The Impact of Technology on Labor Share: A Review of Theory and Empirical Evidence

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Abstract

This literature review examines the impact of technology on labor share, a key economic indicator that reflects the proportion of income allocated to labor. The theoretical framework centers on Acemoglu and Restrepo's (2019) task-based model, which introduces different types of technolog and how they affect labor share through substitution, displacement, reinstatement, and composition effects. The review further maps the empirical evidence to the respective theoretical effects and discusses key concerns regarding internal and external validity, providing a comprehensive synthesis of the relationship between technological change and labor compensation.

Contents

1 Introduction

1.1 Why studying labor share?

The labor share is defined as the fraction of economic output that accrues to workers as compensation in exchange for their labor (definition from U.S. Bureau of Labor Statistics), while capital share is the fraction of output paid as capital's income. In most literature labor share and capital share sum up to one by definition; but for example in BARKAI (2020), pure profit is separated from capital's income, to study how the rise of profit share contributes to the fall of labor share. We think functional income distribution is worth studying because of the following three reasons:

First, it is a measure of income distribution. Bowley studied how World War I has impacted national income distribution in UK from data in 1880-1913. Among several proposed methods (including distribution among land, capital, labor; per unit land/ per hour worked; among people; among income class; among property and labor), he chose the last two methods because of data availability. It should be mentioned that the connection between functional income distribution and inequality in personal income distribution is controversial in different literature (discussed in Bengtsson and Waldenström (2015)). And this indicator cannot measure between-labor inequality.

Second, we can evaluate plausibility of certain models from labor share data. In Gollin (2002), some growth and trade models imply constant factor shares across country and across time. Whether factors shares are constant in reality helps to justify whether these models are reasonable.

Third, labor/capital share data is used in estimating TFP, which is a difference between output growth and factor income share weighted average of the growth of labor and capital.

Therefore, whether labor share is constant and its magnitude are both interesting.

1.2 Global trend and measurement issues

Before looking at the global decline in labor share, it should be noticed that some measurement issues affect the labor share data we observe. Self-employed people's total income needs to be artificially decomposed into labor and capital income. In Elsby et al. (2013), "labor approach", "asset approach" and "economy wide approach" decomposition methods generate different labor share data. All three methods display a decline of US labor share from 1980s, but "labor approach" shows a $\frac{1}{3}$ more decline of the one calculated by the other two methods. "Labor approach" is the method used by US Bureau of Labor Statistics (BLS) in producing headline labor share data because of data availability.

Both gross and net value added(gross minus depreciation) can be used, depending on what we are interested in. Labor share in gross value added can measure how compensation tracks productivity, net value added is appropriate to show worker's share in the output available for consumption.

In US headline measure, labor share hovered around a mean of 63.6 percent from 1948 through 1987, and shows a decline trend since late 1980s, and an increase recently.(See Figure 2 in appendix)

Karabarbounis and Neiman (2013) focus on labor share in the corporate sector, which accounts for roughly 60 percent of the economy's total gross value added both in the U.S. and globally. Economic activities is divided into corporate, household, and government sectors in System of National Account standards. The household sector includes unincorporated businesses, sole proprietors, nonprofits serving households, and the actual and imputed rental income accruing to noncorporate owners of housing. The corporate sector includes financial and nonfinancial corporations. By focusing on labor share in the corporate sector, they sidestep the issue of separating labor and capital for unincorporated businesses and sole proprietors. They show that from 1975 to 2012, global corporate sector labor share drop from around 64 percent to 59 percent. Most countries exhibit downward trend. (See Figure 3 and 4 in appendix)

1.3 From technology perspective

What account for the decline of labor share? In this literature review, we choose to explain from technology perspective, because theory and empirical evidence are plausible for us. But other reasons may also contribute to labor share decline. Autor et al. (2020) argues that "market toughness"(might caused by globalization or other reasons) leads to concentration in an industry, where some superstar firms capture high share of industry output. In imperfect competition situation, firms with high market share typically have larger price-cost markup and thus lower labor share. Therefore, sales concentration in an industry leads to labor share decline as the weight of low labor share firms increase. Using US data, Elsby et al (2013) finds that THE decline of labor share after 1980s is mainly driven by within industry decline in payroll shares, particularly in manufacturing and trade. They identify a strong correlation between increase of import exposure and decline in labor share at industry level. We need further studies to justify whether these arguments are plausible and whether technology progress can be viewed as the most important factor driving labor share decline.

In the following, we provide empirical evidence that technology affect labor share. Autor and Salomons (2018) proxy industry technological progress as TFP growth[1] and discover that in 1970-2007, TFP growth leads to 0.27 percentage points decrease in aggregate labor share annually, or around 10 percentage points decrease during these 37 years (0.27 * 37). It should be mentioned that their data is collected from 19 developed countries. The aggregate effect is the sum of own-industry, customer-supplier linkage, final demand, and composition effects.

This study proxies all kinds of technological progress by TFP growth, because they can all raise productivity. While we see technology negatively impact labor share overall, some technologies may be labor-displacing and reduce labor share, and some have opposite effects.

Built on other relevant literature, we will distinguish different kinds of technology and explain how they affect labor share in theory and provide relevant empirical evidence. In figure 1 we present a general framework of this literature review. Our article proceeds as follows: section 2 formalizes potential mechanisms of how different types of technology impact labor share; section 3 presents relevant empirical evidence that supports the mechanisms; section 4 discusses our considerations and provides the research gap. And appendix A provides figures that we cite from literature.

[1] Data comes from EUKLEMS. Timmer et al. (2007) describes the method of estimating TFP growth in EUKLEMS: Each industry j has its own production function (but doesn't explicitly define) $Y_j = f_j(K_j, L_j, X_j, T)$, where Y is output, K is capital, L is labor, X is intermediate input, T is technology. Under profit maximizing and competitive markets assumptions, $\Delta lnt_j = \Delta lnY_j - v_j^X \Delta lnX_j - v_j^K \Delta lnK_j - v_j^L \Delta lnL_j$, where v_j^X, v_j^K, v_j^L is weight of the input cost to nominal value of output.

