# How Has Recent Technology Changed the Labor Market? A Quantitative Macroeconomic Perspective

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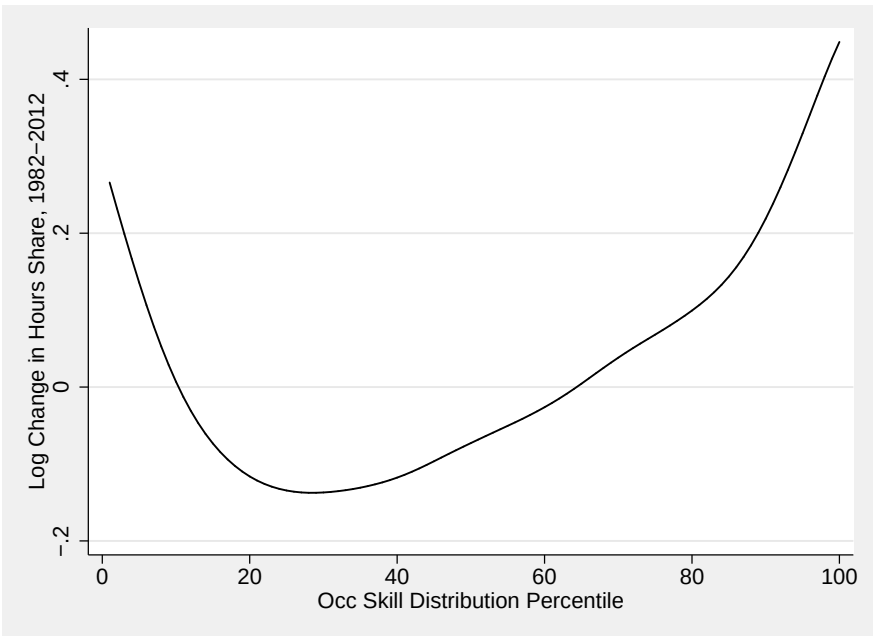
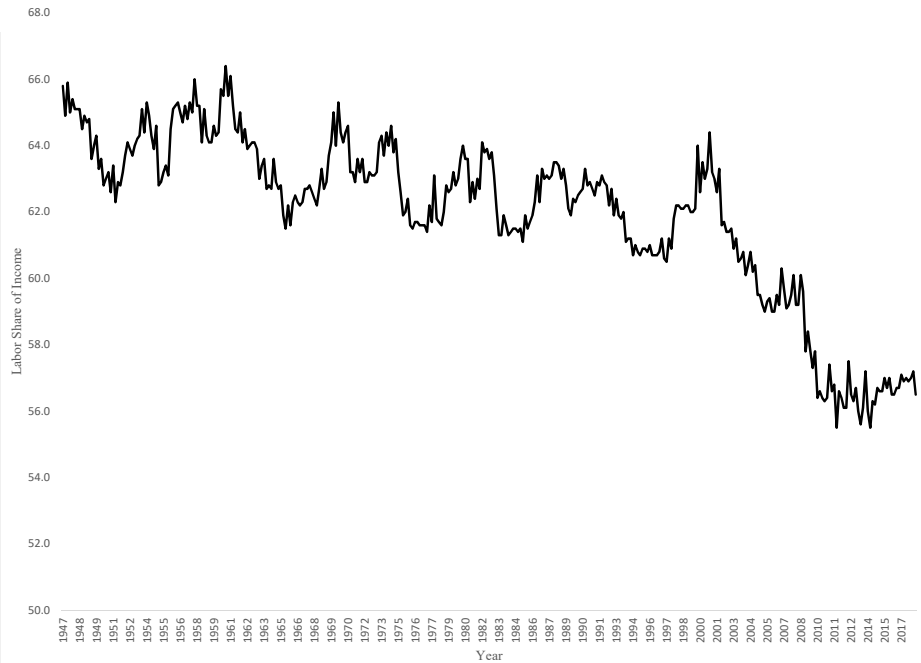
# Two Major Changes in Labor Markets

- U.S. labor markets of last several decades characterized by job polarization and declining labor share of income




- Job polarization also in Europe (Goos, Manning and Salomons (2009,2014); Michaels, Natraj and Van Reenen (2014)); labor share decline worldwide (Karabarbounis and Neiman (2013))

