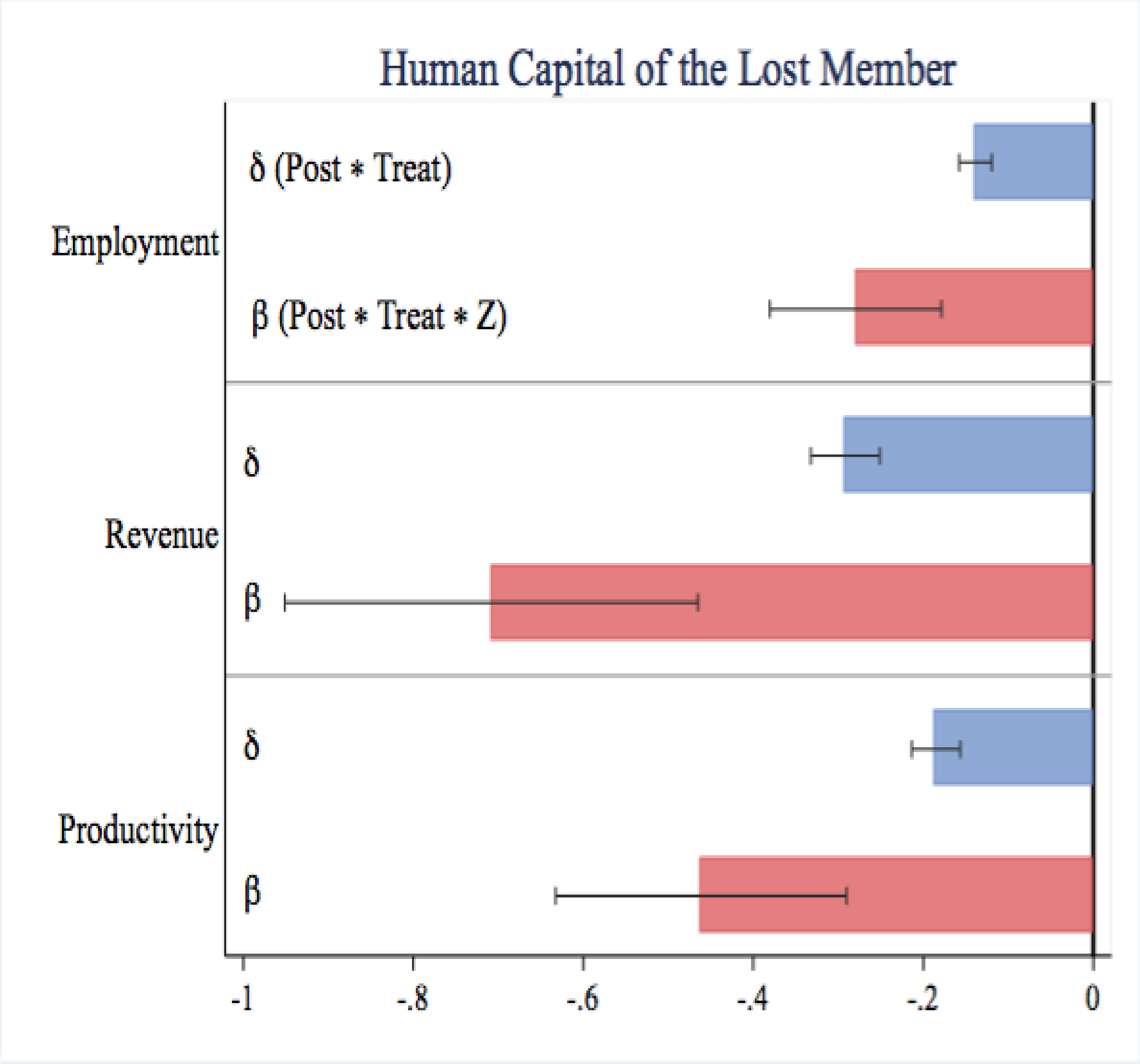
Bonus questions and facts about entrepreneurship

- Enormous heterogeneity in outcomes.
- Where does this come from?
  - Ex ante vs. ex post heterogeneity.
  - Ex ante:
    - Entrepreneurial ability
      - Is it the founder or founding team.
    - Stochastic draw of business ideas have permanent component
  - Ex post:
    - Businesses continually subject to persistent shocks.
    - Might also be subject to “new permanent shock when new technologies are introduced:
      - GM not so good at Robotics?