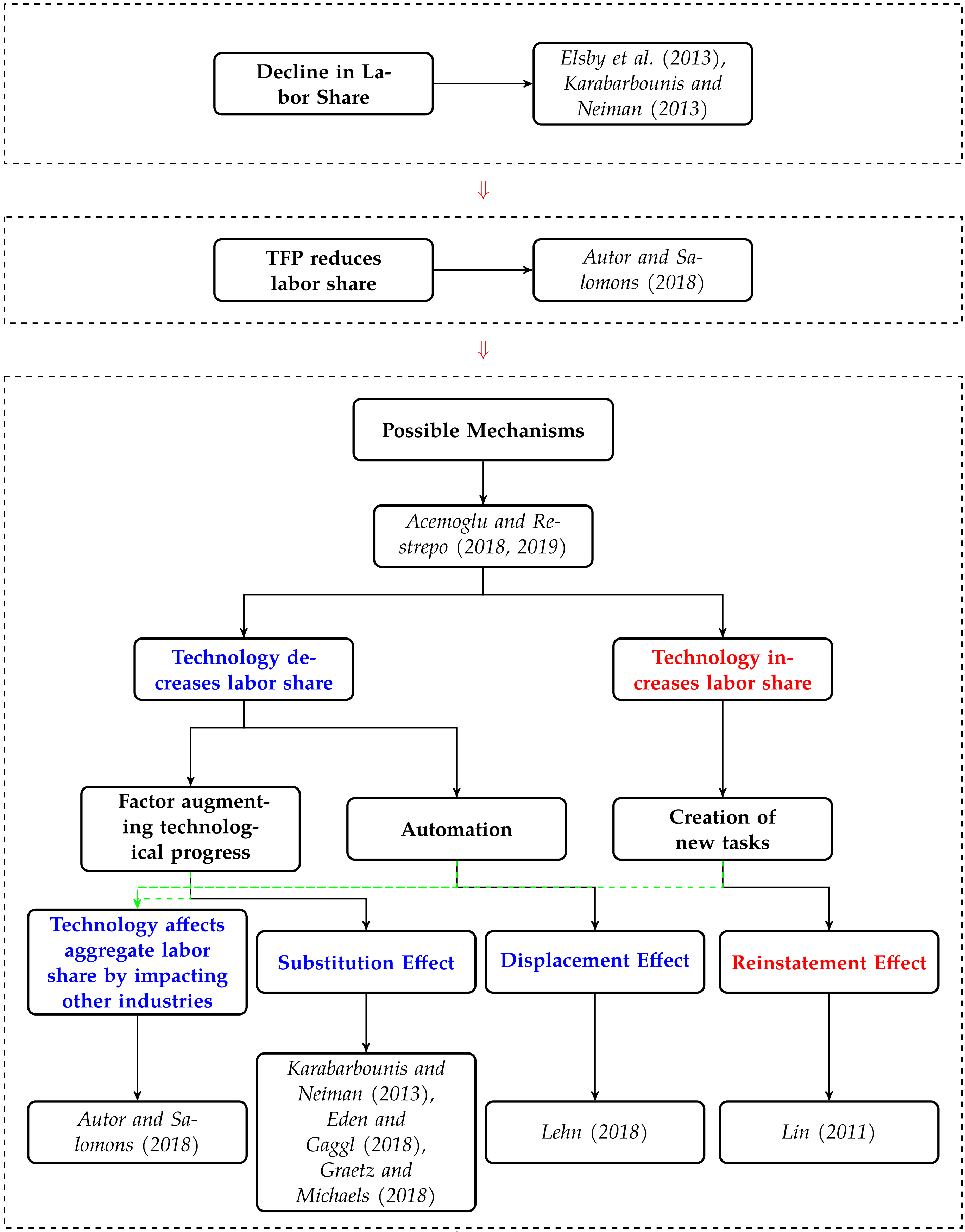


Figure 1: Framework of Our Literature Review

2 How technologies impact labor share

In this section, we employ task-based model from Acemoglu and Restrepo (2019) as our guidance to examine possible mechanisms through which labor share is affected. In section 2.1, we present the task-based model [2] embedded in CES production function, and specify the assumptions imposed on this model. In section 2.2, we introduce three types of technology and how they affect labor share through substitution effect, displacement effect, reinstatement effect respectively in a single -sector economy and composition effect in a multi-sector economy.

2.1 Model set-up

1. **Production function in a single-sector economy given as follows:**

$$Y = \Pi(I,N)\left(\Gamma(I,N)^{\frac{1}{\delta}}(A^L L)^{\frac{\delta-1}{\delta}} + (1-\Gamma(I,N))^{\frac{1}{\delta}}(A^K K)^{\frac{\delta-1}{\delta}}\right)^{\frac{\delta}{\delta-1}} \tag{1}$$

   where:

   1)L and K denotes labor and capital respectively;

   2)Factor augmenting technology A^L and A^K increase the productivity of labor and capital respectively;

   3)δ denotes the elasticity of substitution between tasks and also between capital and labor;

   4)I and N denotes automation and new tasks respectively, and $\Gamma(I,N)$ denotes task content, namely the allocation of tasks to capital and labor;

   5)$\Pi(I,N)$ denotes Hicks neutral productivity.

2. **Assumption in this model:**

   1)Tasks above automation ability I can only be performed by labor;

   2)Tasks below I are produced with capital, because firms are cost-minimizing;

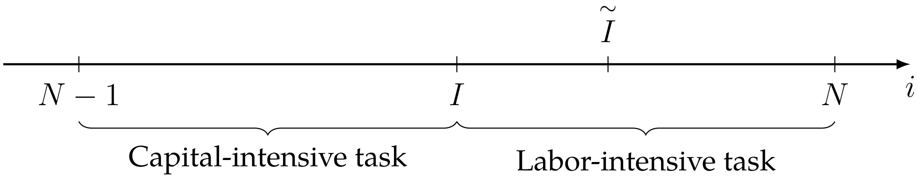
   3)Creation of new tasks denoted by N are adopted immediately and in favor of labor.

