Technology Adoption and the Slowdown in Skilled Labour Demand 2024 Annual Conference of the Scottish Economics Society

Aniket Baksy

Digital Futures at Work Research Centre, University of Sussex

April 16, 2024

Introduction

- Two central dimensions of rising inequality
 - labour income inequality across skill groups
 - "functional": labour vs capital income
- Summarized by two key aggregates:
 - ► The skill premium
 - ► The labour share of income
- ► Theories of initial rise in inequality, 1980-2000:
 - introduction + diffusion of new tech embodied in ever-cheaper capital goods
 - that complement skilled labour, substitute for/displace unskilled labour

GHK (1998), KORV (2000), Acemoglu-Restrepo (2019), ...



Introduction



Given observed paths for tech change, these theories fail to explain Typical Exercise

Other Explanations

- slowing growth in skill premium
- decline in labour share post 2000



Introduction: This Project

Key challenge: Calibrated models predict very rapid growth in skilled labour demand.

Ohanian-Orak-Shen (2022), Castex et al (2022), Maliar-Maliar-Tsener (2022)

This paper: a resolution of this challenge, based on a simple idea:

Endogenous directed technology adoption.

Introduction: This Project

Key challenge: Calibrated models predict very rapid growth in skilled labour demand.

Ohanian-Orak-Shen (2022), Castex et al (2022), Maliar-Maliar-Tsener (2022)

This paper: a resolution of this challenge, based on a simple idea:

Endogenous directed technology adoption.

- ▶ Rising skill premium ⇒ skilled labour becomes relatively more expensive to hire
- ⇒ firms adopt less skill/more capital intensive technologies
- → weaker growth in skilled labour demand

The New Hork Times https://www.nytimes.com/2011/03/05/science/05legal.html

SMARTER THAN YOU THINK

Armies of Expensive Lawyers, Replaced by Cheaper Software

By John Markoff March 4, 2011

As Goldman Embraces Auto Masters of the Universe Are	matic Threa) ai	n k	; ;	È	v e	e	n	Ì	ť	10	2
						T						1
Software that works on Wall Street is changing how business is done and who												•
profits from it.												•
												•
B. No. 10 Barrow Char												•
By Nanette Byrnes Feor	ary 7,2017											

- ► Macro: Quantify role of mechanism in dynamic GE model of costly tech adoption
 - ► Acemoglu-Restrepo meets Krusell, Ohanian, Rios-Rull, Violante
 - ▶ Key idea: tech adoption \implies short-run capital-labour elast. of subst. \neq long-run

• Micro: Case study of accountants in the US

- ► Macro: Quantify role of mechanism in dynamic GE model of costly tech adoption
 - Acemoglu-Restrepo meets Krusell, Ohanian, Rios-Rull, Violante
 - ▶ Key idea: tech adoption \implies short-run capital-labour elast. of subst. \neq long-run
 - ▶ Model accounts for both slowdown in skill premium and decline in labour share
 - ▶ Without tech adoption: 2019 skill prem. 8-10 pp higher, labour share 10 pp higher
- ► Micro: Case study of accountants in the US

- ▶ Macro: Quantify role of mechanism in dynamic GE model of costly tech adoption
 - Acemoglu-Restrepo meets Krusell, Ohanian, Rios-Rull, Violante
 - ▶ Key idea: tech adoption \implies short-run capital-labour elast. of subst. \neq long-run
 - ▶ Model accounts for both slowdown in skill premium and decline in labour share
 - ▶ Without tech adoption: 2019 skill prem. 8-10 pp higher, labour share 10 pp higher
- ► Micro: Case study of accountants in the US
 - ▶ microdata on use of accounting software \rightarrow exposure to tech adoption

- ▶ Macro: Quantify role of mechanism in dynamic GE model of costly tech adoption
 - Acemoglu-Restrepo meets Krusell, Ohanian, Rios-Rull, Violante
 - ▶ Key idea: tech adoption \implies short-run capital-labour elast. of subst. \neq long-run
 - Model accounts for both slowdown in skill premium and decline in labour share
 - ▶ Without tech adoption: 2019 skill prem. 8-10 pp higher, labour share 10 pp higher
- ► Micro: Case study of accountants in the US
 - ▶ microdata on use of accounting software \rightarrow exposure to tech adoption
 - ▶ higher *initial* accountant wages → higher *subsequent* adoption growth
 - higher adoption growth \rightarrow slower wage growth

 $\rightarrow:$ real flows

 \rightarrow : payments

Intermediate	Good	Firms 🕩 tech

Household • HH Problem



- $\rightarrow:$ real flows
- \rightarrow : payments

Intermediate Good Firms • tech

Produce differentiated intermediates

Household **HH** Problem



- $\rightarrow:$ real flows
- \rightarrow : payments

$$w_{s}\ell_{s} + w_{u}\ell_{u} + r_{k}k + \Pi$$

$$\ell_{s},\ell_{u},k$$

Intermediate Good Firms • tech

- Produce differentiated intermediates
- ▶ Rent k, hire ℓ_s, ℓ_u from household



 \rightarrow : real flows

 \rightarrow : payments



- $\rightarrow:$ real flows
- \rightarrow : payments



p(s)y(s)

y(s)

Intermediate Good Firms • tech

- Produce differentiated intermediates
- Rent k, hire ℓ_s, ℓ_u from household
- Sell intermediates to retailer
- invest to adopt new tech over time

Next: Describing Technology

Household • HH Problem

Retailer • details



 \rightarrow : payments



- $\rightarrow:$ real flows
- $\rightarrow:$ payments



p(s)y(s)

y(s)

Intermediate Good Firms • tech

- Produce differentiated intermediates
- Rent k, hire ℓ_s, ℓ_u from household
- Sell intermediates to retailer
- invest to adopt new tech over time

Household **•** HH Problem

- consume/save, endowed with ℓ_s, ℓ_u
- capital vs global bonds paying \bar{r}

$$1+ar{r}=rac{r_{kt}+q_{kt}(1-\delta)}{q_{kt-1}}$$

Retailer 🕩 details

$$Y = \left(\int y(s)^{\frac{\alpha-1}{\alpha}} ds\right)^{\frac{\alpha}{\alpha-1}}$$



















