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Technology and the Future of Work

by Adrian Peralta-Alva and Agustin Roitman

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Technology and the Future of Work

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Abstract

This paper uses a DSGE model to simulate the impact of technological change on labor markets and income distribution. It finds that technological advances offers prospects for stronger productivity and growth, but brings risks of increased income polarization. This calls for inclusive policies tailored to country-specific circumstances and preferences, such as investment in human capital to facilitate retooling of low-skilled workers so that they can partake in the gains of technological change, and redistributive policies (such as differentiated income tax cuts) to help reallocate gains. Policies are also needed to facilitate the process of adjustment.[1]

JEL Classification Numbers: E24, E25, E37, E60

Keywords: Technology, labor markets, income distribution

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I. INTRODUCTION

Technological progress boosts living standards, but can be a source of disruption. Technological advances can raise overall productivity and income. But they can also lead to structural change, creating new jobs and sectors while displacing and changing others, with major repercussions for some parts of the population.

Anxiety about the adverse impact of new technologies on jobs and incomes is not new. It dates back at least to the Luddites movement at the outset of the Industrial Revolution (Mokyr, Vickers, and Ziebarth, 2015) and has been a recurring theme. For instance, John Maynard Keynes (1930) warned about the possibility of "technological unemployment." Anxiety re-emerged in the 1960s following a period of particularly high productivity growth post-World War II (National Commission on Technology, Automation and Economic Progress, 1966) and in the 1980s at the outset of the Information and Communication Technologies (ICT) revolution (National Academy of Sciences, 1987).

Is this time different? Fears have recently been rekindled, partly because the latest wave of technological innovation has come at a time of already timid growth of real wages and a falling share of labor in national income, particularly for low-skilled workers. Looking forward, new technological advances—when they diffuse more widely—may be even more disruptive, especially from automation and falling capital goods prices. In assessing the opportunities and challenges of innovation, this paper focuses on two specific channels through which technology can affect labor markets and income distribution.

Machines can perform an increasing range of tasks reserved for humans in the past. ICT have eliminated many office jobs performing routine tasks, and progress in robotics has changed manufacturing. But technological advances powered by the rise in Artificial Intelligence (AI) have the potential to transform work in a more fundamental way: as robots get more productive, more tasks in the future could be performed by a combination of machines and AI instead of labor.

Capital has also become cheaper relative to labor. The diffusion of ICT led to advances in innovation and invention of new and increasingly cheaper capital goods and production processes. These have incentivized firms to substitute machines for routine tasks, contributing to falling labor shares—or shifts in the distribution of national income away from labor— and income polarization (IMF, 2017a). Further declines in capital goods prices—driven by productivity gains in ICT—may have similar effects, even without fundamental changes in how machines and labor are used for production.

Is there a role for policies? Model based simulations suggest that technological advances offer prospects for higher productivity and stronger growth, but also bring with them risks of increased income polarization and a need to deal with the challenges of adjustment. In the first instance, reforms to lift growth are critical (see, for example, IMF (2017b)). But, historically, policies to spread the gains from growth more widely were an important part of the way economies transformed in the wake of technological change (Acemoglu and Robinson, 2002).

This paper explores policies to enable countries to harness the benefits of technological change for a broad group of their populations, tailored to their social preferences. We show that such policies, if well designed, could boost growth even further. For instance, investment in human capital is key to allow low-skilled workers partake in the gains of technological change. Redistributive policies, such as differentiated income tax cuts, can also help reallocate gains (though they come with efficiency losses). At the same time, policymakers need to get ready to facilitate the process of adjustment, as technological advances change individual jobs, whole professions, and potentially the sectoral makeup of economies.

The remainder of the paper is organized as follows. Section II presents a literature review. The following section presents relevant historical facts to document labor market outcomes associated with technological advances. Section IV discussed two specific technology-related drivers that can potentially affect labor markets and income distribution, and are the focus of the paper. This is followed by three sections describing the model, its calibration, and simulations respectively. Section VIII presents the policy implications based on the model simulations, and section IX concludes.

II. Literature Review

It is difficult to narrowly define technology, technological advances, and technological disruptions, and the ways it affects different sectors and markets. The impact of technology is multifaceted, with specific impacts on jobs, sectors, and income distribution. This is why there is a large literature tackling these issues at the sectoral and microeconomic level.

Few studies provide an encompassing macroeconomic approach to tackle the potential impact of new technologies on labor markets and income distribution. This paper contributes to filling that gap. Autor and Solomons (2017) show that new technologies and the associated rise in productivity contributed to higher incomes and aggregate demand, supporting job creation. Gruen (2017) highlights that changes have been dramatic, with shifts in the sectoral composition of employment over time. In terms of demand for skills, Katz and Autor (1999) note that the increase in educational wage premia was most prominent in the U.S., but observable—albeit to a lesser degree—in other economies.

Regarding trends in labor shares, in many Advanced Economies (AEs) a downward trend in labor shares between 1980s and the late 2000s has been associated with a move toward more capital-intensive production methods, which in turn has been linked to falling prices of capital goods (IMF, 2017a). However, other factors, such as globalization, have been at work as well, as noted by Elsby, Hobjin, and Sahin (2013). Barkai, (2016), as well as Autor et al. (2017) highlight growing market power of companies as yet another element potentially shaping labor income shares.

