**RESEARCH PROJECT IDEAS**

The Growth of Low-Skill Service Jobs

and the Polarization of the US Labor Market†

In net, employment changes in the United States during this period were strongly U-shaped

in skill level, with relative employment declines in the middle of the distribution and

relative gains at the tails. Notably, this pattern of employment polarization is not

unique to the United States. Although not recognized until recently, a similar “polarization”

of employment by skill level has been underway in numerous industrialized

economies in the last 20 to 30 years. (MAKE TIME SERIES FOR CHANGES IN EMPLOYMENT WAGES, SKILL PERCENTILE?)

These simple exercises make a critical point: to interpret the pronounced polarization

of employment and wages in the United States and potentially in other

advanced countries, it is necessary to understand the rapid rise of employment and

wages in service occupations. The primary hypothesis advanced by this paper is that

polarization is driven by the interaction between two forces: consumer preferences, which favor variety over specialization; and non-neutral technological progress, which greatly reduces the cost of accomplishing routine, codifiable job tasks but has a comparatively minor impact on the cost of performing in-person service tasks. If consumer preferences do not admit close substitutes for the tangible outputs of service occupations—such as restaurant meals, house-cleaning, security services, and home health assistance—non-neutral technological progress concentrated in goods production (by which we mean non-service occupation activities) has the potential to raise aggregate demand for service outputs and ultimately increase employment and wages in service occupations.

We develop these implications in a general equilibrium model of “routine-task”

replacing technological change, building upon Autor, Levy, and Murnane (2003)—

henceforth, ALM—Weiss (2008), and in a broader sense, Baumol’s (1967) model

of unbalanced technological progress.8 Technological progress in our model takes

the form of an ongoing decline in the cost of computerizing routine tasks, which

can be performed both by computer capital and low-skill (“noncollege”) workers in

the production of goods. The adoption of computers substitutes for low-skill workers

performing routine tasks—such as bookkeeping, clerical work, and repetitive

production and monitoring activities—which are readily computerized because

they follow precise, well-defined procedures. Importantly, occupations intensive

in these tasks are most commonplace in the middle of the occupational skill and

wage distribution.

Alongside unbalanced technological progress, we evaluate numerous alternative

explanations for the pronounced differences in wage and employment polarization

across more and less routine-intensive labor markets, including deindustrialization,

offshoring, rising demand for home production substitutes among households with

high education and earnings, and growing low-skill immigration. None of these

alternatives appears central to our findings.

We explore these implications, starting with computer adoption, by using a measure

of geographic computer penetration developed by Doms and Lewis (2006) and

also employed in Beaudry, Doms, and Lewis (2010). Based on private sector surveys

of computer inventories, this measure counts the number of personal computers per

employee at the firm level, which is a relevant, albeit incomplete, measure of computer

adoption. Doms and Lewis purge this measure of industry by establishment size

fixed effects using a linear regression model and aggregate the adjusted variable

to the level of local labor markets. We match the Doms and Lewis “adjusted

computers-per-worker” measure for the years 1990 and 2002 to commuting zones.33

Following the approach of Doms, Dunne, and Troske (1997), we treat the 1990 level

of this variable as the “change” from 1980 to 1990, thus assuming that PC use was

close to zero in all areas in 1980. We approximate the change in this variable over

the subsequent decade using 5/6 of the 1990 to 2002 first-difference.34

This paper proposes an integrated explanation and conducts a detailed empirical

analysis of the forces behind the changing shape of low education, low wage

employment in the US labor market. We hypothesize that recent computerization

has substituted for low-skill workers in performing routine tasks while complementing

the abstract, creative, problem-solving, and coordination tasks performed

by highly-educated workers. As the declining price of computer technology has

driven down the wage paid to routine tasks, low-skill workers have reallocated

their labor supply to service occupations, which are difficult to automate because

they rely heavily on dexterity, flexible interpersonal communication, and direct

physical proximity. Our conceptual model shows that if the demand for these service

outputs does not admit close substitutes, then substitution of information

technology for routine tasks used in goods production can induce rising wages

and employment in low-skill service occupations. This hypothesis builds on

Baumol’s (1967) model of unbalanced technological progress by broadening it to

the study of skill demands and wage structure (in addition to Baumol’s focus on

sectoral composition).