Model: Describing an Intermediate Firm's Technology Model Structure Fau



Next: Intermediate Goods Firms' Problem 5/21

 $V(\lambda_s, \lambda_u, z)$

Firm's Value at start of period

- A firm enters a period with a predetermined technology $s = (\lambda_s, \lambda_u, z)$.
 - λ_s, λ_u : capital feasibility cutoffs
 - \blacktriangleright z: TFP, follows AR(1) in logs

$$\underbrace{\mathcal{V}(\lambda_{s},\lambda_{u},z)}_{\text{Firm's Value}} = \underbrace{\pi(\lambda_{s},\lambda_{u},z)}_{\text{Flow Profits}}$$

- A firm enters a period with a predetermined technology $s = (\lambda_s, \lambda_u, z)$.
- Hires labour of each type, rents capital from households, static profit max Profit Max.

$$\underbrace{V(\lambda_{s}, \lambda_{u}, z)}_{\text{Firm's Value}} = \underbrace{\pi(\lambda_{s}, \lambda_{u}, z)}_{\text{Flow Profits}} + \underbrace{p_{E} \times 0}_{\text{Value if exit}}$$

- A firm enters a period with a predetermined technology $s = (\lambda_s, \lambda_u, z)$.
- Hires labour of each type, rents capital from households, static profit max Profit Max.
- After production, a fraction p_E of firms exit, replaced by new entrants
 - entrants draw z from stationary distribution of AR(1) for z
 - and start with λ_{sE} , λ_{uE} = mean value of λ_s , λ_u over active firms in period of entry



- A firm enters a period with a predetermined technology $s = (\lambda_s, \lambda_u, z)$.
- Hires labour of each type, rents capital from households, static profit max Profit Max.
- After production, a fraction p_E of firms exit, replaced by new entrants
- Firms that don't exit invest in new tech adoption ...



- A firm enters a period with a predetermined technology $s = (\lambda_s, \lambda_u, z)$.
- Hires labour of each type, rents capital from households, static profit max Profit Max.
- After production, a fraction p_E of firms exit, replaced by new entrants
- Firms that don't exit invest in new tech adoption ...
- ... and begin next period with a new, more capital-intensive technology.

- Show how firm allocates labour and capital across tasks it performs
- Show how falling q_k generates incentives to adopt more capital intensive technologies
- ► Tech adoption breaks link between short and long-run capital-labour substitutability

Roadmap

Show how firm allocates labour and capital across tasks it performs

• Show how falling q_k generates incentives to adopt more capital intensive technologies

▶ Tech adoption breaks link between short and long-run capital-labour substitutability

Allocating Factors across Tasks: Cost Minimization • Formal Cost Min. Problem



Allocating Factors across Tasks: Cost Minimization • Formal Cost Min. Problem



- productivity of labour increasing in task index
- \implies Unit cost of producing any task with labour downward sloping in task index

Allocating Factors across Tasks: Cost Minimization • Formal Cost Min. Problem



• Unit cost of producing a task with capital constant across task index at r_k
Allocating Factors across Tasks: Cost Minimization • Formal Cost Min. Problem



• Define $\hat{\lambda}_i(w_i, r_k)$ as **cutoff** task index below which *optimal* to use k

Allocating Factors across Tasks: Cost Minimization • Formal Cost Min. Problem



- Consider a firm whose capital feasibility cutoff $\lambda_i < \hat{\lambda}_i$
- Firm is constrained: for tasks in $[\lambda_i, \hat{\lambda}_i]$ optimal to use k but not feasible

Allocating Factors across Tasks: Cost Minimization • Formal Cost Min. Problem



Cost-minimizing allocation of factors to tasks:

- Use capital for tasks in $[0, \lambda_i^*]$ where $\lambda_i^* = \min\{\lambda_i, \hat{\lambda}_i\}$, (e.g. here, $\lambda_i^* = \lambda_i < \hat{\lambda}_i$)
- and use labour of type *i* for tasks in $(\lambda_i^*, 1]$.

- Show how firm allocates labour and capital across tasks it performs
- Show how falling q_k generates incentives to adopt more capital intensive technologies
- ▶ Tech adoption breaks link between short and long-run capital-labour substitutability



• Start with a firm for which
$$\lambda_i = \hat{\lambda}_i$$

 \Rightarrow no incentives to change λ_i .



• Start with a firm for which $\lambda_i = \hat{\lambda}_i$

 \implies no incentives to change λ_i .

 \downarrow capital price $q_k \implies$ capital rental cost $r_k \downarrow$



- Start with a firm for which $\lambda_i = \hat{\lambda}_i$ \implies no incentives to change λ_i .
- ↓ capital price q_k ⇒ capital rental cost r_k↓
 All else equal, ↓ r_k shifts Â_i to the right to Â'_i



- Show how firm allocates labour and capital across tasks it performs
- Show how falling q_k generates incentives to adopt more capital intensive technologies
- ► Tech adoption breaks link between short and long-run capital-labour substitutability

Key Intuition: Long-run Substitutability > Short Run

$$c\left(\lambda_{s},\lambda_{u},z\right) = \frac{1}{z}\left[\mu^{\sigma}P_{Gu}(\cdot)^{1-\sigma} + (1-\mu)^{\sigma}P_{Gs}(\cdot)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \quad \text{where for } i = s, u$$

$$P_{Gi}(\lambda_{i}) = \left[r_{kt}^{1-\rho}\Psi_{ki}\left(\lambda_{i}^{*}\right) + w_{i}^{1-\rho}\Psi_{\ell i}\left(\lambda_{i}^{*}\right)\right]^{\frac{1}{1-\rho}}$$

$$k_{0}$$

Key Intuition: Long-run Substitutability > Short Run

$$c(\lambda_{s},\lambda_{u},z) = \frac{1}{z} \left[\mu^{\sigma} P_{Gu}(\cdot)^{1-\sigma} + (1-\mu)^{\sigma} P_{Gs}(\cdot)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \quad \text{where for } i = s, u$$

$$P_{Gi}(\lambda_{i}) = \left[r_{kt}^{1-\rho} \underbrace{\Psi_{ki}(\lambda_{i}^{*})}_{\text{fixed}} + w_{i}^{1-\rho} \underbrace{\Psi_{\ell i}(\lambda_{i}^{*})}_{\text{fixed}} \right]^{\frac{1}{1-\rho}} \quad k \bigwedge_{\substack{w_{s1} \\ w_{s1} \\ w_{s1$$

Short-run substitution conditional on technology λ_s, λ_u: move along fixed isoquant, governed by ρ