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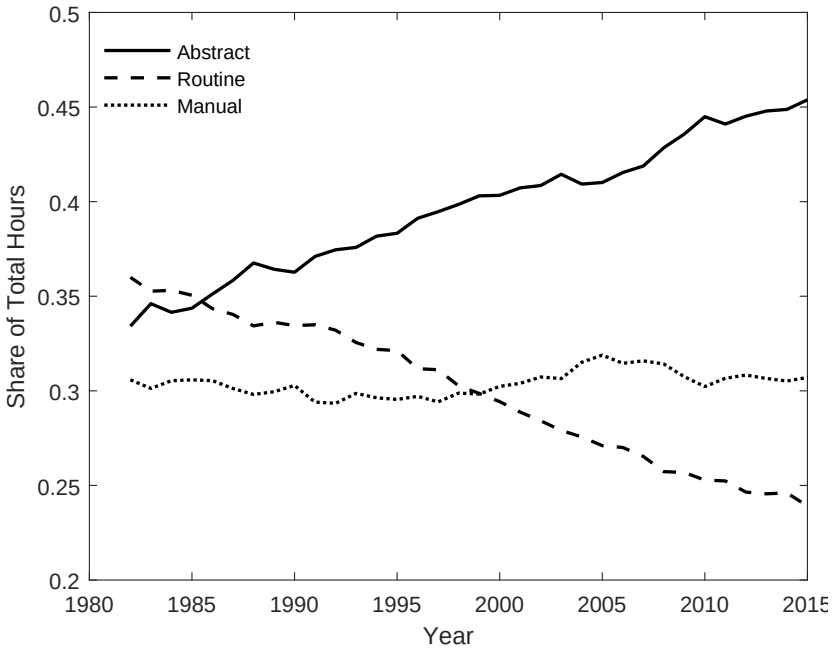


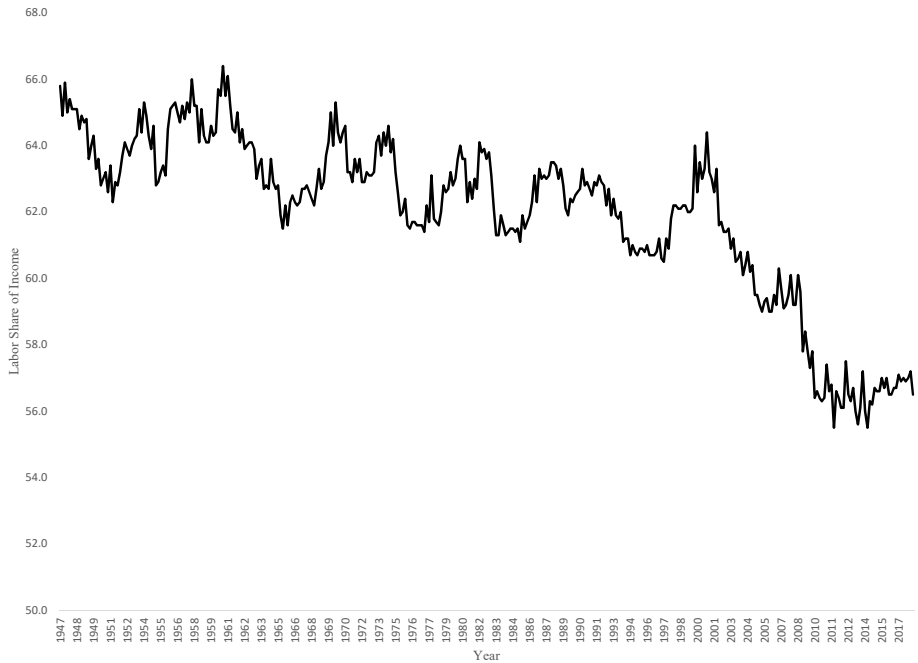


- Not just U.S. – job polarization also in Europe (Goos, Manning and Salomons (2009,2014); Michaels, Natraj and Van Reenen (2014)) , labor share decline worldwide (Karabarbounis and Neiman (2013))

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- **What We Know**: Lots of empirical evidence supporting that technology of some form is a key driver of these changes
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  - Highlight findings using neoclassical theory for polarization and labor share
  - Discuss recent and ongoing work to further address channels through which technology impacts polarization and the labor share

# Machines are Getting Cheaper

- Benchmark way to think of technological change is that innovation makes machines cheaper and cheaper over time