Automation and New Tasks: How

Technology Displaces and Reinstates

Labor

Our results suggest that it is the combination of adverse shifts in the task

content of production—driven by accelerated automation and decelerating

reinstatement—and weak productivity growth that accounts for the sluggish growth

of labor demand over the last three decades and especially since 2000. Why has the

balance between automation and new tasks changed recently? Why has productivity

growth been so disappointing despite the acceleration in automation technologies?

Though we do not have complete answers to these questions, our conceptual framework

points to a number of ideas worth considering.

There are two basic reasons why the balance between automation and new

tasks may have changed. First, the innovation possibilities frontier linking these two

types of technological change may have shifted, facilitating further automation and

making the creation of new tasks more difficult (for a formal analysis, see Acemoglu

and Restrepo 2018a).

We find a second reason for a change in this balance more plausible: that

is, the US economy may have moved along a given innovation possibilities frontier

because incentives for automation have increased and those for creating new

tasks have declined. Several factors may push in this direction. The US tax code

aggressively subsidizes the use of equipment (for example, via various tax credits

and accelerated amortization) and taxes the employment of labor (for example, via

payroll taxes). A tendency towards further (and potentially excessive) automation

may have been reinforced by the growing focus on automation and use of artificial

intelligence for removing the human element from most of the production

process. This focus has recently been boosted both by the central role that large

tech companies have come to play in innovation with their business model based

on automation and small workforces, and by the vision of many of the luminaries

of the tech world (think of the efforts of Tesla to automate production extensively,

which turned out to be very costly). Finally, the declining government support for

innovation may have also contributed by discouraging research with longer horizons,

which likely further disadvantaged the creation of new tasks (which bear fruit

more slowly) relative to automation.

This list of factors may contribute not just to the changing balance between

automation and new tasks, but also to the slowdown in productivity growth. First,

because new tasks contribute to productivity, slower reinstatement will be associated

with slower productivity growth…Second, if innovations in both automation and new tasks are

subject to diminishing returns (within a given period of time or over time), a significant

change in the balance between these two types of new technologies will push us

towards more marginal developments and cause slower productivity growth. Third,

as we emphasized earlier, productivity gains from automation could be quite small

for so-so technologies—when automation substitutes for tasks in which labor was

already productive and capital is not yet very effective…Finally, in Acemoglu and Restrepo (2018d), we suggest there may be a mismatch between the available skills of the workforce

and the needs for new technologies.

**\*\*\* Look at cofounding factors \*\*\***

Explaining Job Polarization:

Routine-Biased Technological Change and Offshoring

The “Skill-Biased Technological Change” hypothesis (SBTC)—see Katz and

Autor (1999); Goldin and Katz (2008, 2009); and Acemoglu and Autor (2011) for

excellent overviews—arose from the observation that demand is shifting in favor

of more educated workers.

The main hypotheses put forward to explain job polarization are that recent technological

change is biased toward replacing labor in routine tasks (what we call routine-

biased technological change (RBTC)) and that there is task offshoring (itself

partially influenced by technological change), and that both of these forces decrease

the demand for middling relative to high-skilled and low-skilled occupations (Autor,

Levy, and Murnane 2003; Autor, Katz, and Kearney 2006, 2008; Goos and Manning

2007; Autor and Dorn 2013).

The second contribution of this paper is to develop and

estimate a model—that has its roots in the canonical model first developed by Katz

and Murphy (1992) for the analysis of SBTC—to quantify the importance of RBTC

and offshoring in explaining job polarization. Our estimates suggest that RBTC is

much more important than offshoring. We show that this model explains not just

overall job polarization but also its within-industry and between-industry components

that are both empirically important. Within each industry there is a shift away

from routine occupations leading to within-industry job polarization. But RBTC

also leads to significant between-industry shifts in the structure of employment. On

the one hand, an industry affected by RBTC will use less employment to produce a

given level of output which will cause occupational employment shares to polarize

even if output shares do not. On the other hand, industries intense in routine tasks

will see a larger decrease in relative costs and output prices leading to a shift in

product demand toward these industries (as was first pointed out by Baumol 1967).

We show that, in our data, this effect attenuates between-industry job polarization

but does not overturn it.