Loss of founding team member due to premature death has large, negative persistent effects







Findings suggest more than just founder matters. Persistent effect of loss of founding team points to core business Idea embodied in founding team matters. Organizational capital in formation period important

Devil in the Details – Productivity Measurement and Estimation

TFPQ vs TFPR vs RLP vs RPR vs RPI – alphabet soup of micro productivity measures.

- Start with simple one factor model to illustrate conceptual issues

$Q_{it} = A_{it}x_{it}^{\gamma}$, $P_{it} = D_{it}Q_{it}^{\varphi-1}$, Markup= $1/\varphi$

TFPQ = A_{it} and TFPR = $P_{it}Q_{it}/x_{it}^{\gamma} = P_{it}A_{it} = D_{it}A_{it}^{\varphi}x_{it}^{\gamma(\varphi-1)}$

$$R_{it} = D_{it}A_{it}^{\varphi}x_{it}^{\gamma\varphi}, RPR = \frac{R_{it}}{x_{it}^{\gamma\varphi}} = D_{it}A_{it}^{\varphi}$$

$$RPI = P_{it}\ Q_{it}/x_{it} = D_{it}A_{it}^{\varphi}x_{it}^{\gamma\varphi-1}$$

Both TFPR and RPI endogenous. RPR measures fundamentals (just need revenue elasticities)

Under CRS, RPI=TFPR

RPR is a measure of fundamentals that can be constructed from standard revenue and input data

- $RPR = \frac{R_{it}}{x_{it}^{\gamma\varphi}} = D_{it}A_{it}^{\varphi}$ (The residual from estimating revenue function consistently).
  - Key: Estimate REVENUE elasticities of revenue function – not output elasticities
  - Examples: Cooper and Haltiwanger (2006) AND (without always recognizing it) those estimating "production functions" using proxy methods.
  - Many misstate they are estimating production function but they are estimating revenue function.
  - Estimating revenue function has advantages and disadvantages.

Digging Deeper in TFPQ vs. Revenue Productivity

- To shed more light on these issues useful to start with static optimizing model:
- $\pi_{it} = P_{it}Q_{it} - c_{it}x_{it}$
- $x_{it} = [\frac{\gamma\varphi D_{it}A_{it}^{\varphi}}{c_{it}}]^{1/(1-\gamma\varphi)}$ (More productive/higher demand larger)
- $TFPR = P_{it}A_{it} = \frac{c_{it}}{\gamma\varphi}x_{it}^{1-\gamma} = \frac{c_{it}}{\gamma\varphi}\,[\frac{\gamma\varphi D_{it}A_{it}^{\varphi}}{c_{it}}]^{(1-\gamma)/(1-\gamma\varphi)}$
- $RPI = P_{it}Q_{it}/x_{it} = \frac{c_{it}}{\gamma\varphi}$ (Importantly distinct from TFPR and simpler?)
- Under CRS and common costs:
  - $TFPR = P_{it}A_{it} = RPI = P_{it}Y_{it}/x_{it} = \frac{c_t}{\varphi}$
- Equalization of marginal revenue products with CRS, CES and no heterogeneity in input costs yields no dispersion in TFPR and RPI.
- Empirically enormous dispersion in TFPR and RPI. Where from? Frictions and Distortions?
  - Hopenhayn and Rogerson (1993) emphasized adjustment frictions. Restuccia and Rogerson (2008), Hsieh and Klenow (2009) and Bartelsman, Haltiwanger and Scarpetta emphasized idiosyncratic distortions.