[2] The original task-based model given as $Y = \left(\int_{N-1}^{N} Y(i)^{\frac{\delta-1}{\delta}} dz\right)^{\frac{\delta}{\delta-1}}$, where $Y(i)$ denotes output of individual task i

3. **Labor share derived from our production function is shown as follow:**

$$s^L = \frac{1}{1 + \frac{1-\Gamma(I,N)}{\Gamma(I,N)} \left(\frac{A^L}{W} \frac{R}{A^K} \right)^{1-\delta}} \tag{2}$$

4. **Illustration of model set-up**



Note: 1)Task indexed by i, i in $[N-1, N]$, productivity of labor in task i denoted by γ_l is increasing in i, and the opposite for productivity of capital γ_k;

2)$\widetilde{I}$ denotes the threshold at which $\frac{W}{A^L \gamma_l} = \frac{R}{A^K \gamma_k}$, suggesting firms are indifferent between using capital and labor given the same effective factor price;

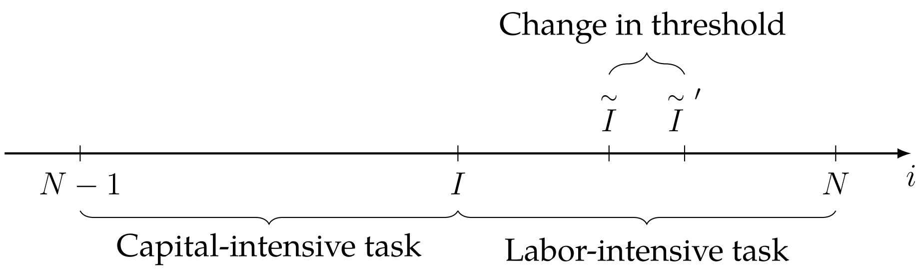
3)In our setting, we only consider the situation where $\widetilde{I}$ is above I.

2.2 Possible mechanisms

We first introduce three mechanisms that cause the change in labor demand and labor share in a single-sector economy as follows:

1. **Illustration of substitution effect caused by factor-augmenting technological progress:**

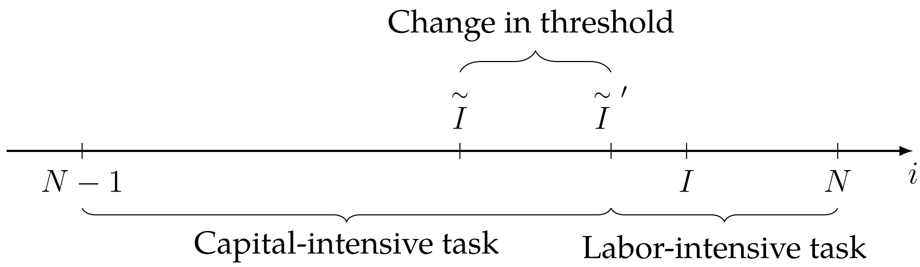
(a) Original version:



Mechanism of substitution effect: As effective wage $\frac{W}{A^L}$ rises relative to effective rental rate of capital $\frac{R}{A^K}$ due to factor-augmenting technological progress across all tasks, the price of capital-intensive tasks is cheaper than the price of labor - intensive tasks. And thus firms tend to substitute capital-intensive tasks for labor-intensive tasks under the precondition that this two types of task are substitute to each other ($\delta > 1$). Furthermore, wage will decline in response to lower labor demand. As a result, labor share declines.

(b) Relaxed version:

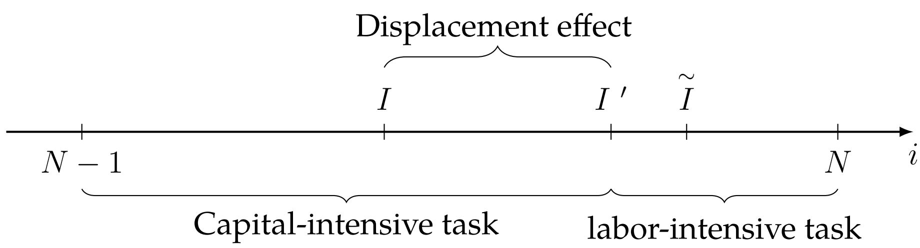
We should also notice that if we relax the restriction allowing that $\widetilde{I}$ falls below I in a single-sector economy, substitution effect still holds. This scenario is given as follow:



Note: In this economy, we assume that tasks above $\widetilde{I}$ can only be performed by labor and tasks below $\widetilde{I}$ are performed by capital because firms are cost-minimizing.

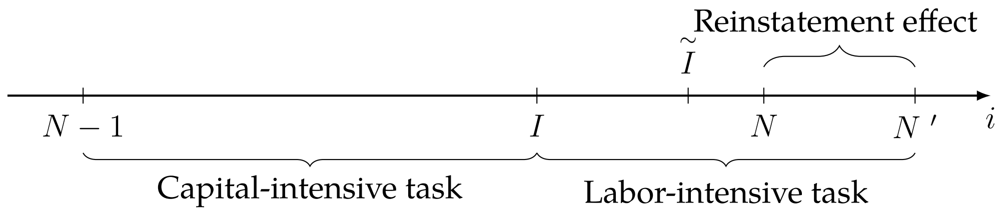
Mechanism of substitution effect: In addition to the argument associated with substitution effect mentioned above, this change in $\widetilde{I}$ also changes task content, and thus all tasks $i \in [\widetilde{I}, \widetilde{I}']$ performed previously by labor are now produced by capital only due to the cheaper effective rental rate of capital and cost-minimizing firms.