1



Key Intuition: Long-run Substitutability > Short Run

$$c(\lambda_{s},\lambda_{u},z) = \frac{1}{z} \left[\mu^{\sigma} P_{Gu}(\cdot)^{1-\sigma} + (1-\mu)^{\sigma} P_{Gs}(\cdot)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \quad \text{where for } i = s, u$$

$$P_{Gi}(\lambda_{i}) = \left[r_{kt}^{1-\rho} \underbrace{\Psi_{ki}(\lambda_{i}^{*})}_{\text{variable}} + w_{i}^{1-\rho} \underbrace{\Psi_{\ell i}(\lambda_{i}^{*})}_{\text{variable}} \right]^{\frac{1}{1-\rho}} \quad k \quad \bigvee_{k} \underbrace{\Psi_{ki}(\lambda_{i}^{*})}_{\text{variable}} + w_{i}^{1-\rho} \underbrace{\Psi_{\ell i}(\lambda_{i}^{*})}_{\text{variable}} \right] \quad k \quad \bigvee_{k} \underbrace{\Psi_{ki}(\lambda_{i}^{*})}_{\text{variable}} + w_{i}^{1-\rho} \underbrace{\Psi_{\ell i}(\lambda_{i}^{*})}_{\text{variable}} + w_{i}^{1-\rho} \underbrace{\Psi_{\ell i}(\lambda_{i}^{*})}_{\text{vari$$

- Short-run substitution conditional on technology λ_s, λ_u: move along fixed isoquant, governed by ρ
- Long-run substitution allowing λ_s, λ_u to change: additionally, shifts in isoquants, governed by shape of ψ_i(·)



Quantitative Experiment



Model discipline:

- ▶ details
- target micro estimates of short/long run elasticities
- Model validation: model consistent with
- ▶ values

- output elasticities of capital and labour
- changes in moments of ℓ_s/ℓ_u distribution

• Model inputs for quantitative expt.:

- ▶ details
- relative price of capital q_k , DiCecio (2009)
- relative supply of skilled ℓ_s/ℓ_u , CPS
- assume linear decline in growth rate to 0 post 2019
- perfect foresight transition b/n initial/final SS

Fixed $\kappa \implies$ Incentive to $\uparrow \lambda_s$ vs λ_u mostly depend on steepness of unit costs.

Initial steady state: $\downarrow r_k$ induces disproportionate \uparrow in λ_u .



Over time: incentives to raise λ_s rise.



By 2019: incentives to raise lambdas are larger



Key Success: Model matches behavior of skill premium and labor share



Note: calibration does not target either series' dynamics

Model gets both series right, a success that has eluded the literature

Counterfactual: No Endogenous Tech Adoption



• Counterfactual: all firms use their 1980 steady state values of λ_s , λ_u throughout

Counterfactual misses slowdown of skill premium and the decline in labour share

Source of decline in labour share



Figure: Data: BEA-BLS Integrated National Accounts and CPS. Data series constructed by distributing non-farm business labor share into skilled/unskilled based on respective group shares of total labor income in the CPS ASEC \rightarrow Details. Model: $\frac{w_it\ell_{it}}{Y_t}$.

- Model consistent with behavior of *skill-specific* labor shares
- Pre 2000 stability in labor share:
 - Rising skilled share offsets falling unskilled share
- Post 2000 decline in labor share:
 - Slowing skilled share no longer offsets falling unskilled share
- Counterfactual:
 - ► overpredicts ↑ skilled share
 - ► underpredicts ↓ unskilled share

Micro Evidence: Case study of Accountants

- So far: macro evidence, now: micro evidence from experience of accountants
- Establishment-level use of accounting software: Harte-Hanks/Aberdeen CiTDB

In 2009,	the Coupa Cafe at the GSB	used	Intuit Quickbooks	to maintain its general ledger.
\sim				
Year	Establishment (identity $+$ address $+$ sector)		Manufacturer + Model	Brief description of use case

Micro Evidence: Case study of Accountants

- So far: macro evidence, now: micro evidence from experience of accountants
- Establishment-level use of accounting software: Harte-Hanks/Aberdeen CiTDB

Construct commuting-zone level adoption rates

$$FracAdopt_{ct} = \frac{1}{N_{ct}^{estabs}} \sum_{i \in c} \underbrace{\omega_{it}}_{\mathsf{Estab. weight}} \mathbf{1}_{it} (i \text{ adopted accounting software at date } \leq t)$$

A Case Study: Higher Wages associated with More Adoption

- First show that where accountants were expensive to hire, adoption was more rapid
- **Specification**:

$$\underbrace{\Delta_{t-10,t} \textit{FracAdopt}_{ct}^{\textit{ACCT}}}_{\text{10-yr chg in shr. estabs. adopting Acct tech}} = \beta_0 + \beta_1 \underbrace{\log w_{s,ct-10}}_{\text{Init. (log) wages}} + \delta_s + \mathbf{x}'_{ct-10}\gamma + \varepsilon_{ct}$$

▶ Wage *levels* may be endogenous to subsequent adoption growth

A Case Study: Higher Wages associated with More Adoption

- First show that where accountants were expensive to hire, adoption was more rapid
- **Specification**:

$$\underbrace{\Delta_{t-10,t} \textit{FracAdopt}_{ct}^{\textit{ACCT}}}_{\text{10-yr chg in shr. estabs. adopting Acct tech}} = \beta_0 + \beta_1 \underbrace{\log w_{s,ct-10}}_{\text{Init. (log) wages}} + \delta_s + \mathbf{x}'_{ct-10}\gamma + \varepsilon_{ct}$$

- ▶ Wage *levels* may be endogenous to subsequent adoption growth
- ► IV strategy: implementation of the 150 hour rule.
 - ▶ Rule raised study requirements for CPA exam from 120 to 150 hours
 - Substantial decline in supply, 8-9% increase in wages of accountants
 - Identifying assumption: timing of rule implementation not affected by forces driving tech adoption across states

A Case Study: Higher Wages associated with More Adoption

 $\beta_1 > 0$: Regions with higher initial accountant wages saw faster adoption growth.