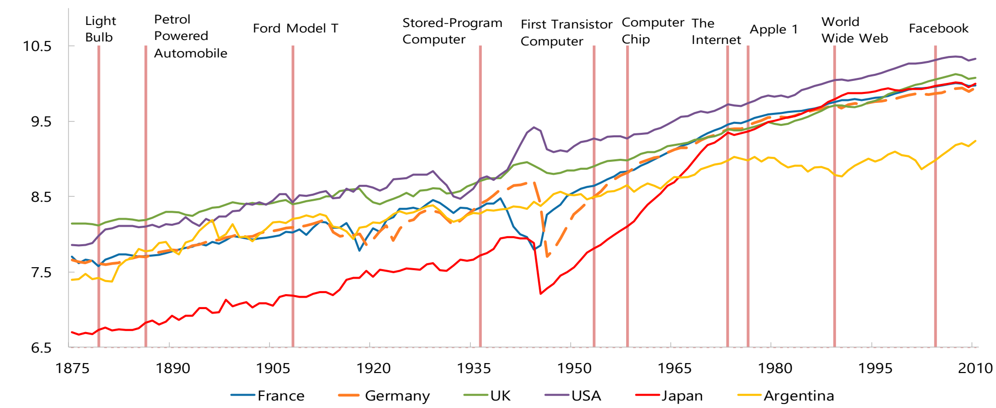
Garbade and Silber (1978) note that advances in communications technologies were particularly important for financial integration. Indeed, the legacy of the global financial crisis has been linked in part to less productivity-enhancing investment, including in ICT and intangibles (IMF, 2017b), slowing the diffusion of new technologies. More broadly, Brynjolfsson et al. (2017) explains the paradox of rapid technological advances and slow productivity growth largely by implementation lags, as new technologies have not yet diffused widely. Bloom et al. (2017) argue that research productivity has been falling in many fields, and Gordon (2015) argues that overall productivity growth has been in long-run decline. But Jovanovic and Rousseau (2005) note that there is historical evidence of sluggish productivity growth followed by an acceleration, particularly in the case of advances in general purpose technologies (where productivity gains can be realized only after complementary innovations are developed and implemented). In AEs, efficiency gains from global integration contributed to productivity growth, and, for firms close to the technology frontier, global competition has been shown to increase innovation incentives (Aghion et al., 2015).

Comin and Hobijn (2010) document that cross-country lags in the adoption of new technologies today are significantly shorter than in the past. Some studies question the role of declining capital good prices in explaining the dynamics of the labor share. Autor et al. (2017) note that for these declines to have an impact, the elasticity of substitution between capital and labor must be higher than typically found in empirical studies. IMF (2017a) shows that, due to higher routine exposure, the elasticity of substitution in AEs is sufficiently high for the decline in capital goods prices to have a negative impact on labor shares. The ICT revolution has made the global economy more connected. And as noted by Baldwin (2016) this has contributed to outsourcing and spreading manufacturing production through global value chains. For instance, IMF (2017a) finds that participation in global value chains has been one of the factors behind the decline in labor shares: it has been associated with offshoring tasks that are labor-intensive for AEs, but capital-intensive for Emerging and Developing Economies (EMDEs). Elsby, Hobjin, and Sahin (2013) similarly show that labor share decline in the U.S. was deeper in industries more affected by increasing imports.

III. FACTS

Fact # 1. Innovation fosters growth. While the time lags between particular inventions and their eventual broad diffusion can be long and change over time, technology has been key to productivity growth since the first industrial revolution, which in turn, has underpinned strong per-capita GDP growth (Figure 1). A series of significant innovations such as the steam engine, railway, electricity, and the combustion engine, as well as improvements in production methods, infrastructure, health outcomes, and educational attainment supported productivity growth throughout the 19th and 20th century, resulting in vast gains in living standards. The ICT revolution boosted productivity again at the turn of the 21st century.

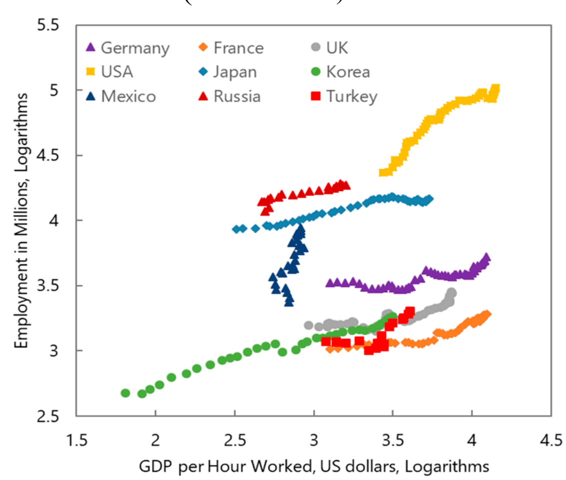
Figure 1. Technological Innovation Has Underpinned the Rise in Living Standards
(GDP per capita, 1990 Int. GK$, logarithms)



Source: Maddison Project and IMF Staff Calculations.
Notes: GK$ refers to the Geary–Khamis dollar, more commonly known as the international dollar.

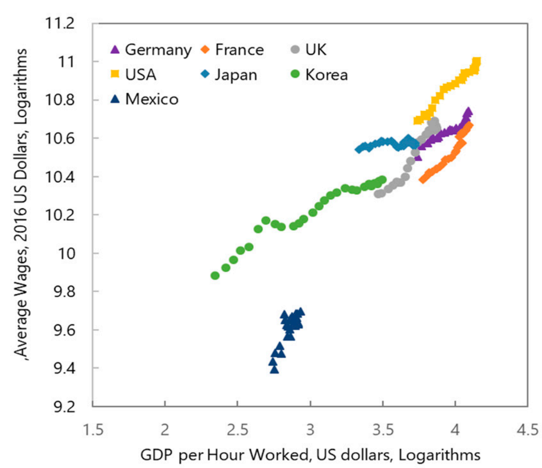
Fact # 2. Historically, concerns about 'technological' unemployment proved unwarranted. Notwithstanding a trend toward shorter working hours (and shorter-term fluctuations in labor force participation and unemployment rates), there is no evidence of a persistent negative impact of new technologies on the overall demand for labor. New technologies displaced some jobs, but created complementary new tasks. And the associated rise in productivity contributed to higher incomes and aggregate demand, supporting job creation (Figure 2). Real wages have also increased rather than declined. Trends in real wages followed those in productivity, which resulted in an unprecedented growth in labor income since the start of the Industrial Revolution (even though the share of gains from productivity advances accruing to workers has fluctuated over time (Figure 3).