2. **Illustration of displacement effect caused by automation:**



Mechanism of displacement effect: Labors are displaced from the tasks previously allocated to them with capital due to the improvement of automation ability, in addition to relatively cheaper rental rate of capital. Automation may not make capital or labor more productive, but change the task content in favor of capital, that is, the improvement of automation ability (the increase in I) decreases $\Gamma(I, N)$. Furthermore, displacement of labor leads to lower wage, and thus lower labor share ensues as a result.

3. **Illustration of reinstatement effect caused by creation of new tasks:**



Mechanism of reinstatement effect: Advance in technology also creates new labor-intensive tasks that increases $\Gamma(I, N)$ by increasing N, which reintroduce labor into these new tasks. Higher demand for labor leads to higher wage. Consequently, labor share declines.

Next, we switch from the single-sector economy to a multi-sector economy and investigate another effect generated by this three technologies and how it can affect labor share in the whole economy.

1. **Composition effect generated by automation, factor-augmenting technology and creation of new tasks:**

Labor share in a multi-sector economy can be calculated as follow:

$$labor\, share = \sum_{i \in I} labor\, share\, i \times share\, of\, value\, added\, i \tag{3}$$

where I denotes all sectors in economy, and i is individual sector.

Mechanism of composition effect: The adoption of technologies in sector i can change the share of value-added across sectors, either by expanding or shrinking its on relative sector size, or by reallocating economic activities in other sectors, which leads to change in share of value added and leaves labor share unchanged in other sectors. According to Equation 3, this change in sectoral composition may lead to decline in aggregate labor share.

3 Empirical Evidence

In this section, we link literature that investigates the impact of technology on labor share to our possible mechanisms. It is worth noting that mechanisms mentioned above are mainly based on the task-based framework from Acemoglu and Restrepo (2019). Therefore, it could be of inaccuracy when we map the empirical evidence in the real world to the theoretical mechanisms; moreover, there could also be some differences when we categorize literature which employs other conceptual frameworks, such as CES production function, to these mechanisms which is based on the task-based model.

In the process of classification, we follow the rule that if the empirical evidence satisfying the most important property of the mechanism, we say that it reflects the specific effect:

- **Substitution Effect**: The literature studies how the relative price of capital affect labor share;
- **Displacement Effect**: The literature studies how the improvement of automation ability affect labor demand, and hence labor share;
- **Reinstatement Effect**: The literature studies how the technology creates new work and hence increase the labor demand;
- **Composition Effect and Other Micro-macro Links**: The literature studies how much of change in labor share stems from within-industry change and across-industry change.

3.1 Substitution Effect

Several studies have looked into the potential mechanism of substitution effect by which firms may tend to shift away from labor to capital in response to the decrease in relative cost of capital caused by technology.

Decline in Relative Price of Capital

Karabarbounis and Neiman (2013) document a coexistence of declining trend in labor share and in relative price of investment goods due to the information and communication technology [3], finding that countries or industries experiencing greater decline in the relative price of investment goods also experienced larger decline in labor share (see Figure 5 and Figure 6

[3] For abbreviation, we denote information and communication technology as ICT througout this paper.

in Appendix), and the fall of relative price of investment goods can account for roughly fifty percent of the labor share decline.

This paper uses the cross-sectional variation to identify the elasticity of substitution between capital and labor of 1.25, which is a nonstandard estimate in relevant literature, but consistent with the fact that, in the case of $\sigma > 1$ (capital and labor are more substitutable), firms will substitute more capital for labor in response to a decrease in the cost of capital and hence leads to a labor share decline. Given this elasticity estimate, they find the 25% decline in the global relative price of investment goods drives down labor share by 2.6 percentage point in a CES economy, therefore, explaining half of the observed 5 percentage point decline in labor share globally.

Decline in Relative Price of ICT Capital

As a corroboration and further work, Eden and Gaggl (2018) find that changes in the relative "effective" price of ICT capital can account for half of labor share decline in the U.S. during 1950 to 2013. The key difference from Karabarbounis and Neiman (2013) is that this paper explicitly distinguishes between ICT capital and Non-ICT capital, as well as between routine labor and non-routine labor based on the classification in Acemoglu and Autor (2010).

Using data from the BEA's detailed fixed asset accounts, this paper finds the decline in the relative price of capital is mostly driven by the decline in the relative ICT capital price, whilst the relative price of non-ICT capital has remained roughly stable during the period (See Figure 7 in appendix). Using data from the U.S. Current Population Survey from the March supplements (CPS-MARCH) starting in 1967 and from the CPS outgoing rotation groups (CPS-ORG) starting in 1979, this paper also discovers that the declining labor share in the U.S. is completely coming from the declining income share of routine occupation, whereas the income share of non-routine occupation has been rising (see Figure 8). And combining the observation on the side of capital share that ICT capital share increased by 3.46 p.p. since 1950 to 2013 [4], they suggest that part of the U.S. labor share decrease of 6.52 p.p. should have reallocated to the increase of ICT capital share, indicating half of the labor share decline is

[4] Non-ICT income share exhibited a rising trend since 2000s, but it kept stationary after picking out the structures and residential capital income which we postulate that cannot replace labor thus cannot account for the decline in labor share.

attributable to the reallocation of income from labor towards ICT capital.

Further, this paper estimates a nearly unitary elasticity of substitution between capital and labor, while the elasticity between ICT capital and routine labor is estimated to be 2.14 in 1950 and 3.27 in 2013. Their elasticity estimates reflect the fact that the decline in capital prices is mostly concentrated on the ICT capital, which is more substitutable to routine labor.