Dispersion in revenue productivity? Distortions, frictions, heterogeneous input prices, heterogeneous technology or markups?

- Simplified RR (2009)/HK (2009) model but useful here in this measurement/concept discussion:
- $\pi_{it} = (1 - \tau_{it})P_{it}Q_{it} - c_{it}x_{it}$
- Under CRS:
  - $TFPR = P_{it}A_{it} = RPI = \frac{P_{it}Q_{it}}{x_{it}} = \frac{c_t}{\varphi(1-\tau_{it})}$
- But all of this depends on very strong assumptions:
  - Isoelastic demand, Cobb-Douglas technology with CRS, common costs.
- More generally, the markup for firm i is given by: $\mu_{it} = P_{it}/MC_{it}$
- In general then: $TFPR = \ P_{it}A_{it}$= $\mu_{it}MC_{it}A_{it}$
- Under constant returns to scale then this is equal to: $TFPR = \ P_{it}A_{it}$= $\mu_{it}c_{it}/(1 - \tau_{it}) = RPI$. Note MC inclusive of wedges. Thus variable markups and heterogeneous factor prices yield dispersion in TFPR and RPI
  - Evidence of increasing markups with fundamentals (incomplete pass through)
- But under non constant returns to scale with heterogeneous technologies this generalizes to (even without wedges):

$$TFPR = P_{it}A_{it} = \frac{\mu_{it}c_{it}}{\gamma_{it}} \left[\frac{\gamma_i(\frac{1}{\mu_{it}})D_{it}A_{it}^{1/\mu_{it}}}{c_{it}}\right]^{(1-\gamma_{it})/(1-\gamma_{it}/\mu_{it})}$$, RPI= $\frac{P_{it}Q_{it}}{x_{it}}$= $\frac{\mu_{it}c_{it}}{\gamma_{it}}$

Does DeLoecker and Eeckhout help sort this out?
Not necessarily – many of the same identification problems

$Q_{it} = A_{it} x_{it}^{\theta} z_{it}^{\beta}$ Where x is the variable factor and z is a fixed (quasi-fixed) factor

First order condition for variable factor implies:

$\mu_{it} = \theta / \alpha_{it}^{V}$ $\alpha_{it}^{V} = c_{it} x_{it} / P_{it} Q_{it}$

DE method uses proxy based estimates of revenue function for θ. But revenue elasticites are functions of both factor and demand elasticities.

DE method robust to heterogeneous input prices as long as price takers in input markets. Heterogeneous monopsony power causes Further identification issues.

But this can be rewritten as:

$RPI(x)_{it} = P_{it} Q_{it} / \, x_{it} = c_{it} \mu_{it} / \theta$ This is identical to the above RPI

Heterogeneous technologies over time implies (so variation in cost shares α_{it}^{V} or $RPI(x)_{it}$ may be driven by idiosyncratic markups or technology) :

$\mu_{it} = \theta_{it} / \alpha_{it}^{V}$ $RPI(x)_{it} = P_{it} Q_{it} / \, x_{it} = c_{it} \mu_{it} / \theta_{it}$

Why important? Are changes in labor share due to changing markups or technology?

Estimating RPR with multiple factors

Revenue Product Residual (RPR) with multiple factors

- Let $P_{it} = D_{et} Q_{it}^{\varphi_i - 1}$, $Q_{it} = A_{it} \prod_j X_{ijt}^{\alpha_j}$, Markup = $1/\varphi_i$
- Then revenue is given by (in logs):

$$p_{it} + q_{it} = \sum_j \beta_j x_{ijt} + \varphi \quad a_{it} + d_{it}$$

- Estimate via proxy methods, parameter estimates are *revenue elasticities* $\beta_j = \varphi \quad \alpha_j$
- $RPR_{it} = p_{it} + q_{it} - \sum_j \beta_j x_{ijt} = \varphi \quad a_{it} + d_{it}$, only a function of TFPQ and demand shocks!
- RPR_{it} is proportional to the TFPQ measure used by Hsieh and Klenow (2009, 2014).
- $RPR_{it} = \left(\frac{1}{\varphi}\right) TFPQ_{it}^{HK}$ where (but need factor/demand elasticities)

$$TFPQ_{it}^{HK} = \left(\frac{1}{\varphi}\right)(p_{it} + q_{it}) - \sum_j \alpha_j x_{ijt}$$