Figure 2. Productivity Associated with More Employment…
(1970–2016)



Source: OECD

Figure 3. Productivity Associated with Higher Wages
(1990–2016)

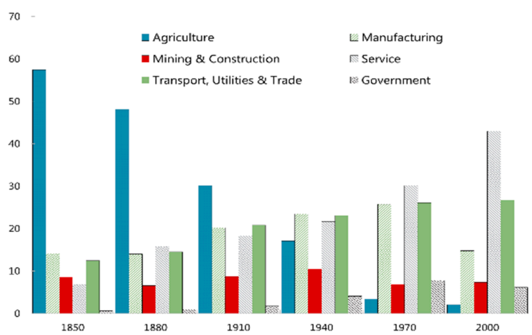


Source: OECD

Fact # 3. Adjustment to change has triggered sectoral reallocations. Technological change has eliminated some jobs and transformed others. Over time, new jobs have been created, as reflected in growing aggregate employment. But changes have been dramatic, as illustrated in shifts in the sectoral composition of employment over time, for instance from agriculture to manufacturing, and more recently from manufacturing to services (Figure 4 shows the adjustment process for the U.S., but similar shifts have occurred in other AEs and EMDEs.[2]

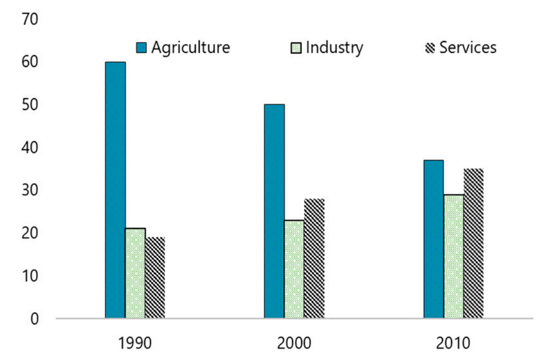
Figure 4. Technological Change Has Contributed to Sectoral Reallocation
(Percent of labor force)

U.S.



Source: U.S. Census Bureau and IMF Staff Calculations.
Notes: In the 1850-1910 samples, the industry of employment was inferred from the reported occupation.

China



Source: International Labour Organization

F*act # 4. Gains from sectoral reallocations within the labor force have sometimes been spread unevenly, particularly in recent decades.* Some skills have become redundant, impacting employment and skill premia. Demand for some skills has declined with new technologies (for instance, ICT eliminated many routine office jobs). For some, this led to a move to less skill-intensive and lower-paying jobs; and, while this has not systematically impacted aggregate unemployment and labor force participation rates, other workers became unemployed or dropped from the labor force altogether. In contrast, demand for skills complementary to new technologies has increased. Taken together, this contributed to a hollowing out of middle-skilled jobs in many AEs in the past three decades. It also led to a polarization of income gains—favoring high-skilled and disadvantaging low-skilled labor, which has been an important factor behind the rise in inequality in the past three decades (Figure 5). High-skilled jobs required increasingly higher educational attainment, in some countries driving educational wage premia fueled by slower labor supply adjustment (Figure 6).

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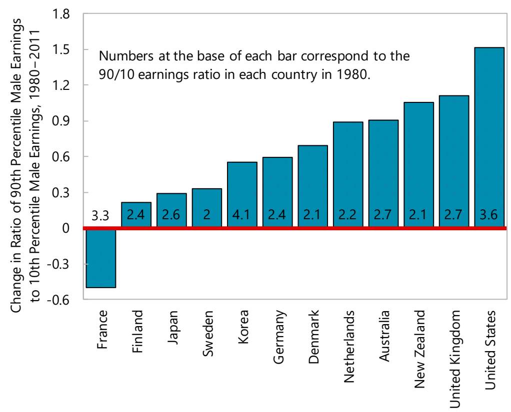
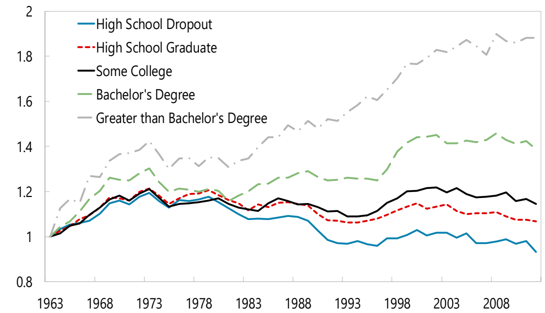
[2] See Gruen (2017).

Figure 5. Earnings Polarization Accompanied by…



Source: Autor (2014).

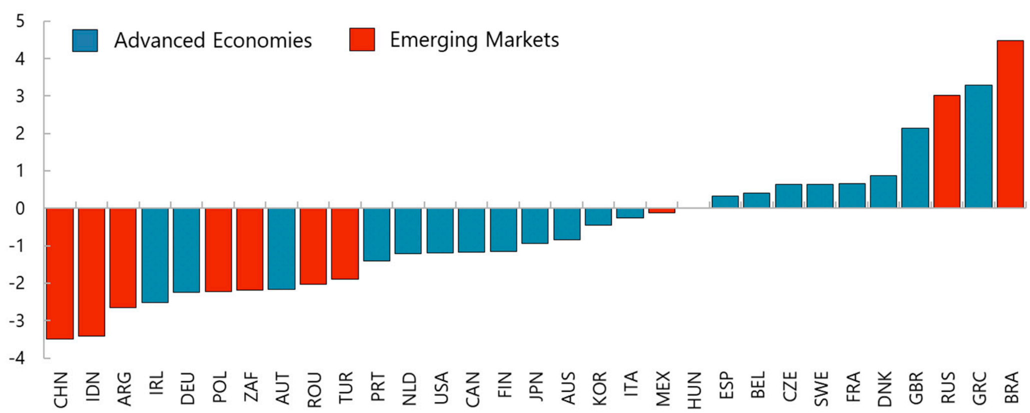
Figure 6. …Increasing Educational Wage Premia in Some Economies
(Real wage level of full time U.S. male workers relative to 1963)



Source: Autor (2014).

Fact # 5. Technological advances can affect the labor share of income. Declines in labor shares have occurred in the past, most notably in periods of fast technological change. For instance, many AEs and EMs have experienced a downward trend in labor shares between the 1980s and late 2000s, at a time where there was a move toward more capital-intensive production methods, which in turn has been linked to falling prices of capital goods (Figure 7; IMF, 2017a).