Decline in Relative Price of Robots

Although Graetz and Michaels (2018) does not provide direct evidence on the impact of robot adoption on labor share, it does touch on a more micro level of substitution effect. Graetz and Michaels use the data from the International Federation of Robotics (2006) and find that, in the six major developed countries (the United States, France, Germany, Italy, Sweden and the United Kingdom), the price of industrial robots rapidly declined over the period of 1990 to 2005. Based on the task-based framework nested in the CES production function similar to Acemoglu and Restrepo (2018) and the OLS and 2SLS estimates (using panel country-industry data in 17 countries from 1993 to 2007), they suggest that robots reduce the employment and wage bill share of low-skilled workers and have negligible impact on middle- and high-skilled workers, which is consistent with the evidence from Eden and Gaggl (2018) that the fall of capital cost contributed to the declining labor share of routine occupation, and hence the declining trend in aggregate labor share.

3.2 Displacement Effect

Lehn (2018) argues the decline in labor share in US has been driven by the replacement of labor in routine occupations and, after 2000s, in certain abstract occupations with substantial routine task content. Using data from CPS, the author first decomposes labor share[5] into three occupational labor shares: manual, routine, and abstract component, given as follow:

$$labor\ share_t = \frac{(W_m H_m)_t}{Y_t} + \frac{(W_r H_r)_t}{Y_t} + \frac{(W_a H_a)_t}{Y_t} \tag{4}$$

[5] In this paper, labor share is calculated as employee's compensation out of value added, referred as "compensation piece of payroll labor share"

The result plotted in Figure 9 suggests a pattern which associates the decline in aggregate labor share with the decline in routine occupation labor share and a slowdown of growth in abstract occupation labor share controlling for industry composition changes.

Next, the author investigates the first hypothesis that decline in aggregate labor share is driven by replacement of labor in routine occupation. Firstly, the author defines three different measures of "routine replaceability"[6] as an indicator of replacement of labor. Then, the author employs cross-sectional data at industry level and conduct IV regression controlling for endogeneity problems. The result suggests that the effect of replacement of labors in routine occupations on change in labor share is large, significant and robust.

Similarly, the author investigates the second hypothesis that acceleration of decline in aggregate labor share after 2000s is driven by replacement of labor in abstract occupation with high routine task content. The result indicates that this channel has played an important role in the accelerated decline of the labor share since 2000s.

It is plausible to connect this empirical evidence to displacement effect, because the author stresses the relationship between occupational task content and decline in labor share. And the research conveys a key point that labor have been displaced from occupations with substantial routine task content. However, the author doesn't dig into the relationship between automation and replacement of labor, we need to refer to Figure 10 from Acemoglu and Restrepo (2019) as a complement which presents that labor demand has decreased by roughly 10% over last 3 decades due to the change in task content driven by strong displacement effect and weak reinstatement effect. Putting this two pictures together, we can make speculative but logical association: Acceleration of automation accounts for replacement of labor in routine occupations and with deceleration of creation of new tasks combined accounts for replacement of labor in some certain abstract occupations. As a result, aggregate labor share has experiencing a decline in labor share since 1980 and an acceleration of decline since 2000.

[6] Routine replaceability: The fraction of the wage bill paid to routine occupations, the fraction of total hours worked in routine occupations, and the level of the real wage in routine occupations.

3.3 Reinstatement Effect

Since the effect of creation of new tasks is usually countervailed by other forces, such as substitution effect and displacement effect, it is hard to pick out and directly explore its link to labor share empirically. Lin (2011) presents some evidence that technology adoption has brought about new work. For instance, information and communication technology has resulted in the rise of Internet developers, web designers and data scientists. In this paper he compiles three lists of newly classified job titles[7] from the U.S. classification indexes in 1977, 1991, and 2000 and further estimates that 8.5 percent of employees working in the newly classified work which were not catalogued in 1965, 8.2 percent employed in the new work in 1990 compared with that in 1977, and 4.4 percent employed in the new work in 2000 compared with that in 1990. Also, using the data of new job titles from Lin (2011), Acemoglu and Restrepo (2018) shows occupations (based on the classification of Census Detailed Occupation) with more new job titles experienced larger employment growth over the period 1980 to 2015, testifying the impact of introduction of new tasks on labor market.

3.4 Relative importance of own industry, customer-supplier linkage, final demand and composition effect

In previous sections, we use empirical evidence to illustrate substitution effect, displacement effect and reinstatement effect. These are mechanisms associated with how an industry's technological progress impacts the industry's own labor share. But technology may impact the aggregate labor share in an economy through other channels. In Acemoglu and Restrepo (2019), "automation" and "new task creation" technology in a sector can change share of value added for industries in an economy (either through changing value added in the own industry or other industries) and lead to a change in aggregate labor share. This is called "composition effect". In Autor and Salomons (2018), besides own industry and composition effect, the authors also investigate how technological progress in an industry impact its supplier and customer industry's labor share (customer-supplier linkage effect), and impact other industry's labor share by changing overall demand in the economy (final demand ef-

[7] It refers to "new occupation titles/new occupational categories/new work" in Lin (2011), and refers to "new job titles" in Acemoglu and Restrepo (2018)

fect).

Regressing one industry's log labor share annual change on log own-industry TFP change, average log supplier industry TFP change, average log customer industry TFP change, and a set of fixed effects (equation 5), the authors find that: one percent rise in an industry's TFP predicts a fall of 0.58 percentage points in this industry's labor share over a 5-year horizon. Average TFP growth in its supplier and customer industries has insignificant effects on an industry's labor share.

$$\Delta lnY_{it} = \beta_0 + \sum_{k=0}^{5} \beta_1^k \Delta lnTFP_{i,t-k} + \sum_{k=0}^{5} \beta_2^k \Delta lnTFP_{j\neq i,t-k}^{supplier} + \sum_{k=0}^{5} \beta_3^k \Delta lnTFP_{j\neq i,t-k}^{customer} + \text{fixed effect} + \epsilon_{it} \tag{5}$$

Regressing one industry's log labor share annual change on log aggregate real/nominal value-added change in the country and fixed effect (equation 6), it is found that one log point gain in country-level value added predicts a modest but significant rise in this country's other industry labor share (0.071). As technological change in one industry may have impact on economy's final demand, it indirectly affect other industry's labor share.

$$\Delta lnY_{it} = \lambda_0 + \sum_{k=0}^{5} \lambda_1^k \Delta lnVA_{j\neq i,t-k} + \text{fixed effect} + \epsilon_{it} \tag{6}$$

Further, A rise in own-industry TFP growth predicts a fall in this industry's value added with an elasticity of -0.58. So, if rapid TFP growth occurs in industries with low labor share, aggregate labor share will be raised.