B. Routineness and Offshorability of Occupations

Following the recommendation of Autor (2013) that researchers use, as far as

is possible, off-the-shelf measures for the content of occupations, our measure of

the routineness of an occupation is the Routine Task Intensity (RTI) index used

by Autor and Dorn (2013) and Autor, Dorn, and Hanson (2013)3 mapped into our

European occupational classification and normalized to have zero mean and unit

standard deviation. The resulting RTI index is reported in column 3 of Table 1. RTI

is highest at 2.24 for office clerks (41) and lowest at −1.52 for managers of small

enterprises (13)

While the literature seems to be settling on using the RTI measure as the best way

to capture the impact of recent technological progress, there is, as yet, no similar

consensus measure about an occupation’s offshorability to capture the impact of

offshoring. We use a measure taken from Blinder and Krueger (2013).4 Using the

individual level Princeton Data Improvement Initiative (PDII) dataset, Blinder and

Krueger (2013) report three measures of offshorability: one self-reported, one a

combination of self-reported questions made internally consistent, and the last one

which is based on professional coders’ assessment of the ease with which each

occupation could potentially be offshored. Blinder and Krueger (2013) conclude

that their third measure is preferred. For our analyses, we convert this preferred

measure into our European occupational classification and normalize it to have zero

mean and unit standard deviation. The resulting values are reported in column 4 of

Table 1. The most offshorable are machine operators and assemblers (82) at 2.35

and the least offshorable are drivers and mobile plant operators (83) at −1.

Why Are There Still So Many Jobs?

The History and Future of Workplace

Automation

Because jobs that are intensive in either abstract or manual tasks are gener

Ally found at opposite ends of the occupational skill spectrum—in professional,

managerial, and technical occupations on the one hand, and in service and laborer

occupations on the other—this reasoning implies that computerization of “routine”

job tasks may lead to the simultaneous growth of high-education, high-wage jobs at

one end and low-education, low-wage jobs at the other end, both at the expense

of middle-wage, middle education jobs—a phenomenon that Goos and Manning

(2003) called “job polarization.” A large body of US and international evidence

confirms the presence of employment polarization at the level of industries, locali

ties, and national labor markets (Autor, Katz, and Kearney 2006, 2008; Goos and

Manning 2007; Autor and Dorn 2013; Michaels, Natraj, and Van Reenen 2014;

Goos, Manning, and Salomons 2014; Graetz and Michaels 2015; Autor, Dorn, and

Hanson 2015)

As Figure 2 illustrates, the rapid employment growth in both high- and

low-education jobs has substantially reduced the share of employment accounted

for by “middle-skill” jobs. In 1979, the four middle-skill occupations (sales; office

and administrative workers; production workers; and operatives) accounted for

60 percent of employment. In 2007, this number was 49 percent, and in 2012, it

was 46 percent. The employment share of service occupations was essentially flat

between 1959 and 1979, and so their rapid growth since 1980 marks a sharp trend

reversal (Autor and Dorn 2013).

As noted earlier, technological change is far from the only factor affecting US

labor markets in the last 15 years. For example, the deceleration of wage growth

and changes in occupational patterns in the US labor market after 2000, and

further after 2007, is surely associated to some extent with two types of macro

economic events. First, there are the business cycle effects—the bursting of the

“dot-com” bubble in 2000, and the collapse of the housing market and the ensuing

financial crisis in 2007–2008—both of which curtailed investment and innovative

activity. Second, there are the employment dislocations in the US labor market

brought about by rapid globalization, particularly the sharp rise of import pene

tration from China following its accession to the World Trade Organization in

2001 (Autor, Dorn, and Hanson 2013; Pierce and Schott 2012; Acemoglu, Autor,

Dorn, Hanson, and Price forthcoming). China’s rapid rise to a premier manufac

Turing exporter had far-reaching impacts on US workers, reducing employment

in directly import-competing US manufacturing industries and depressing labor

demand in both manufacturing and nonmanufacturing sectors that served as

upstream suppliers to these industries.

Of course, these forces are in various ways linked with the spread of automation

and technology. Advances in information and communications technologies

have changed job demands in US workplaces directly and also indirectly, by making

it increasingly feasible and cost-effective for firms to source, monitor, and coordinate

complex production processes at disparate locations worldwide and altering

competitive conditions for US manufacturers and workers. This multidimensional

complementarity among causal factors makes it both conceptually and empirically

difficult to isolate the “pure” effect of any one factor.