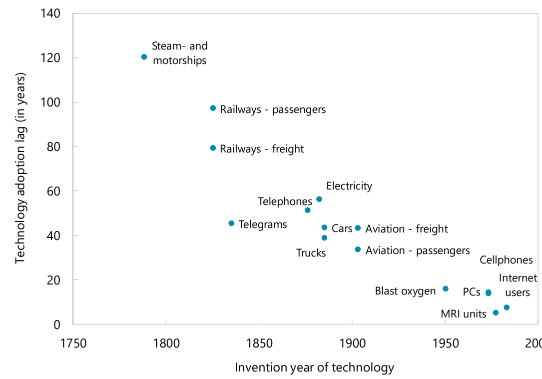
Figure 7. Estimated Trends in Labor Shares by Country, 1991–2014
(Percent points per 10 years)



Source: April 2017 WEO.

Fact # 6. Technological change and global economic integration are intertwined.

Figure 8. Technology Adoption Lags Have Decreased Over Time



Source: Comin and Hobijn (2010).
Notes: Technology adoption lag is a mean estimated lag in cross-country technology diffusion.

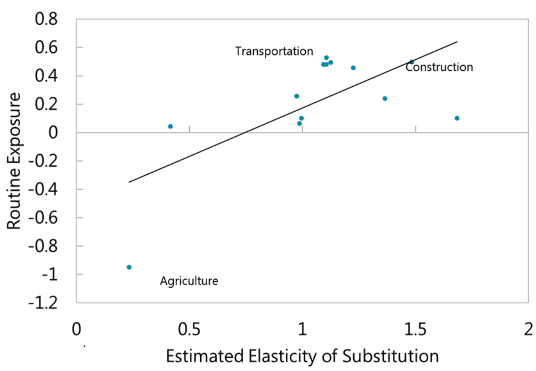
Technology fosters economic and financial integration, which in turn enable technology transfer across countries. Falling transportation costs due to the widespread use of containers, and, more recently, the ICT revolution are both examples of technological progress driving integration via cross-border trade and financial flows. Global efficiency gains have expanded the variety of available goods and services at lower prices, enabling further integration. Trade and financial integration supported innovation, investment, and diffusion of knowledge across the world. In AEs, efficiency gains from global integration contributed to productivity growth, and for firms close to the technology frontier, global competition has been shown to increase innovation incentives (Aghion et al., 2015). For EMDEs, investments by local affiliates of multinational companies and technology embedded in imported goods (the share of imported high-tech products in GDP has risen by more than half since the mid-1990s) allowed easier access to foreign know-how. As a result, cross-country lags in the adoption of new technologies have been reduced from almost 100 years in the 1800s, to 20 years today (Figure 8).

IV. Two Possible Drivers of Labor Income Shares and Polarization

Technological advances can manifest as (i) automation and (ii) falling prices of capital goods, which are interrelated factors that drive productivity growth. They have also been linked to the decline in labor shares and income polarization as: (i) the automation of tasks routinely performed by labor affect substitutability between capital and labor; and (ii) the falling relative prices of investment goods encourage substitution away from labor. A higher degree of routine tasks is typically associated with a larger elasticity of substitution between capital and labor, and therefore with a greater job replacement risk if the price of capital goods falls (Figure 9). IMF (2017a) finds this mechanism to be a leading explanation behind the fall in the labor share for AEs, where middle-skilled workers performing routine tasks have been most susceptible to automation (Figure 10).

Figure 9. Elasticity of Substitution Correlated with Degree of Task Routinization

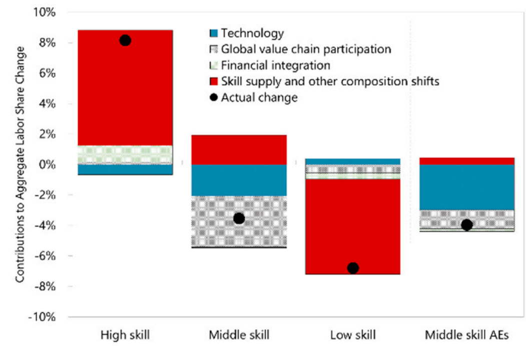
(By sector, 1992–2014)



Source: April 2017 WEO.
Notes: Routine exposure is measured by aggregate routine task intensity index (Autor and Dorn, 2013); smaller number reflects lower exposure to "routinizability."

Figure 10. Technological Change and Global Value Chains Contributed to Integration

(By Skill, 1995–2009)



Source: April 2017 WEO.
Notes: Decompositions are derived from aggregate labor share regressions by skill group. Middle-skill advanced economies refers to the decomposition of the aggregate middle-skilled labor share, using only the advanced economy subsample in the regression. Contribution of skill supply and other shifts in composition is the combined effect of educational composition and the regression constant.

A. Automation

There is some preliminary evidence indicating that if the trend toward automation continues, more cognitive tasks could become replaceable by machines, increasing substitutability between some forms of capital and human labor.

- *Many jobs could be affected, particularly in AEs*. McKinsey (2017) estimates that 375 million workers globally (14 percent of the global workforce) may be at the risk of job losses by 2030 in their baseline scenario. The risk is seen as higher for workers in AEs, with about 23 percent of jobs potentially affected in the U.S. (and up to 44 percent in a fast-automation scenario, which is broadly consistent with 47 percent estimated by Frey and Osborne (2017)). Estimates for EMDEs are considerably lower (e.g., about 13 percent for Mexico, 9 percent for India, and 16 percent for China), which reflects differences in the sectoral composition of production. Other studies project smaller impacts.[3]

[3] Arntz et al. (2016) predict that only 9 percent of jobs in OECD countries are automatable, based on a methodology distinguishing between jobs (which may survive, though in a different form as automation progresses) and their constituent tasks (which may become automatable). Using the same methodology, Ahmed and Chen (2017) estimate automatability at 1 percent for Vietnam.