Effect on change in share of adopting firms $\Delta_{t-10 ightarrow t}$ <i>FracAdopt</i> $_{ct}^{ACCT}$						
	OLS	IV				
$\log w_{s,ct-10}$	0.167*** (0.055)	1.798** (0.749)				
State FE Race Comp., Age, Income, Industry Controls	Y Y	Y Y				
Ν	1,386	1,386				

Table: An observation is a commuting zone-year pair. Observations weighted by commuting zone population in initial period. Data on wages from Census 1990 2000, 2010. Data on rising adoption of Accounting technologies from Computer Intelligence Technology Database (CiTDB). All regressions include state fixed effects. Standard errors clustered at the commuting zone level in parentheses. *, **, *** indicate statistical significance at 0.1, 0.05 and 0.01% respectively.

A Case Study: Faster Adoption of Tech and Slower Wage Growth

▶ Now show that ↑ tech adoption associated with ↓ growth in accountant wages.

Specification:

$$\underbrace{\Delta_{t-10,t} \log w_{s,ct}^{ACCT}}_{\text{10-yr chg in (log) wages}} = \beta_0 + \beta_1 \underbrace{\Delta_{t-10,t} \textit{FracAdopt}_{ct}^{ACCT}}_{\text{10-yr chg in shr. estabs.}}_{\text{adopting acct. software}} + \delta_c + \mathbf{x}'_{ct-10}\gamma + \varepsilon_{ct}$$

Identifying Assumption: adoption growth conditionally unrelated to other forces driving accountant wage growth across commuting zones within a state.

A Case Study: Faster Adoption of Tech and Slower Wage Growth

 $\beta_1 < 0$: Accountants in comm. zones with higher tech adoption saw slower wage growth.

	$\Delta w_{s,ct}$	$\Delta w_{s,ct}$	$\Delta w_{s,ct}$	$\Delta w_{u,ct}$
$\Delta FracAdopt_{ct}^{ACCT}$	-0.162*** (0.0359)	-0.153*** (0.0356)	-0.0996*** (0.0338)	0.0244 (0.0176)
State FE	Y	Y	Y	Y
Race Comp. Controls	Y	Y	Y	Y
Age Controls	N	Y	Y	Y
Income, Industry Controls	Ν	Ν	Y	Y
Num. Obs.	1,386	1,386	1,386	1,386

Table: An observation is a 10-year change in skilled wage growth and a 10-year change in cumulative adoption rates as defined above in a commuting zone-year pair. Observations weighted by commuting zone population in initial period. Data on wage growth from ACS 1990, 2000, 2010. Data on rising adoption of Accounting technologies from Computer Intelligence Technology Database (CiTDB). All regressions include state fixed effects. Standard errors clustered at the commuting zone level in parentheses. *, **, *** indicate statistical significance at 10, 5 and 1% respectively.

Conclusion

- Existing literature struggles to explain evolution of inequality post 2000
- I contribute a model that can
- ► Key ingredient: rising skill premium induces adoption of less skill intensive tech
- which raises the long-run substitutability between capital and skilled labour
- micro evidence: high accountant wages raised accounting software adoption, which subsequently hurt their wage growth

Thank You!

aniket.baksy@sussex.ac.uk

Appendix Slides

Counterfactual increase in labour share

Suppose firms solve the problem

$$\max_{k_{st},k_{et},\ell_{st},\ell_{ut}} \underbrace{A_t k_{st}^{\alpha} \left[\mu \ell_{ut}^{\sigma} + (\lambda k_t^{\rho} + (1-\lambda) \ell_{st}^{\rho})^{\frac{\sigma}{\rho}} \right]^{\frac{1-\alpha}{\sigma}}}_{F(k_{st},k_{et},\ell_{st},\ell_{ut})} - w_{st}\ell_{st} - w_{ut}\ell_{ut} - r_{et}k_{et} - r_{st}k_{st}$$

Hypothesize risk-neutral investors investing in both capital types so by no-arbitrage

$$q_t F_{ke,t+1} + (1-\delta_{eq}) \mathbb{E}\left(rac{q_t}{q_{t+1}}
ight) = F_{ks,t+1} + (1-\delta_{st,t+1})$$

- Using (transformation of) firm's FOCs for labour + this arbitrage equation, estimate model's parameters α, μ, λ, σ, ρ.
 - Exercise: given path of observables k_s , k_e , ℓ_s , ℓ_u and q_k estimate parameters to maximize fit of equations
- Compute implied labour share

$$LSH = \frac{\ell_{st}F_{\ell st} + \ell_{ut}F_{\ell ut}}{F(\cdot)}$$

Counterfactual increase in labour share • back



Figure: Ohanian, Orak and Shen (2021)

- Note: NOT a consequence of *method* used to estimate production function
 - Other methods of production function estimation get the same result Polgreen and Silos (2008)
 - Robust to definition of labour share (gross vs net)
- Instead, a consequence of the fact that capital and skilled labour are estimated to be gross complements.

Data and Definitions • back • More details

- ▶ Data: CPS ASEC, 1980-2019
- ▶ full-time-full-year, ages 18-65
- ► Wages: hourly labour earnings
- composition-adjusted Lemieux '06, Autor '19
- account for topcoding Hoffman et al '20
- collapse data to five bins by education
 - group into skilled/unskilled



Figure: CPS ASEC 1980-2019. Workers aged 18-65 FTFY employed last year. Composition-adjusted residual mean hourly labour earnings constructed as in Autor (2019) residualized on sex, race, experience.

Data and Definitions • back • More details

- ▶ Data: CPS ASEC, 1980-2019
- ▶ full-time-full-year, ages 18-65
- ► Wages: hourly labour earnings
- composition-adjusted Lemieux '06, Autor '19
- account for topcoding Hoffman et al '20
- collapse data to five bins by education
 - group into skilled/unskilled
 - w_s, w_u : labour-supply weighted mean

 $SkillPrem_t = \log w_{st} - \log w_{ut}$



Figure: CPS ASEC 1980-2019. Workers aged 18-65 FTFY employed last year. Composition-adjusted residual mean hourly labour earnings constructed as in Autor (2019) residualized on sex, race, experience.

Construction of the Skill Premium

- ▶ Data: CPS ASEC from IPUMS USA, 1980-2019.
 - Employed FTFY last year
 - labour income = wage income + farm income + proprietors' income
 - Drop top 1% by labour income in each year
 - Deflated by GDPDEF
- ▶ Group all individuals into experience, age, region bins and 5 education bins.
- Calculate labour-supply weights (demog. weight \times hrs worked) for all individuals.
- Calculate bin-specific average weights over the period 1963-2005: "composition-adjusted" weights for labour supply.