Regression coefficients are aggregated to country level by multiplying average industry TFP growth and adding across industries. Results show that own industry TFP growth reduces aggregate labor share by 0.14 percentage points in a year. Supplier, customer's TFP growth and final demand effect have small effects on aggregate labor share, with -0.01, -0.06, -0.02 percentage points annually. Composition effect decreases aggregate labor share by 0.046 percentage points. Putting together, all four channels predict a decline of 0.27 percentage points in labor share annually, and most effect comes from own industry change.

4 Discussion

In this section we bring up some concerns raised by the literature review on this topic, focusing primarily on internal validity and external validity issues.

4.1 Internal Validity

We don't fully understand some assumptions and mechanisms in Acemoglu and Restrepo (2019).

1. Tasks are assumed to be imperfect substitutes. Therefore, the original substitution effect is defined as when real capital price becomes relatively lower, the tasks that are performed by capital substitute for the tasks performed by labor. However, this cannot apply to a production chain where tasks are necessary parts of one product, for example writing and printing for making a book, then the tasks cannot substitute each other.

2. Displacement effect theoretically exist, but seems hard to find in empirical literature. So does it exist in reality? In theory, when capital's ability improve and can perform more tasks, labors are replaced by capital because lower prices are assumed to motivate firms to do this. However in reality, maybe the capital with new ability can be very expensive, so it is not cost minimizing for firms to replace labor immediately but only adopting the new technology after the price falling down, which could be the reason that there is more empirical evidence supporting substitution effect whilst less for displacement effect.

4.2 External Validity

Next, we think about whether task-based model is necessary to understand the impact of technology on labor market. The first question that arises is, whether task-based model is better compared with the traditional CES production function (For instance, equation 7)?

$$Y_t = F(K_t, N_t) = (\alpha_k (A_{K,t} K_t)^{\frac{\sigma-1}{\sigma}} + (1-\alpha_k)(A_{N,t} N_t)^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}} \tag{7}$$

Acemoglu argues in his paper that standard CES model assumes technology make all production inputs more efficient, however there also exists some technology that do not make factors more productive but change the allocation of tasks between factors. A large body of literature already discuss about the prevalence of skill-biased technical change in which technological progress only takes place on some certain type of tasks, and only the corresponding labor will be displaced by machines. Therefore, we agree it is not plausible to study the effect of technology on labor share by just using the CES production function as shown in equation 7.

To better fit into reality, one alternative and improvement of the classical CES production function could be a framework in which production is composed of routine and non-routine components given as follow:

$$Y = A\left(\gamma(F(A^K K, A_l^L L))^{\frac{\delta-1}{\delta}} + (1-\gamma)(F(A^K K, A_h^L L))^{\frac{\delta-1}{\delta}}\right)^{\frac{\delta}{\delta-1}} \tag{8}$$

where $F(A^K K, A_l^L L)$ and $F(A^K K, A_h^L L)$ represents output of routine tasks and of non-routine tasks respectively. A_l^L and A_h^L denotes productivity of routine labor and of non-routine labor respectively, A^K denotes productivity of capital. A denotes Hicks neutral productivity. γ is routine task content. δ is elasticity of substitution between two types of task.

Since the assumptions from task-based model that all tasks are substitute or complement and tasks which are automatable are perform by capital are not compelling to us and hard to relate to reality, this modified CES function incorporates two types of task which can be performed by capital and corresponding types of labor, which is more consistent with other relevant literature and related to reality, as opposed to both task-based model and standard CES function, in explanation of labor share.

4.3 Why is 21^{st} century different?

Except for Lehn (2018) which provides indirect evidence for the accelerating decline in labor share since 2000s, we do not find convincing evidence to strengthen the argument which links deceleration of creation of new tasks and acceleration of automation to slowdown of growth in decline of abstract labor share. Plus, the decline in price of ICT capital in Figure 7 slows down since 2000s implies that this cause for labor share decline since 1980 can not account for acceleration of decline since 2000s either.

4.4 Policy Implication

Should policy makers intervene the declining of labor share? In our framework, labor share decline comes mainly from replacing middle-skilled labor by capital. Therefore, whether labor share decline is related to welfare loss depending on how these displaced workers are reallocated. We will further study this question.

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A Appendix

Figure 2: US non-farm business labor share 1947-2022. Data from US Bureau of Labor Statistics.

Figure 3: Global labor share 1975-2012. *From Karabarbounis and Neiman (2013)*

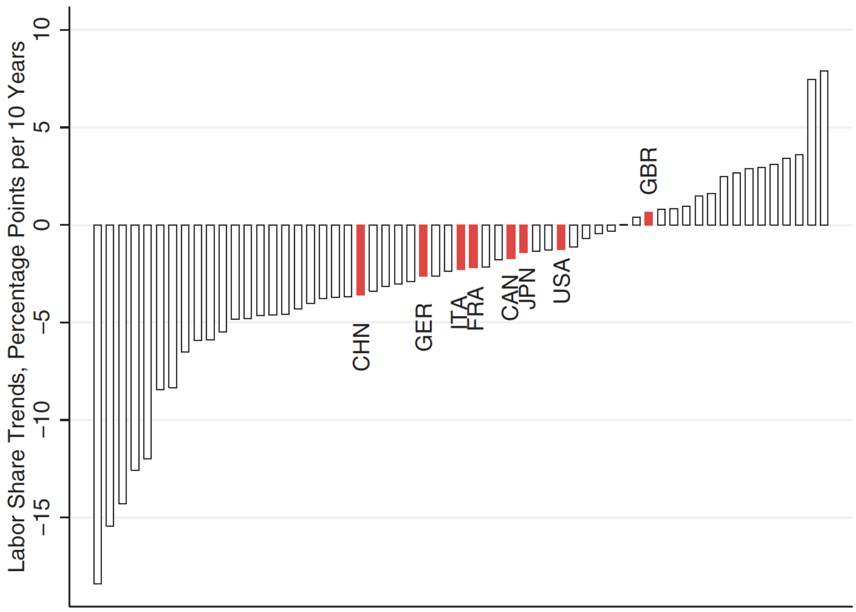

Figure 4: 46 countries corporate sector labor share trend, 1975-2012. *From Karabarbounis and Neiman (2013)*