Automatability may decrease with the level of education. There is consensus that high-skilled occupations are the least susceptible to automation.[4] The impact on low- and middle-skilled jobs is less certain. McKinsey (2017) estimates that the hollowing-out of the middle class will continue, with automation disproportionally affecting middle-income workers. In contrast, Frey and Osborne (2017) and Arntz et al. (2016) suggest a break in this trend, with automation mainly substituting for low-skilled jobs. New, yet unknown activities may boost demand for different skills in the future, amplifying this uncertainty.

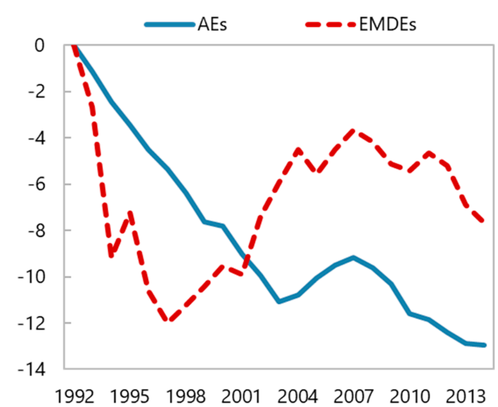
Although growing fast, evidence about automation and its associated risks is still limited compared to traditional economic variables (e.g., GDP). Measurement and statistical issues related to technological advances are not fully developed yet, partly because automation comprises multiple dimensions. For example, there could be jobs susceptible to automation, hence displacing workers. But if tasks (not jobs) are susceptible to automation, then automation may not eliminate jobs, but rather transform them.

B. Falling Prices of Capital Goods

Like automation, declines in capital goods prices can increase GDP, but can also benefit disproportionately the higher-skilled. A downward trend in the real price of capital goods observed for AEs, and to some extent EMs, could continue as technological advances in ICT improve the design and production efficiency for investment goods (Figure 11). For a given degree of substitutability of labor by capital, making capital more affordable for firms can yield broadly the same effects as automation—over time, firms will increase capital and use more machines and fewer workers producing greater output. In general, it will be low-skilled labor that is most easily replaced by capital while the demand for high-skilled workers might go up—for example, because they develop or otherwise complement production capacities. As a consequence, and depending on the size of the price drop for capital, we would expect relative wages to react broadly along the same trajectory as under the automation (for given prices of capital).

Figure 11. Relative Price of Investment

(Percent change relative to 1990)



Source: April 2017 WEO

[4] Substitutability, though, is not always correlated with the degree of formal education. For instance, Frey and Osborne (2017) suggest that kindergarten teachers are less "computerizable" than paralegals.

This paper focuses on automation and falling prices of capital goods as the key factors potentially affecting future growth, and developments in inequality. We use a DSGE model to illustrate their impact on both. For our purpose, and in the model, automation is defined as an increase in the elasticity of substitution between capital and labor.

V. Model

The simulations we present below employ the DSGE model developed by Lizarazo, Peralta-Alva and Puy (2017).[5] There are two key ingredients in the model. First, the economy produces three different goods (manufacturing, low skill services, and high skill services), which differ in terms of their tradability, labor, and skill intensity. Second, consumers have non-homothetic preferences over these goods, reflecting the increasing share of expenditures on services as income grows, characteristic of U.S. data. This is a heterogeneous agents model which assumes that capital is a substitute for (an aggregate of) middle- and low-skilled labor with an elasticity of 1.5, while capital and high-skilled labor are complements. The distribution of skills is exogenous and constant (the implications of shifts in this distribution—driven by policies—are discussed in the simulations section below).

The model is calibrated to the U.S., as a benchmark economy. Quantitative analysis is based on comparisons across steady states, thus abstracting from transitional dynamics. Still, the model allows for a detailed discussion of both capital goods prices and automation, as well as their impact on workers of different skill levels (low, middle, and high), making it suitable for a broad range of policy simulations.

VI. Model Simulations

We use the model to illustrate the potential trade-off between growth and inequality. The model analyzes steady-state impacts of two possible sources of technological change. To be precise, we model "technology shocks" as either an increase in the elasticity of substitution between capital and labor (e.g., automation), or a fall in the price of capital goods. In both cases, a "technology shock" boosts productivity and income, while having an uneven impact across different groups of workers depending on their skills.

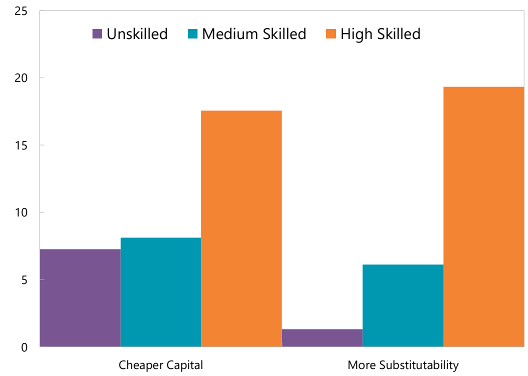
- Assuming a 20 percent drop in the relative price of capital goods, which is broadly consistent with the pace of decline observed in the U.S. since the 1980s, GDP rises by 14½ percent over the long term compared with the baseline, but—since higher-skilled labor is considered to be complementary to capital—higher-skilled workers generally benefit more than the low-skilled. Specifically, cheaper capital goods increase income by 16 percent for high-skilled workers, and by about 7 percent for both low- and middle-skilled workers.

[5] See Appendix for details.

- Given the lack of precise time series estimates for changes in the elasticity of substitution between capital and labor, as captured by our CES production functions, we anchor the analysis of the impact of further increases in substitutability on a change that produces the same 14½ percent increase in GDP. This requires a 10 percent increase in the elasticity of substitution between capital and labor. Higher substitutability between capital and labor generates more inequality than the decline in capital goods prices, producing little or no benefit to low-skilled workers, while high-skilled workers' consumption increases by almost 20 percent (Figure 12).

Figure 12. Cheaper Capital Has Less Distributional Impact Than More Substitutability

(Percent change of income from the baseline)



Source: IMF Staff Calculations.

Simulations show a positive impact on aggregate income, but it disproportionally benefits the high-skilled, particularly when there is higher substitutability of capital and labor.