Standard cost minimization frequently used to estimate factor elasticities:

$$\min \mathrm{TC} = wL + rK$$

$$s.t.\ Y = AK^{\alpha}L^{\beta}$$

$$\frac{wL}{TC} = \frac{\beta}{\alpha + \beta}$$

$$\frac{rK}{TC} = \frac{\alpha}{\alpha + \beta}$$

- Common to assume CRS so that cost shares immediately yield factor elasticities.
- But can still use cost minimization to yield the above and Estimate RTS via IV or Proxy methods.
- Cost share approach assumes through aggregation first order conditions hold.

Control function approach (with CES demand)

$$r_{it} = q_{it} + p_{it} = \sum_j \beta_j x_{ijt} + \varphi a_{it} + d_{it}$$

Rewrite:

$$\widetilde{q_{it}} = \sum_j \beta_j x_{ijt} + \omega_{it} + \varepsilon_{it}$$

Where ω_{it}= $\varphi a_{it} + d_{it}$, $\widetilde{q_{it}} = r_{it} + \varepsilon_{it}$, ε_{it} is measurement error. Consider conditional input demand for say materials:

$$m_{it} = h(k_{it}, l_{it}, \omega_{it})$$

Invert this (as long as monotonic):

$$\omega_{it} = h^{-1}(k_{it}, l_{it}, m_{it})$$

Implying:

$$\widetilde{q_{it}} = \sum_j \beta_j x_{ijt} + h^{-1}(k_{it}, l_{it}, m_{it}) + \varepsilon_{it}$$

Also, specify flexible AR process:

$$\omega_{it} = g(\omega_{it-1}) + \eta_{it}$$

Estimation approaches and issues:

- Ackerberg, Caves and Fraser (2015) and De Loecker et. al. (2016):
  - Use flexible polynomial in first stage. This eliminates measurement error.
  - Use flexible Dynamic Panel GMM in second stage (i.e., specify flexible polynomial for AR process)
  - Moment conditions:
    - Innovation to composite productivity measure uncorrelated with lagged instruments.
- Issues:
  - Is coefficient on flexible proxy for materials identified?
    - Ghandi et. al. (2016) argue maybe not and suggest imposing discipline from first order condition of materials.
    - De Loecker et. al. (2016) argue identified by serially correlated shocks (e.g., idiosyncratic materials price shocks)
      - But if latter are present then should include in control function.
    - De Loecker, Eeckhout and Unger (2018) (DEU) argue that serially correlated composite productivity sufficient.
  - Variable markups?
    - Ideally need output and input prices at firm/plant level to estimate production function rather than revenue function. See Eslava and Haltiwanger (2019)
    - Alternatively, DEU argue that proxies for markups can be included.
  - Revenue function estimation potentially problematic if processes for demand shock and TFPQ differ. Evidence suggests they do.

Taking stock

- Estimate factor elasticities:
  - Cost share approach (strong assumptions)
  - Need P and Q data to estimate separately/jointly factor and demand elasticities (rare)
  - With P and Q data can permit heterogeneous factor and demand elasticities (and use proxy methods). For example, translog production and VES demand.
- Estimate markups:
  - DE method (very strong assumptions)
  - P and Q data (still need identifying assumptions, e.g., RW (2018) and HRW(2016) without input data or EH (2018) with input data).
- Estimate revenue elasticities:
  - Proxy methods well suited for this approach and can permit heterogeneous revenue elasticities (e.g., translog) across firms.