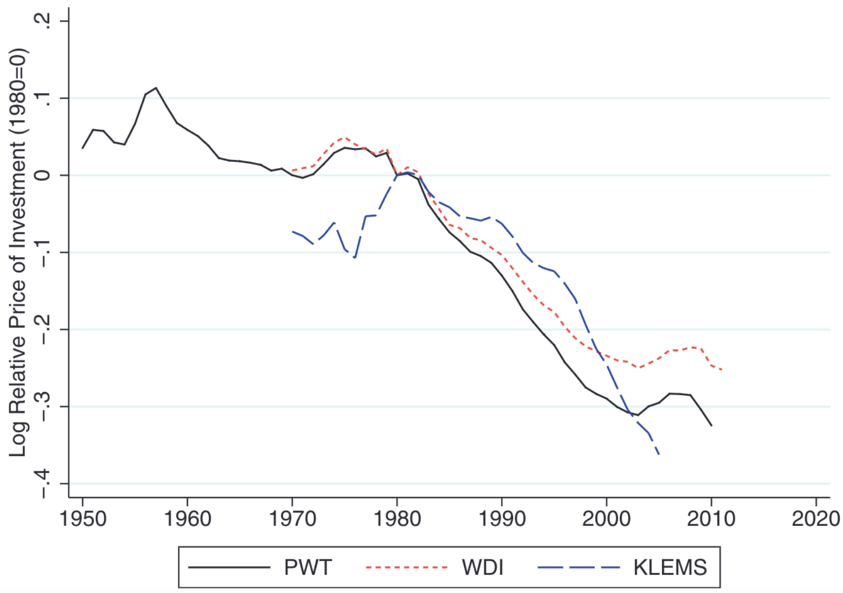

Figure 5: Declining Global Price of Investment Goods. *From Karabarbounis and Neiman (2013)*

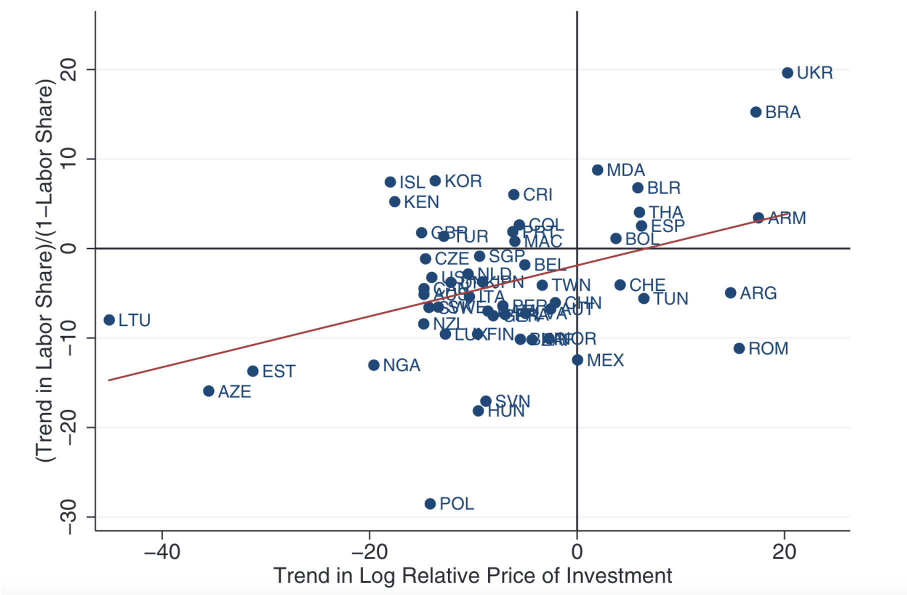

Figure 6: Labor Share and Relative Price of Investment. *From Karabarbounis and Neiman (2013)*

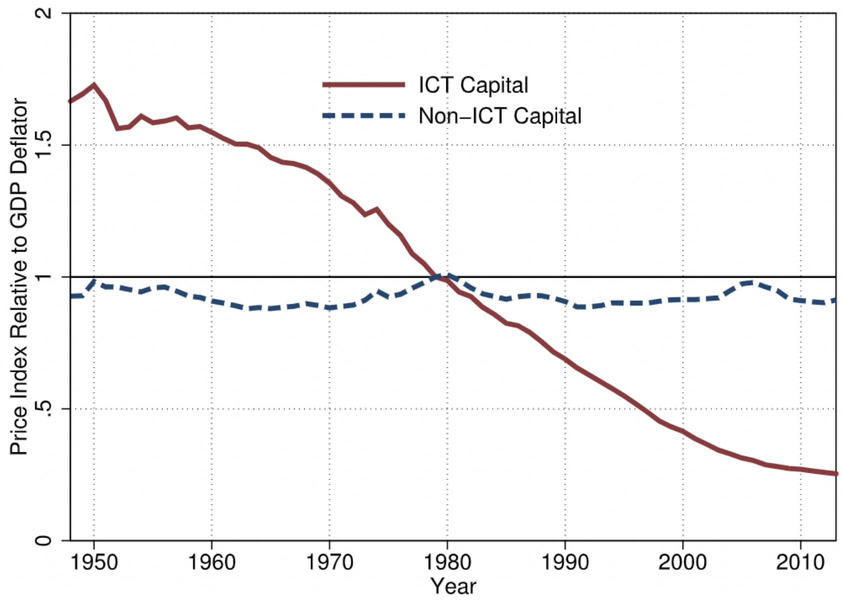

Figure 7: Relative Capital Prices. *F*rom Eden and Gaggl (2018)