VII. Policy Implications

This section looks into policies to adjust to "technology shocks". Depending on societies' preferences regarding the trade-off between equality and higher output, policies could have a role to ensure that the gains of growth are shared more equally. To that end governments could alter the distribution of market income through education and other human-capital formation policies (such as life-long learning), or adjust net incomes through the tax-benefit system.

Two alternative policy responses are considered for both "an automation shock" and "a drop in the price of capital" to spread the GDP gains more evenly: redistribution through higher education spending leading to improvements in human capital for low-skilled workers; and differentiated income tax cuts. For simplicity and to better understand the underlying mechanisms at work, the model assumes that these policy interventions are financed either by reducing unproductive government consumption, or by an increase in the VAT rate (the latter has an efficiency cost).

A. Higher education spending

We simulate a 4-percentage points reduction in the share of low-skilled workers, 2 percentage points of which become medium-skilled and the other 2 become high-skilled.

Based on data on education costs in the U.S, the cost of such a change could range from 1 to 3 percent of U.S. GDP. We use a mid-point estimate of 2 percent of GDP. This calibration implies that financing this policy requires an increase of 2.5 percentage points in the VAT rate relative to a no-education-policy-response baseline.

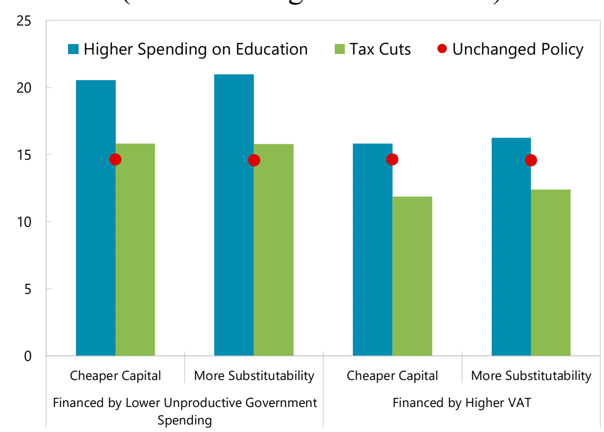
B. Tax Cuts

We assume a reduction in effective income tax rates of 6 percentage points for households with incomes close to the median, and gradual but rapidly declining cuts for households with higher incomes (a cut of 2 percentage points for households with three times the median income and no cut for households with incomes above 4 times the median). The revenue cost of this measure is equivalent to about 2 percent of GDP (so also equivalent to 2.5 percentage point increase in the VAT rate).

C. Policy Impacts

Both policies display relatively limited costs, and fairly large income gains from technological advances for all groups. When financed through cuts in unproductive public spending, the improvement in human capital boosts GDP gains from 14½ percent (impact of technological change alone) to 20½-21 percent (combining the impact of technological and policy changes), while the tax cut results in GDP gains of about 16 percent. Financing these policies by an increase in the VAT rate—given its efficiency cost—reduces the gains to about 16 percent for human capital improvement, and to 12–12½ percent for tax cuts (Figure 13).

Figure 13. Spending on Education Boosts Income Gains; Gains After Tax Cut are Smaller but Sizeable
(Percent change from baseline)



Source: IMF Staff Calculations.

Education spending may be a particularly effective policy tool. In addition to raising the income of the low-skilled, it also lifts the level of GDP beyond the baseline by increasing the aggregate level of human capital in the economy. If it is financed by the increase in the VAT rate, low-skilled workers gain between 25 and 31 percent in income, depending on whether technological advances come in the form of lower capital goods prices or an increase in capital-labor substitutability (Figure 14). High-skilled workers' income increases between 9 and 12 percent in this case, while middle-skilled workers gain 2 to 3 percent (reflecting the tax incidence of the assumed VAT reform—higher education spending would be neutral for the middle-skilled if financed by cuts in unproductive spending). Of course, the simulation assumes that education spending is well targeted and enhances the human capital of the low skilled.

Taxation can help redistribute gains. Differentiated income tax cuts, by construction, are a readily available tool to help ensure that the gains from technological advances are shared more evenly. For instance, the simulations suggest that following the middle-class-focused tax cut (of six percent for households with incomes close to the median, and decreasing to zero for those with incomes four times higher than the median), the gains of technological change would be shared more evenly across skill groups and roughly equally if the change is coming in the form of a drop in the price of capital goods (Figure 15).

Higher education spending is a more efficient policy option. Adding to the human capital of low-skilled workers allows them to profit from technological progress. It also makes low-skilled workers scarcer, boosting their wages. The tax cuts, by construction, help redistribute asymmetric gains, spreading them roughly equal across skill groups. This policy is less efficient in terms of its GDP effects and does not address the root problem (namely improving the human capital of individuals so that they can benefit from skill based technological change), changing the income distribution ex-post.

Figure 14. Human Capital Investment Disproportionally Benefits Low-Skilled Workers
(Percent change from the baseline)

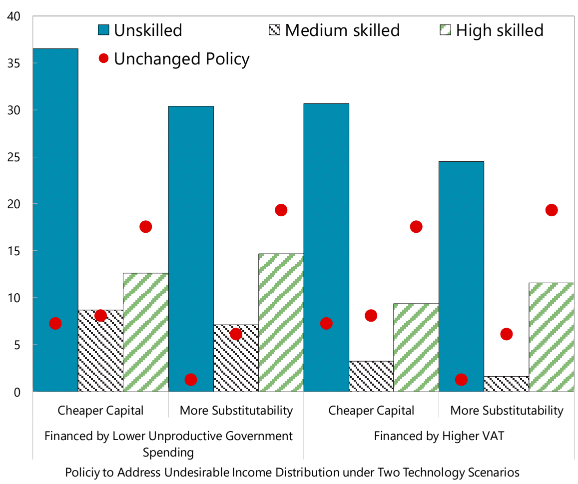
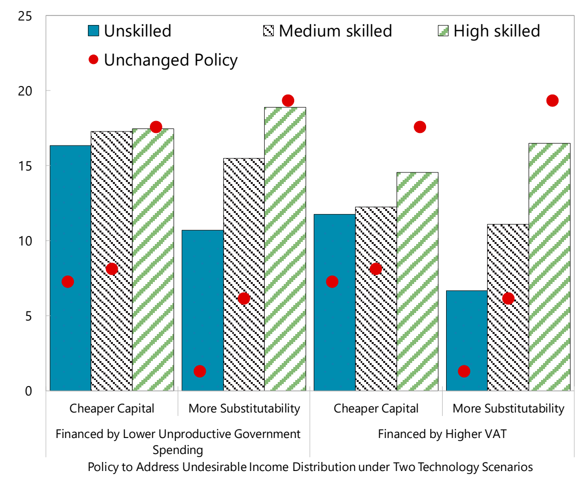


Figure 15. Taxes Redistribute Income Gains But Not Equally
(Percent change from the baseline)



Source: IMF Staff Calculations.