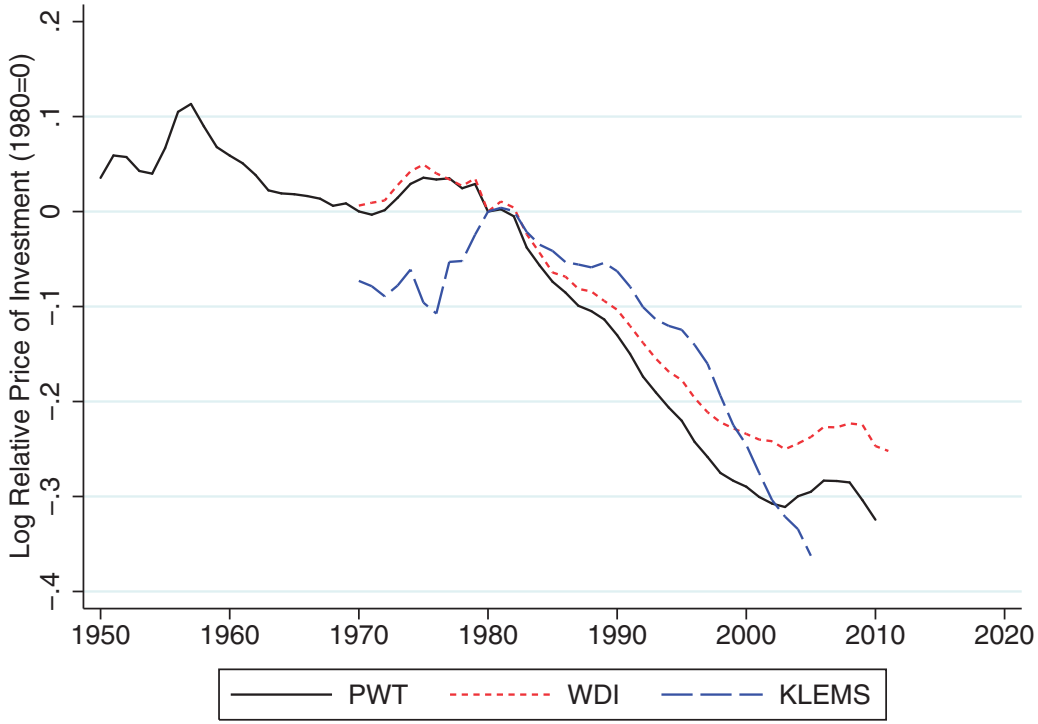


FIGURE VII

Declining Global Price of Investment Goods

Source: Karabarbounis and Neiman (2013)

- Reduction in price of machines impacts labor demand – firms to substitute from certain workers to machines, reducing labor income and changing job composition

# Neoclassical Production Framework

- Aggregate production function (in spirit of Autor and Dorn (2013)):

$$Y = K^{1-\alpha}\left[\mu_{nr} L_{nr}^{\frac{\gamma_{nr}-1}{\gamma_{nr}}} + (1-\mu_{nr})\left\{\mu_r L_r^{\frac{\gamma_r-1}{\gamma_r}} + (1-\mu_r) M^{\frac{\gamma_r-1}{\gamma_r}}\right\}^{\frac{\gamma_r}{\gamma_r-1}\frac{\gamma_{nr}-1}{\gamma_{nr}}}\right]^{(1-\alpha)\frac{\gamma_{nr}}{\gamma_{nr}-1}}$$

$L_{nr}$ : Non-routine workers

$L_r$ : Routine workers

$M$ : Machines

$K$: Other capital

Key parameters: elasticities of substitution ($\gamma_{nr}$, $\gamma_r$), production weights ($\mu_{nr}, \mu_r$)

# Implications for Polarization and Labor Share

- How will declining price of machines ($P_M$) impact share of employment in routine jobs ($s_r$) and labor share of income ($Lsh$)?
- Assuming profit maximization and competitive markets, comparative statics imply:

$$\frac{\partial s_r}{\frac{\partial P_M}{P_M}} = s_r \xi_M (1 - s_r)(\gamma_r - \gamma_{nr})$$

$$\frac{\partial Lsh}{\frac{\partial P_M}{P_M}} = Lsh(1 - Lsh)\left[\left(1 - \xi_M s_{nr}^{inc}\right)\gamma_r + \xi_M s_{nr}^{inc}\gamma_{nr} - 1\right]$$