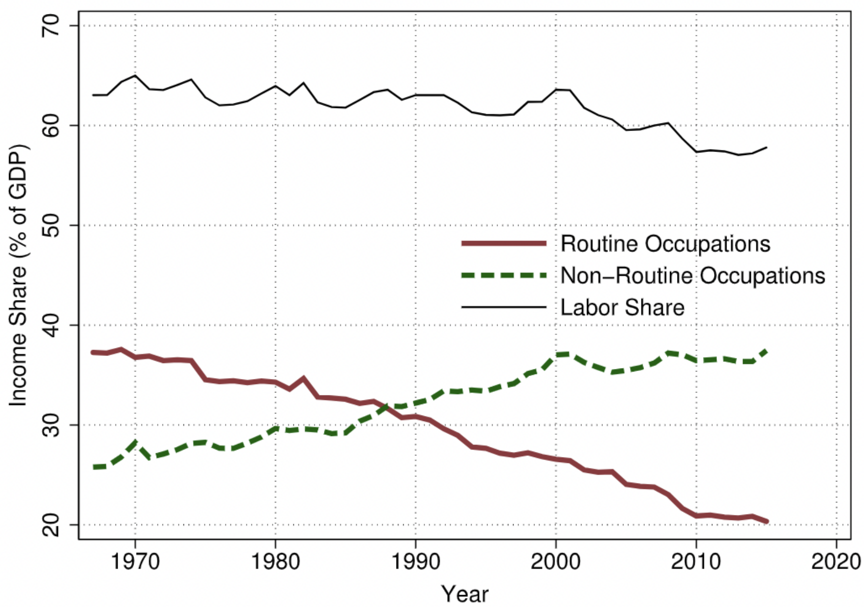

Figure 8: Labor's Income Share. *F*rom Eden and Gaggl (2018)

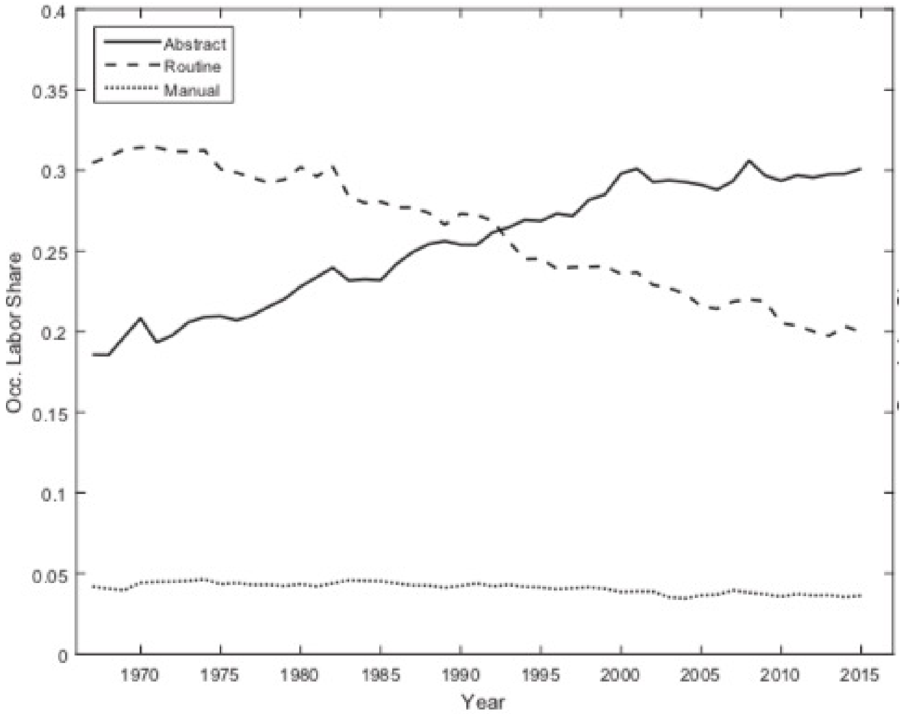

Figure 9: Occupational Labor Shares with Fixed Industry Composition, 1967-2015,Acemoglu and Autor (2010)

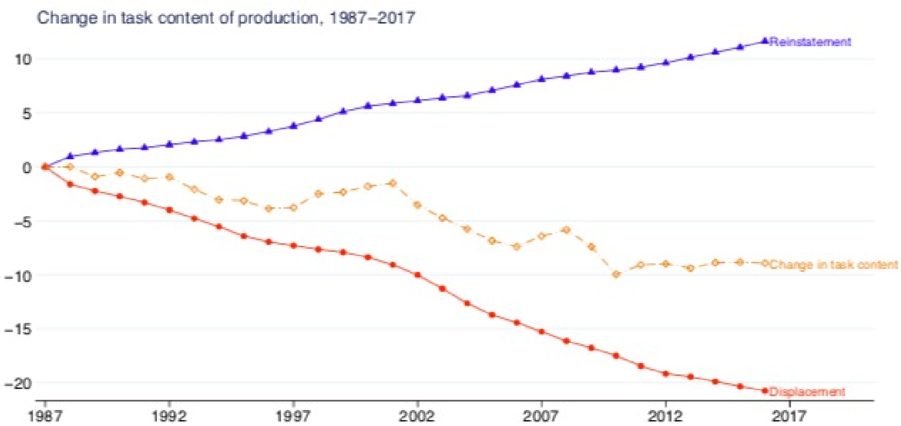

Figure 10: Change in task content of production, 1987-2017, Acemoglu and Restrepo (2019)