Construction of the Skill Premium

- Composition adjustment for wages: follow Autor (2019)
- Regress log hourly wages separately by sex and in each year on dummy variables for 5 education categories, a quartic in experience, three region dummies, race dummies, interactions of the experience quartic with education categories.
- Composition-adjusted mean log wage for each of group in a given year = predicted log wage for whites, living in the mean geographic region, at the relevant experience level (5, 15, 25, or 35 years depending on the experience group).
- Mean log wages for broader groups in each year = weighted averages of the relevant (composition-adjusted) cell means using fixed set of comp.-adj. labour supply weights


Other Explanations for Skill Premium Decline

- Rising supply? Here
- Mismeasured increase in supply? Here
- Industry shifts? Here
- Occupational structure shifts? Here
- Shifts in degree composition? Here
- Selection into Attendance? Here

Other Explanations: Rising Supply (back (other explanations) (back (intro)



$$\operatorname{og}\left(\frac{w_{st}}{w_{ut}}\right) = \gamma_0 + \gamma_1 t + \gamma_2 \operatorname{log}\left(\frac{S_t}{U_t}\right) + \varepsilon_t$$

- estimate regression on 1) KM Sample (1963-87) and 2) 1963-2000
- Neither series accounts for slowdown, especially post 2005 • Estimates
- More complex models like KORV (2000) predict similar patterns

Katz-Murphy Regression Estimates (KM) (back (intro)

$$\log \frac{w_{st}}{w_{ut}} = \gamma_0 + \gamma_1 \log \frac{L_{st}}{L_{ut}} + \gamma_2 t + \epsilon_t$$

	1963-1987	1963-2000	1963-2019
γ_1	-0.436**	-0.293***	-0.181***
	(0.147)	(0.0519)	(0.0344)
γ_2	0.0187**	0.0126***	0.00887***
	(0.00608)	(0.00166)	(0.000840)

- Implied aggregate elasticities of substitution between skilled/unskilled in the canonical model:
 - ▶ 1963-1987: 2.29
 - ▶ 1963-2000: 3.41
 - 1963-2019: 5.52

Other Explanations: Mismeasured Skill Prices (other explanations) (back (intre



- Bowlus et al. (2021) argue that successive cohorts acquire higher human capital per hour worked
 - so conventional labour supply weights underestimate growth in skill supply
- I use their proposed correction:
 - estimate change in skill prices using data from a specific cohort
 - in a range over which the age profile of wages is flat
- even more striking decline in skill prices!

Other Explanations: Industry Shifts (back (other explanations)



Figure: CPS ASEC 1980-2019, Males 16-64. Skill premium = difference in (log of) comp.-adj. residual mean hourly earnings of skilled to unskilled. Skilled = Clg. Grad + Post-Clg. + 1/2 of Some Clg. Earnings residualized on race, age categories and experience categories. Industries defined by consistent Census ind901y codes assigned by IPUMS aggregated to highest level.

Other Explanations: Occupational Structure Shifts (back (other explanations) (back (



Figure: CPS ASEC 1980-2019, Males 16-64. Skill premium = difference in (log of) comp.-adj. residual mean hourly earnings of skilled to unskilled. Skilled = Clg. Grad + Post-Clg. + 1/2 of Some Clg. Earnings residualized on race, age categories and experience categories. Occupations defined by consistent occ1990dd codes (Autor-Dorn (2013)). 12/32

Other Explanations: Degree Composition Shifts (back (other explanations) (back (intro



Figure: National Center for Education Statistics (various years), Undergraduate Retention and Graduation Rates *Condition of Education*. U.S. Department of Education, Institute of Education Sciences. • detailed classification • back

Other Explanations: Selection into Attendance (back (other explanations)) (back (intro)

- Suppose there is a one-dimensional attribute $a \sim F(a)$ such that *i* attends college iff $a_i \geq \bar{a}$.
- In this case, a rise in skilled labour supply \implies decrease in \bar{a} ...
- which reduces avg ability of both skill groups!
- Reducing \bar{a} leads to the best unskilled students leaving for college, reducing their avg ability
- But due to selection, the best unskilled students have lower a than the worst skilled students, reducing the avg ability of the skilled students.
- Given rising costs of college, it is likely that the selection effect may even go the other way around.
- When estimate structural models of college attendance + graduation with selection on ability, typically find selection becoming more important

Kong (2011), Hendricks-Schoellman (2014), Hendricks-Leukhina (2018), ...

The decline in the labour share





The decline in the labour share •••••

- This paper: explanation based on technology adoption
- Explanations based on markups: *complementary* to my explanation

Barkai (2016), Hall (2018), Traina (2018), De Loecker-Eeckhout-Unger (2019)

- My model: markups are constant
- I do not target the dynamics of the labour share in my calibration
 - \blacktriangleright \implies any gap between model and predicted is due to factors I do not model
- My results show limited room for rising markups to reduce the labour share
- Explanations based on measurement of labour share:

capitalization of IPP products	Koh et al (2020)
treatment of real estate	Gutierrez-Piton (2022)
gross vs net	Weitzman (1976), Hulten (1992)

Construction of Skilled and Unskilled labour Shares Dack

- CPS ASEC: construct composition adjusted wages and labour supply weights for five educational groups: LTHS, HS, SC, C, PC.
- Construct wage bills for each group as the product of composition adjusted wages and labour supply weights.
- Construct the skilled share of labour income as

$$\theta_{st}^{L} = \frac{1}{\sum_{i=LTHS,HS,SC,C,PC} w_{it}\ell_{it}} \left(w_{PC,t}\ell_{PC,t} + w_{C,t}\ell_{C,t} + \frac{1}{2}w_{SC,t}\ell_{SC,t} \right)$$

Construct the skilled share of value added as

$$\theta_{st} = \theta_{st}^L \times LSHR_t$$

where $LSHR_t$ is the non-farm business sector labour share.