- Three critical quantitative objects:
  - $\gamma_r, \gamma_{nr}$: elasticities of substitution
  - $\xi_M = \frac{P_M M}{P_M M + w_r L_r}$: share of income machines receive relative to routine workers (function of prices and parameters)
  - $\frac{\partial P_m}{P_m}$: amount of change in price of machines

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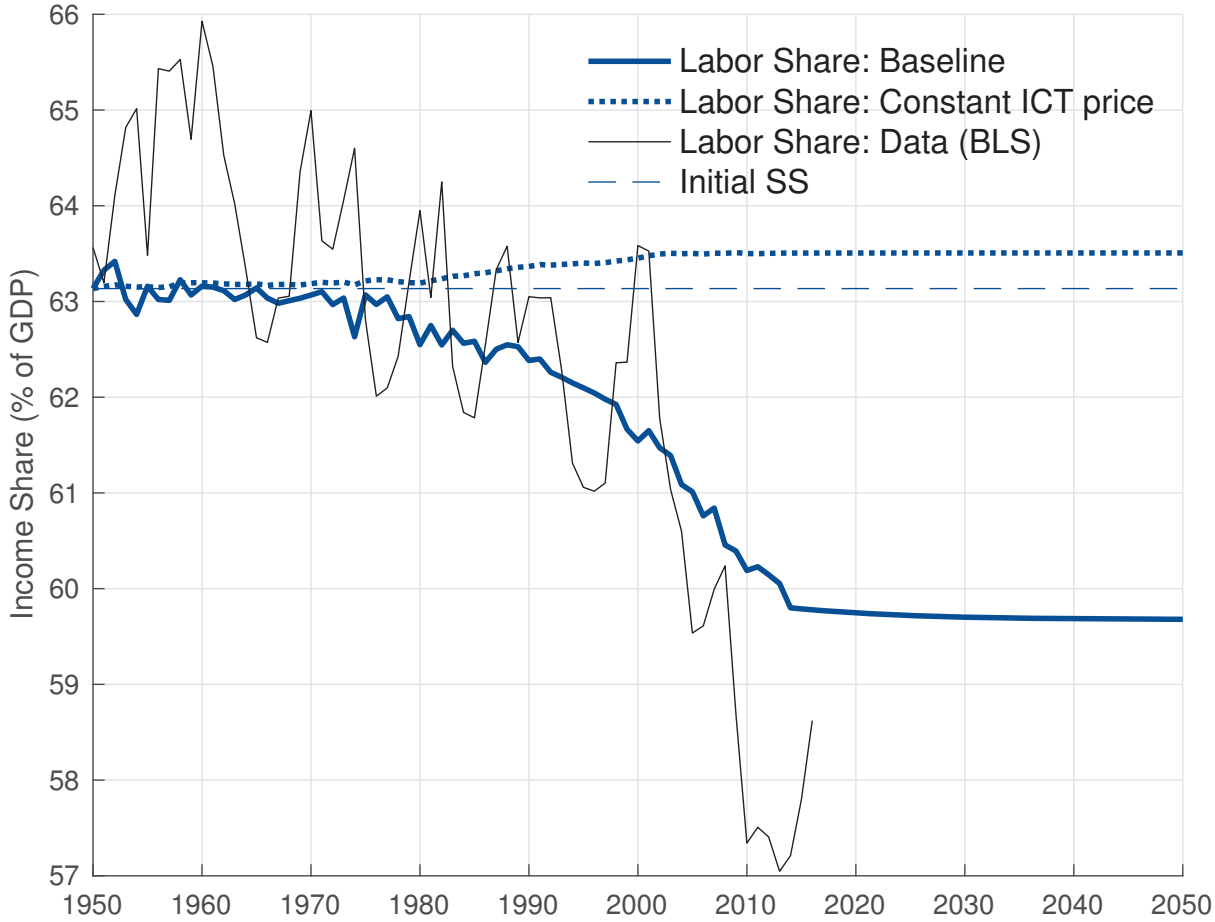
# Findings: Eden and Gaggl (2018b, RED)

- Eden and Gaggl (2018) – use version of this framework to show technological change can account for 50% of labor share decline




- Caveat: requires a re-nesting of routine and non-routine labor – capital-skill complementarity (Krusell et al. (2000)); model can't fit the data with Autor and Dorn (2013) nesting.

