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How automation and other forms of IT affect the middle class: Assessing the estimates

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Introduction

In the last four decades, the US and other industrialized economies have experienced a pronounced drop in the fraction of the population working in middle-waged jobs. Since employment growth has been weighted toward the upper- and lower-tails of the wage distribution, this phenomenon has become known as job polarization. An important literature demonstrates that this change has meant the loss of job opportunities in a certain type of occupation—those that are routine in nature, for which the tasks performed on the job follow a well-defined linear structure or procedural routine. The fact that such occupational tasks are easily automated has led researchers to study the role of recent advances in "automation technologies" in this disappearance of middle-skilled jobs. In this paper, we review the literature regarding polarization and the changing nature of work in the US economy, and discuss its implications for the middle-class.

In Section 2, we first review the literature on job polarization, beginning with a discussion of changes in employment and wages observed over the past 40 years. We continue by discussing the literature that addresses employment adjustment dynamics of "routine workers." As mentioned, the leading hypothesis is that technological advancement lies behind this phenomenon; in Section 3, we discuss the existing evidence and address the hypothesis that "globalization forces" are behind the labor market changes affecting middle-skilled occupations. These employment and wages facts raise the obvious policy question: what can be done in response to these changes? In Section 4, we review the existing theoretical work that aims at providing a framework where policy analysis can be evaluated. Finally, Section 5 points to directions of future work that are crucial in addressing the future of middle-class labor market opportunities.

Job Polarization

In the 1990s, a primary emphasis of economic research was documenting the rise in wage inequality experienced in advanced economies, especially in the US, and understanding its root causes (see, for instance, the seminal work of Katz and Murphy (1992) and the papers published in the same volume of the Quarterly Journal of Economics). An important focus area of this work was dedicated to the rising skill premium—namely, the increasing premium paid to college-educated workers (or, as is often referred to in economics, “high-skilled” workers) relative to those with lower educational credentials. This widening inequality gap was particularly striking since the relative supply of high-skilled workers was increasing, due to increasing college graduation rates.[1] All else equal, as high-skilled workers were becoming more abundant the price paid for their labor services should have fallen, relative to that of the low-skilled (who were becoming relatively more scarce).

Of course, the rationalization of this paradox is simple: all else was not equal. That is, simultaneous to the increase in supply, the demand for high-skilled labor was increasing due to skill-biased technological change: the changing nature of economic activity—brought about by advances in the productive capabilities of machinery, equipment, and software (especially in terms of personal computing and information technology)—was complementary to the highly-educated (see, for instance, Katz and Autor (1999); Violante (2008); Acemoglu and Autor (2011), and the references therein). Those with higher levels of education benefited from these technological advances to a much greater extent than did those with less education.

Within this context, the seminal work of Autor, Katz, and Kearney (2006) (hereafter AKK) documented a new element regarding the evolution of inequality, by looking separately at the top and bottom halves of the wage distribution. Changes in the top half of the wage distribution paint a well-known picture–that the top keeps pulling away from everywhere else. In data from the Bureau of Labor Statistics (BLS), Current Population Survey (CPS), the gap between the median wage and the 90th percentile wage increased by about 20 log points between 1973 and 2004. But since the late-1980s, inequality in the lower half of the distribution (as measured by the ratio between the median and 10th percentile wage) does not continue to worsen. It stops growing, and even narrows (depending on the precise year against which it is measured).

Given this, AKK shift attention to the changing composition of employment by occupation—namely, how much and what type of work is being done in the US economy, when work is delineated by “job.” Ranking occupations by how much they pay in terms of median hourly wage (as measured in the

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1. [1]Another main thrust was in documenting residual “within” inequality, see for instance Juhn, Murphy, and Pierce (1993).

1980 decennial Census), AKK show that the share of total employment in both low-paying and high-paying jobs has increased since 1990 Census. Obviously, this means that the share of employment in middle-wage occupations has fallen.

This phenomenon is displayed for the period 1980-2005 in Figure 1, as taken from Autor and Dorn (2013). Occupations at the very bottom of the wage distribution, and those at or above approximately the 60th percentile have been growing in terms of employment share; by contrast, the middle of the wage distribution has "hollowed out." As such, this pronounced change in the labor market is referred to as job polarization. Clearly these changes in occupational employment have been an important contributor to the overall evolution of wage and income inequality in the US.

Goos and Manning (2007) and AKK relate this to the fact that occupations at different points of the wage distribution differ fundamentally in the nature of tasks they perform. Following Acemoglu and Autor (2011), it is useful to delineate occupations along two dimensions: cognitive versus manual, and routine versus non-routine. The distinction between cognitive and manual occupations is straightforward, characterized by differences in the extent of mental versus physical activity ("brains" versus "brawn," as it were) required on the job. The distinction between routine and non-routine jobs is based on the pioneering work of Autor, Levy, and Murnane (2003). If the tasks involved can be summarized as a relatively small set of specific, repetitive activities accomplished by following well-defined instructions and procedures, the occupation is considered routine. If instead the job entails a larger number of tasks requiring flexibility, creativity, problem-solving, or human interaction, the occupation is non-routine.