Literature • back

- Technological Change, Skills and Inequality: Hicks (1932), Habakkuk (1962), Katz-Murphy (1992), Acemoglu (1998, 2002, 2010, 2011), KORV (2000), Card-DiNardo (2002), Autor-Levy-Murnane (2003), Goldin-Katz (2008, 2010), Allen (2009), Acemoglu-Autor (2011), Mishel et al (2013), Acemoglu-Restrepo (2018), Aum (2018), Valetta (2018), Maliar-Maliar-Tsener (2022), Ohanian-Orak-Shen (2021), Castex-Choi-Dexter (2022), Moll et al (2022), ...
 - directed technical change can account for entire path of skilled labour demand, 1980-2019
- Modern Technologies and the Labour Market: Bartel-Ichniowski-Shaw (2007), Michaels-Natraj-Van Reenen (2014), Frey-Osborne (2014), Autor-Dorn-Hanson (2015), Gaggl-Wright(2017), Acemoglu-Restrepo (2018, 2020, 2022), Agarwal-Gans-Goldfarb (2019), Dillender-Forsythe (2019), Eden-Gaggl (2019), Webb (2020), Bloom et al. (2021), Acemoglu et al (2021), Kogan et al (2021), Hémous-Olsen (2020, 2021), ...
 - model emphasizing ability of new technologies to displace skilled labour
- The Labour Share: Elsby et al (2013), Karabarbounis-Neiman (2014,19), Oberfield-Raval (2014), Hall (2018), Traina (2018), ADKPV (2020), Gutierrez-Piton (2020), Koh et al (2020), Grossman-Oberfield (2021), Hubmer (2021), Hubmer-Restrepo (2022), ...
 - model of labour share consistent with behavior of skilled/unskilled labour shares

Given a technology λ_s , λ_u , z, prices w_s , w_u , r_k choose allocation of capital and labour across tasks $\ell_i(x_i)$, $k_i(x_i)$ to minimize the cost of producing one unit of intermediate good.

 $c(\lambda_s,\lambda_u,z)$

Given a technology λ_s , λ_u , z, prices w_s , w_u , r_k choose allocation of capital and labour across tasks $\ell_i(x_i)$, $k_i(x_i)$ to minimize the cost of producing one unit of intermediate good.

$$c(\lambda_{s},\lambda_{u},z) = \min_{\left\{G_{i},\left\{\mathcal{Y}_{i}(x),\ell_{i}(x),k_{i}(x)\right\}_{x=0}^{1}\right\}_{i=u,s}} \underbrace{\int_{0}^{1} \left(r_{k}k_{u}(x) + w_{u}\ell_{u}(x)\right) dx}_{Cost \text{ of factors}} + \underbrace{\int_{0}^{1} \left(r_{k}k_{s}(x) + w_{s}\ell_{s}(x)\right) dx}_{Cost \text{ of factors}}$$

Given a technology λ_s , λ_u , z, prices w_s , w_u , r_k choose allocation of capital and labour across tasks $\ell_i(x_i)$, $k_i(x_i)$ to minimize the cost of producing one unit of intermediate good.

$$c(\lambda_{s},\lambda_{u},z) = \min_{\left\{G_{i},\left\{\mathcal{Y}_{i}(x),\ell_{i}(x),k_{i}(x)\right\}_{x=0}^{1}\right\}_{i=u,s}} \underbrace{\int_{0}^{1} \left(r_{k}k_{u}(x) + w_{u}\ell_{u}(x)\right) dx}_{Cost \text{ of factors}} + \underbrace{\int_{0}^{1} \left(r_{k}k_{s}(x) + w_{s}\ell_{s}(x)\right) dx}_{Cost \text{ of factors}}$$

subject to, for i = s, u

$$\mathcal{Y}_{i}\left(x_{i}\right) = \begin{cases} \psi_{i}\left(x_{i}\right) \ell_{i}\left(x_{i}\right) + k\left(x_{i}\right) & x_{i} \leq \lambda_{i} \leftarrow \text{capital-feasible tasks} \\ \psi_{i}\left(x_{i}\right) \ell_{i}\left(x_{i}\right) & x_{i} > \lambda_{i} \leftarrow \text{labour-only tasks} \end{cases}$$

Given a technology λ_s , λ_u , z, prices w_s , w_u , r_k choose allocation of capital and labour across tasks $\ell_i(x_i)$, $k_i(x_i)$ to minimize the cost of producing one unit of intermediate good.

$$c(\lambda_{s},\lambda_{u},z) = \min_{\left\{G_{i},\left\{\mathcal{Y}_{i}(x),\ell_{i}(x),k_{i}(x)\right\}_{x=0}^{1}\right\}_{i=u,s}} \underbrace{\int_{0}^{1} \left(r_{k}k_{u}(x) + w_{u}\ell_{u}(x)\right)dx}_{Cost \text{ of factors}} + \underbrace{\int_{0}^{1} \left(r_{k}k_{s}(x) + w_{s}\ell_{s}(x)\right)dx}_{Cost \text{ of factors}}$$

subject to, for i = s, u

$$\mathcal{Y}_{i}\left(x_{i}\right) = \begin{cases} \psi_{i}\left(x_{i}\right)\ell_{i}\left(x_{i}\right)+k\left(x_{i}\right) & x_{i} \leq \lambda_{i} \leftarrow \text{capital-feasible tasks} \\ \psi_{i}\left(x_{i}\right)\ell_{i}\left(x_{i}\right) & x_{i} > \lambda_{i} \leftarrow \text{labour-only tasks} \end{cases}$$

$$G_{i} = \left[\int \mathcal{Y}_{i}\left(x_{i}
ight)^{rac{
ho-1}{
ho}} dx_{i}
ight]^{rac{
ho}{
ho-1}}$$

Given a technology λ_s , λ_u , z, prices w_s , w_u , r_k choose allocation of capital and labour across tasks $\ell_i(x_i)$, $k_i(x_i)$ to minimize the cost of producing one unit of intermediate good.

$$c(\lambda_{s},\lambda_{u},z) = \min_{\left\{G_{i},\left\{\mathcal{Y}_{i}(x),\ell_{i}(x),k_{i}(x)\right\}_{x=0}^{1}\right\}_{i=u,s}} \underbrace{\int_{0}^{1} \left(r_{k}k_{u}(x) + w_{u}\ell_{u}(x)\right)dx}_{Cost \text{ of factors}} + \underbrace{\int_{0}^{1} \left(r_{k}k_{s}(x) + w_{s}\ell_{s}(x)\right)dx}_{Cost \text{ of factors}}$$

subject to, for i = s, u

$$\mathcal{Y}_{i}\left(x_{i}\right) = \begin{cases} \psi_{i}\left(x_{i}\right)\ell_{i}\left(x_{i}\right) + k\left(x_{i}\right) & x_{i} \leq \lambda_{i} \leftarrow \text{capital-feasible tasks} \\ \psi_{i}\left(x_{i}\right)\ell_{i}\left(x_{i}\right) & x_{i} > \lambda_{i} \leftarrow \text{labour-only tasks} \end{cases}$$

$$G_{i} = \left[\int \mathcal{Y}_{i}\left(x_{i}\right)^{\frac{\rho-1}{\rho}} dx_{i}\right]^{\frac{\rho}{\rho-1}} , \qquad z \left[\mu G_{u}^{\frac{\sigma-1}{\sigma}} + (1-\mu)G_{s}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \geq 1$$