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- To exactly match observed polarization, need $\frac{\Delta M}{M} > 20,000\%$ of observed change.
- Results may be sensitive to using prices vs. quantities and capital aggregation (see Eden and Gaggl (2018a, WP))

# Findings: vom Lehn (2018a, WP)

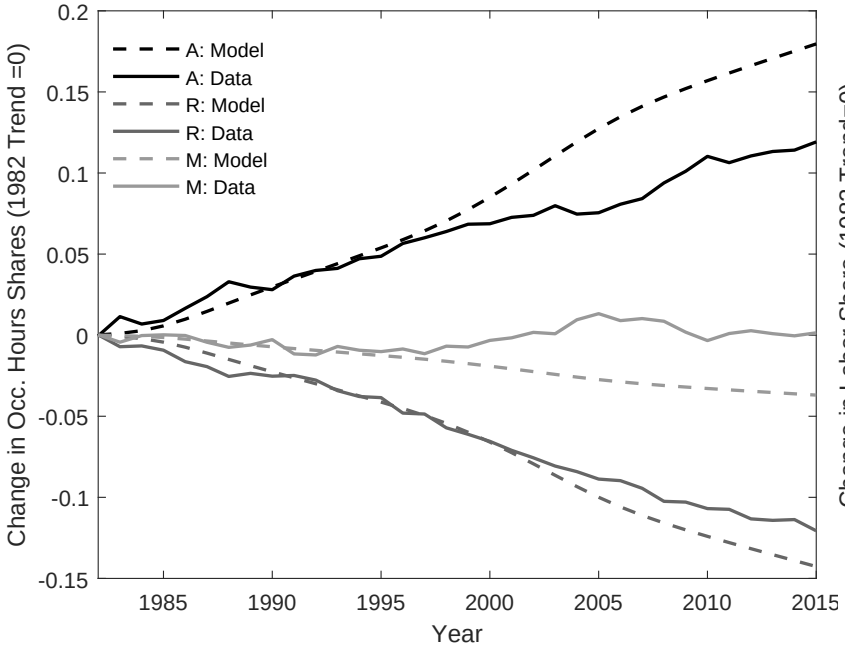
- vom Lehn (2018a) extends production to treat high-skill (abstract) and low-skill (manual) non-routine occupations separately:

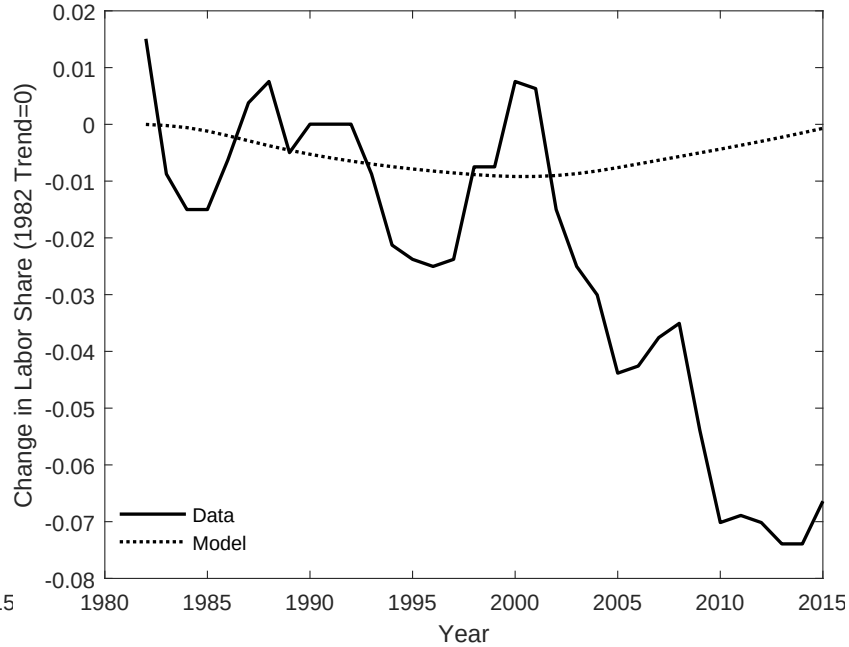
$$Y = \left[ \mu_m L_m^{\frac{\gamma_m - 1}{\gamma_m}} + (1-\mu_m) \left[ \mu_a L_{at}^{\frac{\gamma_a - 1}{\gamma_a}} + (1-\mu_a) \left[ (1-\mu_r) M_t^{\frac{\gamma_r - 1}{\gamma_r}} + \mu_r L_{rt}^{\frac{\gamma_r - 1}{\gamma_r}} \right]^{\frac{\gamma_r(\gamma_a - 1)}{(\gamma_r - 1)\gamma_a}} \right]^{\frac{\gamma_a(\gamma_m - 1)}{(\gamma_a - 1)\gamma_m}} \right]^{\frac{\gamma_m}{\gamma_m - 1}}$$