A combination of both education spending, and tax cuts, could help minimize the risk associated with either. Skill investment tackles the root of the problem—equipping new generations of workers with the skills required to cope with technological advances, while shrinking the supply of increasingly redundant low-skilled labor. At the same time, the lasting effects of today's education policy decisions on the type of human capital future workers will be equipped with, combined with the uncertainty surrounding the type of skills future labor markets will actually need, mean that skill deficiencies may not be tackled effectively. Tax policies can provide some insurance against such risk by tilting the distribution of market income in favor of the relative losers from technological progress. As such, they can be a useful complement to education policies.

D. Limitations

While indicative of potential gains, the results must be interpreted with caution. This is because the model is relatively simple and simulations illustrate only two potential paths for technological change. Furthermore, the model abstracts from transitional dynamics between steady states and hence simulations do not incorporate adjustment costs.

VIII. Conclusion

Historically, technology has enabled an unprecedented growth in labor income, but has also been a source of disruption. Technology has boosted productivity, which, in turn, has driven strong per-capita GDP growth and has been associated with expanding employment. However, the gains in employment and income can come in spurts and tend to favor different sectors over time. This forces deep and sometimes painful structural adjustment, with jobs changing or disappearing in some areas while new jobs are being created elsewhere. Moreover, while there are many reasons for the decline in labor income shares over the last three decades, technological progress in capital goods has played a role. Finally, the distribution of labor income itself has become more unequal as some skills—particularly those associated with more routine tasks—have become redundant, leading to a polarization of income gains favoring high-skilled and disadvantaging low-skilled labor.

This paper focuses on two interrelated factors that can drive the impact of technology on labor markets and income distribution, as in the past: i) automation or, more broadly, an increase in the extent to which capital can technically substitute for labor; and ii) the falling relative prices of capital goods (which encourage the replacement of labor for a given degree of substitutability). Automation could allow machines to perform cognitive but routine tasks now handled by human labor. This would put particular pressure on low-skilled labor doing routine work. Illustrative model simulations indicate that the more easily capital will substitute for labor, the more productivity and overall income growth will pick up. At the same time, this is likely to increase inequality by favoring income from capital and higher-skilled work. A decline in capital goods prices is also likely to benefit the high-skilled vis-à-vis the low-skilled.

Policies can change the impact of technological change. Depending on societies' preferences for growth versus income equality, governments may want to distribute the gains from technology more evenly. Certain policies, if well designed, could mitigate the trade-off between both objectives. For example, illustrative model simulations show that higher education spending would not only allow low-skilled workers to participate in the gains of technological change, it would also increase output; this holds even when taking into account that higher spending will require higher rates of taxation. More generally, while the use of the tax/benefit system to redistribute the gains from technological advances tends to come with some loss in efficiency, the resulting loss in output tends to be relatively small.

APPENDIX

This appendix presents the main technical details of the model, relevant for this paper, which may be needed to better understand the specific transmission channels of shocks, assumptions, and calibration.

Model

A. Production and Firms

The three goods produced are: (i) a manufactured good, called *M* (ii) a low-skilled service, called *L* and (iii) a high-skilled service, called *S*. Although the manufactured good M is tradable (i.e. its price is determined exogenously on international markets and the country is a price-taker), both types of services are assumed to be non-tradable (in the data, these sectors are substantially less tradable than manufacturing, and for the qualitative results of the paper this is what is most important). Markets are assumed to be competitive so that firms and individuals act as price takers and each factor commands its after tax marginal product. Different types of labor (h, x, l) deliver different effective levels of average productivity $\eta^h > \eta^x > \eta^l > 0$, and enter as separate factors of production (so that "effective time" of each type is not a perfect substitute for one another).

<u>Manufacturing Sector</u>:

Manufacturing goods are produced using labor from all type of skills (h, x, l), capital k and intermediate inputs originated in the manufacturing sector itself $m^{M,M}$, and in the high-skill services sector $m^{S,M}$.

$$M = F^M(h, x, l, k, m^{M,M}, m^{S,M}).$$

The manufacturing sector is assumed to be capital intensive. Following the literature on job polarization, capital k and high skill labor h are assumed to be complements as production inputs, while capital is substitute with medium skill labor x and low skill labor l (i.e. those types of jobs are "routinizable" in the sense of Autor (2003) and Abdih and Danninger (2017). Medium and low skill labor are imperfect substitutes.

<u>High-skill Services Sector:</u>

High-skill services are produced using high and medium skill labor, capital and intermediate inputs originated in the manufacturing sector $m^{M,S}$ and in the high-skill services sector itself $m^{S,S}$.

$$S = F^S(h, x, k, m^{M,S}, m^{S,S}).$$

Like in the manufacturing sector, capital and high skill labor are complements in the production of high-skill services, whereas capital and medium skill labor are substitutes.

Low-skill Services Sector:

Low-skill services goods are produced using only low skill and medium skill labor.

$$L = F^L(x, l).$$

Our key results would be qualitatively the same if production of low skill services used capital, as long as this sector is the least capital intensive; quantitatively, the results would not be too different from what we report here, as in the data this sector uses little capital.