Back to Graphical Soln

Given a technology λ_s , λ_u , z, prices w_s , w_u , r_k choose allocation of capital and labour across tasks $\ell_i(x_i)$, $k_i(x_i)$ to minimize the cost of producing one unit of intermediate good.

$$c(\lambda_{s},\lambda_{u},z) = \min_{\left\{G_{i},\left\{\mathcal{Y}_{i}(x),\ell_{i}(x),k_{i}(x)\right\}_{x=0}^{1}\right\}_{i=u,s}} \underbrace{\int_{0}^{1} \left(r_{k}k_{u}(x) + w_{u}\ell_{u}(x)\right)dx}_{Cost \text{ of factors}} + \underbrace{\int_{0}^{1} \left(r_{k}k_{s}(x) + w_{s}\ell_{s}(x)\right)dx}_{Cost \text{ of factors}}$$

subject to, for i = s, u

$$\mathcal{Y}_{i}\left(x_{i}\right) = \begin{cases} \psi_{i}\left(x_{i}\right) \ell_{i}\left(x_{i}\right) + k\left(x_{i}\right) & x_{i} \leq \lambda_{i} \leftarrow \text{capital-feasible tasks} \\ \psi_{i}\left(x_{i}\right) \ell_{i}\left(x_{i}\right) & x_{i} > \lambda_{i} \leftarrow \text{labour-only tasks} \end{cases}$$

$$G_{i} = \left[\int \mathcal{Y}_{i}\left(x_{i}\right)^{\frac{\rho-1}{\rho}} dx_{i}\right]^{\frac{\rho}{\rho-1}} , \qquad z \left[\mu G_{u}^{\frac{\sigma-1}{\sigma}} + (1-\mu)G_{s}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \geq 1$$

 $k_i(x_i) \geq 0$, $\ell_i(x_i) \geq 0$

Back to Graphical Soln

Static Profit Maximization Problem Model Structure Int. Goods Firm Problem

- Let $\lambda \equiv (\lambda_s, \lambda_u)$ so idiosyncratic state of intermediate good firm is $\mathbf{s} = (\lambda, z)$
- Given minimized cost of production $c(\lambda, z)$ choose output and prices
 - subject to demand from domestic final good retailer
 - ▶ who just packages intermediates with constant elasticity $\alpha > 1$ Details

$$\pi(\lambda, z) = \max_{p, y} \left[p - c(\lambda, z) \right] y$$
 subject to $y = p^{-\alpha} Y$

CES demand structure yields price and profit functions

$$p(\lambda, z) = \underbrace{rac{lpha}{lpha - 1}}_{ ext{Constant Markup}} c(\lambda, z) \qquad ; \qquad \pi(\lambda, z) = rac{Y}{lpha^{lpha}} \left(rac{c(\lambda, z)}{lpha - 1}
ight)^{1 - lpha}$$

Technology: Final Goods Retailer Model Structure Profit Max Int. Goods Firm Problem

- Define $M(\mathbf{s}) = \text{mass of firms with state } \mathbf{s}$
- Final goods retailer solves, for $\alpha > 1$,

$$\max_{Y,y(\mathbf{s})} Y - \int p(\mathbf{s})y(s)dM(\mathbf{s}) \qquad \text{subject to} \qquad Y = \left[\int y(\mathbf{s})^{\frac{\alpha-1}{\alpha}}dM(\mathbf{s})\right]^{\frac{\alpha}{\alpha-1}}$$

▶ Static profit max by retailer ⇒ Demand curves for each intermediate good

$$y(\mathbf{s}) = p(\mathbf{s})^{-lpha} Y$$

▶ and marginal cost = price (recall final good is numeraire) implies

$$1 = \int p(\mathbf{s})^{1-lpha} dM(\mathbf{s})$$

Preferences: Households' Problem Model Structure Equilibrium

- Final good is only tradable good
- Rest of world: deep-pocketed risk neutral investors with discount rate β
- trading in assets denominated in final good with interest rate $\bar{r} = \frac{1}{\beta} 1$.
- endowed with skilled labour S_t , unskilled labour $H S_t$ each period (total labour H fixed)
- ▶ path for S_t perfectly foreseen by household (no aggregate shocks)
- enters period with capital K_t , debt D_t paying fixed world interest rate \overline{r}
- optimality conditions for debt and capital choices imply no-arbitrage condition

$$1+ar{r}=rac{r_{kt+1}+(1-\delta)q_{kt+1}}{q_{kt}}$$

Equilibrium (Model Structure) Technology (Bellman Eqn

Given initial measure of firms $M_0(\mathbf{s})$, interest rate \bar{r} , exog paths $\{L_{st}, q_{kt}\}$, an equilibrium is

an allocation consisting of sequences

$$\left\{Y_t, \left\{k_t(\mathbf{s}), \ell_{st}(\mathbf{s}), \ell_{ut}(\mathbf{s}), y_t(\mathbf{s})\right\}_{\mathbf{s}=(\lambda, Z)}\right\}$$

- a sequence of technology choices $\{\lambda_{t+1}(s)\}_{s=(\lambda,Z)}$
- a distribution of firms over s at each date $\{M_t(\mathbf{s})\}$
- a set of prices $\{w_{st}, w_{ut}, r_{kt}, \{p_t(\mathbf{s})\}_{\mathbf{s}}\}$

such that

- ▶ no-arbitrage condition holds, $1 + \bar{r} = rac{r_{kt+1} + q_{kt+1}(1-\delta)}{q_{kt}}$
- Final goods retailer + int. good firms solve profit max problems, latter choose λ' optimally
- ▶ labour markets clear, $\int \ell_{st}(\mathbf{s}, \cdot) dM_t(\mathbf{s}) = L_{st}$ and $\int \ell_{ut}(\mathbf{s}, \cdot) dM_t(\mathbf{s}) = L_{ut}$
- the distribution $M_t(s)$ of firms over the states s follows the law of motion

$$M_{t+1}(Z',\lambda') = (1-p_E) \int \mathbf{1} \{ g_{\lambda t}(s) = \lambda' \} \Pr(Z' \mid Z) \ dM_t(\lambda, Z) + p_E \bar{M} \mathbf{1} \{ \lambda' = \lambda_{Et} \} \int \Pr(Z') \ d\phi^{Stat}(Z')$$