- Measure $\xi_M$ using all equipment capital instead of just ICT; use investment price data to generate price of machines
- To maximize fit of technology hypothesis, calibrate model to match polarization over subsample of the data (1980s)
- General Equilibrium – consider both representative household and heterogeneous workers

# Findings: vom Lehn (2018a, WP)

- Even with favorable calibration, can't match observed polarization and labor share behavior post-2000



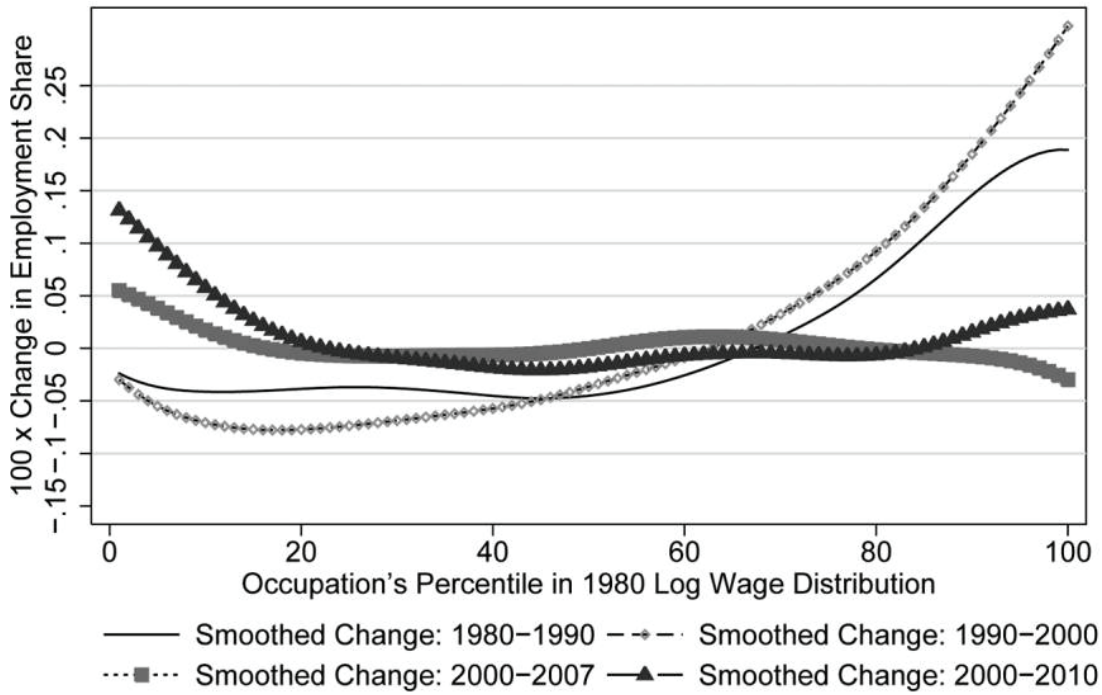

- Robust to labor supply, endogenous occupational and educational choices, calibration window, nesting structures, ICT instead of all equipment
- Can fit data if fall in price of machines counterfactually actually ends in 2000
- *Key point*: single set of elasticities of substitution can't reconcile changing dynamics of polarization over time

# Possible Resolutions

- Other shocks (e.g. trade)
- Changing relationship between technology and high-skill labor
  - due to role of skills in technology production/adoption
  - due to evolution of technological capabilities