B. **Households**

Household's heterogeneity is driven by permanent and transitory differences in labor productivity: permanent differences result from households being born with different levels of skills -they are either low-skill (l), medium skill (x) or high skill (h)-, while transitory differences result from idiosyncratic shocks to household's average deterministic productivity.[6]

Households maximize their expected life time utility from consumption c^i and leisure o^i. Each unit of labor time $1 - o^i$ that they supply to the market is compensated at a market wage w^i. Labor productivity is subject to transitory idiosyncratic shocks. Households must also choose their asset holdings, a^i, taking as given their market return, r. Finally, households must pay consumption (τ^s,τ^L, τ^M, τ^*) and income taxes (which are nonlinear and progressive in income) and are subject to exogenous borrowing constraints.

It is important to note that consumption c^i denotes a vector of 4 types of consumption goods: $c^{s,i}$ is consumption of services with high-skill content, $c^{L,i}$ is consumption of services with low-skill content, $c^{*,i}$ is consumption of imported goods (not produced domestically), and $c^{M,i}$ is consumption of tradable goods (manufactured goods). The numeraire of the economy is manufactured goods M, and their price is normalized to 1.

C. Government

The government consumes manufacturing goods G^M, high-skill services G^S, and low skill services G^L, invests in infrastructure I^G, levies taxes (τ^s, τ^L, τ^M, τ^*, $\tau^{M,M}$, $\tau^{S,M}$, $\tau^{M,S}$, $\tau^{S,S}$, $T(.)$) and issues foreign debt B^* (which carries an exogenously determined rate of interest). Incomes and expenditures yield the government budget constraint, which must be satisfied.

D. Stationary Competitive Equilibrium

Given sequences of the tax rates for final consumption τ^s,τ^L, τ^M, τ^*, the tax rates for intermediate demand of inputs $\tau^{M,M}, \tau^{S,M}, \tau^{M,S}, \tau^{S,S}$, income tax function $T(.)$, government

[6] For example, Conesa and Kruger (2006) present a model were heterogeneity is the result of differences in abilities and age plus transitory shocks to labor productivity.

expenditure G^M, G^S, G^L, and I^G, government's external borrowing B^*, the international interest rate on government's debt r^*, the international prices for consumption goods p^* (and manufacturing goods which is normalized to 1), a competitive equilibrium is such that households and firms solve their respective optimization problems, markets clear, and the government budget constraint is also satisfied. Individuals have rational expectations.

Benchmark Economy

The model is calibrated to account for aggregate and cross-sectional facts of the U.S. economy. Our quantitative analysis therefore departs from the model specification and parameter values estimated by Lizarazo, Peralta-Alva, and Puy (2017), which are such that the model matches key macroeconomic ratios (private investment to GDP, consumption to GDP, etc.), sectoral ratios, as well as key distributional statistics. This steady state of the model, which we denote as the "benchmark US economy" will serve as the baseline for the comparison of different steady states throughout the paper.

A. Preferences

Preferences over consumption and leisure are represented by a period utility of the form

$$u(c,o) = \frac{1}{1-\sigma}\left(c - \omega\frac{(1-o)^{\theta+1}}{\theta+1}\right)^{1-\sigma}$$

The consumption aggregator is given by

$$c = \left[\gamma\left(c^T(c^M,c^*)\right)^{\rho} + (1-\gamma)\left(c^N(c^S,c^L) + \overline{c^N}\right)^{\rho}\right]^{\frac{1}{\rho}}$$

$$c^T = \left[\gamma^T(c^M)^{\rho^T} + (1-\gamma^T)(c^*)^{\rho^T}\right]^{\frac{1}{\rho^T}}$$

$$c^N = \left[\gamma^N(c^L)^{\rho^N} + (1-\gamma^N)(c^S)^{\rho^N}\right]^{\frac{1}{\rho^N}}$$

The coefficient of risk aversion to $\sigma = 2$. The discount factor β is chosen so that the equilibrium of the benchmark has the capital-output ratio close to its value in the data. ω and θ are chosen so that average hours worked in the economy by the household correspond to $\frac{1}{3}$ of their time, and the labor elasticity to wages is approximately $\frac{1}{3}$. The elasticity of substitution between consumption goods is assumed to be 1 (so that $\rho = \rho^T = \rho^N$, and $\rho \to 0$. The setting the parameter $\overline{c^N} > 0$ ensures that income elasticity demand for services increases with income, this parameter is then chosen such that consumption of manufacturing and imported consumption goods share of total consumption is, as in the data, approximately eight percentage points larger for the top quintile than for the bottom quintile of income distribution. The share of services on total consumption $1-\gamma$ and low skill services in total services consumption γ^N are calibrated in such way that, given the shares of high-skill intermediate inputs in the production of manufacturing and high-skill services sectors (derived from input-output data), the model matches the total share of low skilled and high skilled services production in GDP (which corresponds respectively to 30 percent and 50 percent of total GDP). The share of domestically produced goods in tradable goods consumption γ^T is calibrated to match a share of consumption of imports in total consumption expenditure of approx. 10 percent.

B. Household's labor productivity

The permanent component given by skill levels in the model is proxied by education attainment levels in the US population as reported by the Census Bureau (2016). Individuals with high school degree or less as are classified as low skill individuals, and individuals with more than bachelor's degree are high skill individuals. The average labor productivity of medium skill level households is normalized to 1 (i.e., $\eta_x = 1$), and consider differences in average years of education as proxies for differences in skill levels.

Table 1. Skills Parameters

Parameter	Value	Target
μ_l	0.39	Population share with high school degree or less.
μ_x	0.48	Population with some college, no degree, associate degree or bachelor degree.
μ_h	0.13	Population share with a Bachelor's degree or more
η_l	0.7	Approx. 12 years of education.
η_x	1	Approx. 16 years of education.
η_h	1.1	More than 16 years of education.

C. Government

Consumption (and intermediate consumption) taxes are set at 7.5%, which is the approximate mid-point for the range of state sale taxes in US. For the benchmark calibration government consumption is chosen to be 16% of GDP, as the average in the data for the period 2009–15 per the World Bank data.

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