	Parameter	Value	Source/Target
Elast. Subst. across int. goods	α	7.67	Agg Markup 15% (Barkai 2020)
Production Function	$ρ$ $σ$ $μ$ $ρ_z$ $σ_z$	0.49 2.75 0.15 0.95 0.105	$\begin{array}{l} \qquad \qquad$
Comp. Adv. Schedules	$\gamma_s,\gamma_u\ B_s\ B_u$	0.76,1.14 4.41 502.02	Estimates in Berlingieri et al (2022) w _s , w _u in 1980
Exit/Entry Rate	PE	6.2%	Lee and Mukoyama (2015)
Adoption Costs	κ_0	2.3e3	Adoption costs 2.5% of GDP in 2000



- Key for quantification:
 - \blacktriangleright marginal cost of automating each task, κ
 - $\blacktriangleright\,$ elasticity of substitution across tasks, ρ
 - labor productivity schedules $\psi_i(x_i)$
- Idea: jointly calibrate these to hit following moments
 - share of GDP spent on tech upgrading
 - micro estimates of short/long run elasticities of substitution

Calibration: Technology Adoption Cost (Quant. Exerc.) (back (Calib.) Parameter Values

- Technology adoption costs: $\kappa (\lambda'_s \lambda_s) + \kappa (\lambda'_u \lambda_u)$
 - choose κ to target a share of GDP spent on tech upgrading of 2.5% in 2000
 - ▶ robust to targets from 1.5% (\approx Software/GDP) 4.5% (\approx (Software+ICT)/GDP)

Quantification: Labor Productivity Schedules (Quant. Exerc.) (back (Calib.)

Parameter Values

$$\psi_i(x) = B_i \left[x^{\frac{1-\rho-\gamma_i}{\gamma_i}} - 1 \right]^{\frac{1}{1-\rho-\gamma_i}} \quad , \quad \rho + \gamma_i > 1$$

- Under this form for $\psi_i(\cdot)$,
 - ▶ $\rho \rightarrow$ short-run elasticity of substitution between labor and capital
 - For Set ho = 0.45, midpoint of consensus range of estimates in literature. Raval '14, Humlum '19
- Pin down γ_i using *indirect inference*:
 - target estimators of **5**-year elasticities by skill level in response to shocks to q_k
 - using experiment in model to *mimic* exogenous firm-level shocks to q_k
 - which is the variation used in empirical literature to estimate medium-run elasticities
 - target Berlingieri et al (2022): exchange rate shocks affect q_k thru imported capital goods
 Details

Calibration: γ_i parameters (Values (Quant. Exerc.)) (Values Calib.) (Parameter Values

In model, run the following experiment.

- Suppose economy is in 1980 steady state at t = 0.
- At this date, choose one firm and reduce its rental cost of capital by 1% permanently.
- ▶ Holding fixed all other prices, simulate sequences of z and transition paths for this one firm
 - Since capital is cheaper but labour prices are fixed
 - Firm will want to raise λ_s, λ_u in response to such a change
- Calculate change in $\log \ell_i / k$ between dates 0 and 5
- Repeat for all firms in the economy, and compute average value of

$$\frac{1}{CapitalShare_{it}}\frac{\Delta_{t \to t+5}\log\left(\ell_i/k\right)}{\Delta_{t \to t+5}\log q_k} \qquad i=s,u$$

Ensure that the moment above matches Berlingieri et al (2022)'s number.

External Validation of Model Calibration

Model-implied capital-output elasticity in line with estd. production functions

Moment	Gandhi, Navarro, Rivers (2020)	Model
$\frac{d \log y}{d \log k}$ 1980	0.31	0.315

• Model-implied changes in *median* values of ℓ_s/ℓ_u in line with data

Moment	Data	Model
$P50\left(\frac{\ell_{s,1998}}{\ell_{u,1998}}\right)$	0.98	0.91
$P50\left(\frac{\ell_{s,2008}}{\ell_{u,2008}}\right)$	1.10	1.13

Table: Data from Harte-Hanks CiTDB. Skilled and Unskilled labor imputed by allocating reported white collar and blue collar employment to skilled and unskilled categories proportionate to their respective ratios in CPS within industry-year bins.

Quantitative Exercise ••••*

- Feed into model paths for q_k and the rising supply of ℓ_s/ℓ_u
 - Between 1980-2019, follow paths as in data (declining q_k , rising ℓ_s/ℓ_u)
 - After 2019, rate of decline of q_k falls to zero linearly over next 20 years
 - After 2019, rate of increase of ℓ_s/ℓ_u falls to zero linearly over next 20 years
- Compute initial steady state in 1980 and terminal steady state with long-run values of q_k and ℓ_s/ℓ_u
- Assume that in 1980, agents learn of new paths for $q_k, \ell_s/\ell_u$
- Compute equilibrium paths for aggregate variables w_s, w_u, r_k, Y along transition path
- ▶ Counterfactual: same exercise but force firms to use 1980 steady-state λ throughout

Definition of Accounting Software: More Details •••••

- A Technology in Harte-Hanks ≡ a manufacturer + model combination
- Accounting technology:
 - technology class PRG (software)
 - model group, model series, technology definition or technology description includes the terms

{ACCOUNTING, A/P, A/R, G/L}

- ▶ Note: classify technologies *year-by-year* as accounting/non-accounting
- ► Most common: Intuit Accounting (≈ 5% of observations), Microsoft Accounting (≈ 4%), PeopleSoft Accounting (1.9%)

Sampling Weights Construction •••••

Let

- N^{CBP}_{cit} = # establishments in the County Business Practices dataset in year t, industry i (2-dig NAICS) and commuting zone c
- ▶ $N_{cit}^{HH} = \#$ establishments in CiTDB in year t, industry i and commuting zone c
- ▶ For any establishment *i* located in commuting zone *c* and industry *i*,

$$\omega_{it} = \frac{N_{cit}^{CBP}}{N_{cit}^{HH}}$$