# Slowdown in Demand for Skills: Beaudry, Green and Sand (2016, JOLE)

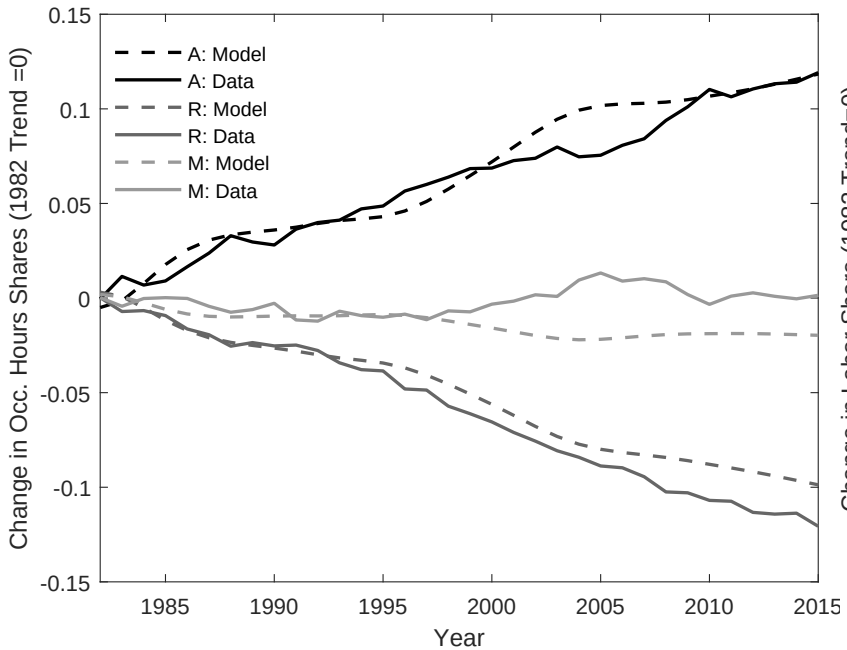
- Beaudry, Green and Sand (2016) find slowing employment growth in high skill jobs post-2000

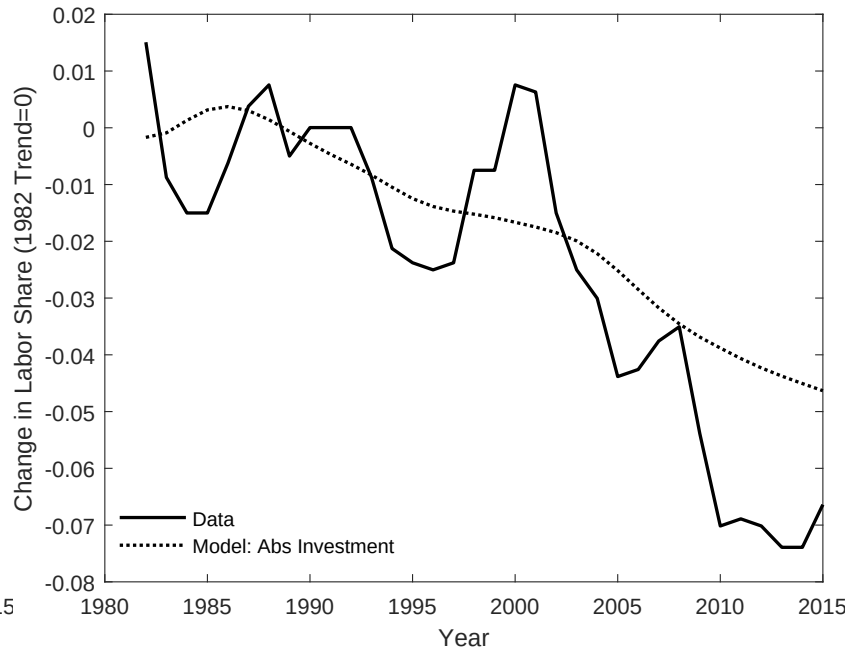



- Hypothesize: Slowing investment post-2000 (due to slowing fall in price of machines) means fewer high skill workers are needed to produce/install/adopt new technology

# Quantitative Application (vom Lehn (2018a, WP))

- Extending neoclassical framework to have high skill workers produce investment improves fit of technology hypothesis




- Caveat: strong assumption about all investment produced by high skill workers

# Evolution of Technology and Skills: vom Lehn (2018b, EER)

- vom Lehn (2018b) studies cross-industry relationship between worker tasks and labor share declines
- Construct measure of high-skill occupations most susceptible to automation – “abstract replaceable”
- OLS and IV evidence finds that industries with large fraction of abstract replaceable jobs in 2004 saw accelerated labor share declines post-2004
- Suggestive evidence that technology may be evolving to replace some high-skill occupations

# Conclusion

- Both anecdotal and empirical evidence suggest that technology has substantially impacted labor markets
- Understanding quantitative mechanisms for *how* technology impacts labor markets still a work in progress
- Key aspect of future research is understanding the exact interaction of technology with higher skilled workers

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