Using the terminology of Goos and Manning (2007), both the "lovely" jobs at the top of the occupational wage distribution, and the "lousy" jobs at the bottom focus on non-routine of tasks. High-paying non-routine cognitive occupations include managerial, professional and technical jobs. Low-wage jobs are largely service occupations involved in the assisting or caring for others, and focus on non-routine manual tasks. Occupations focused on routine tasks, by contrast, tend to occupy the middle of the wage distribution and are, thus, "middleclass jobs".[2]

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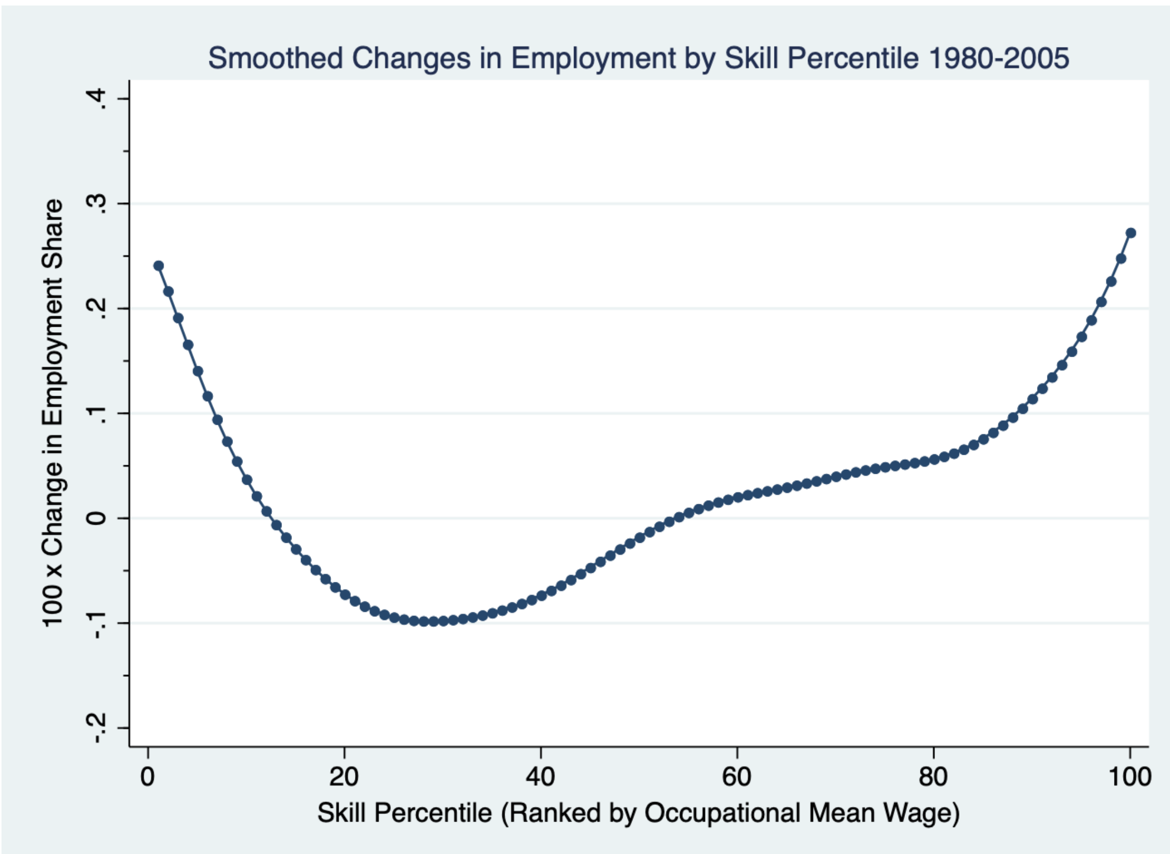
2. [2] To be clear, the pioneering work of Autor, Levy, and Murnane (2003) was the first to demonstrate changes in the task content of employment, with work shifting away from routine tasks. This was based on changes in the occupational distribution, and shown to be largely a within industry phenomenon. The work of Autor, Katz, and Kearney (2006) and Goos and Manning (2007) were the ones to most clearly relate these changes to widening inequality and job polarization.

Using data from the New Earnings Survey and the Labour Force Survey, Goos and Manning (2007) show job polarization has been occuring in the UK, 1975-1999.[3] The top jobs in terms of UK employment growth include the high-wage occupations of financial managers and software engineers (non-routine cognitive), and care assistants and attendants (low-wage, non-routine manual). The slowest growth occupations were machine setters and operators; these are prime examples of routine manual occupations, found in the manufacturing industry. But equally important to the polarization phenomenon are routine cognitive jobs—secretaries and administrative assistants, office clerks, and data entry keyers—located in all industries in an economy.

Figure 1: Job Polarization: Ranking Occupations by Wages



Notes: Smoothed changes in occupational employment share by wage percentile. This figure is reproduced from Autor and Dorn (2013). See text for details.

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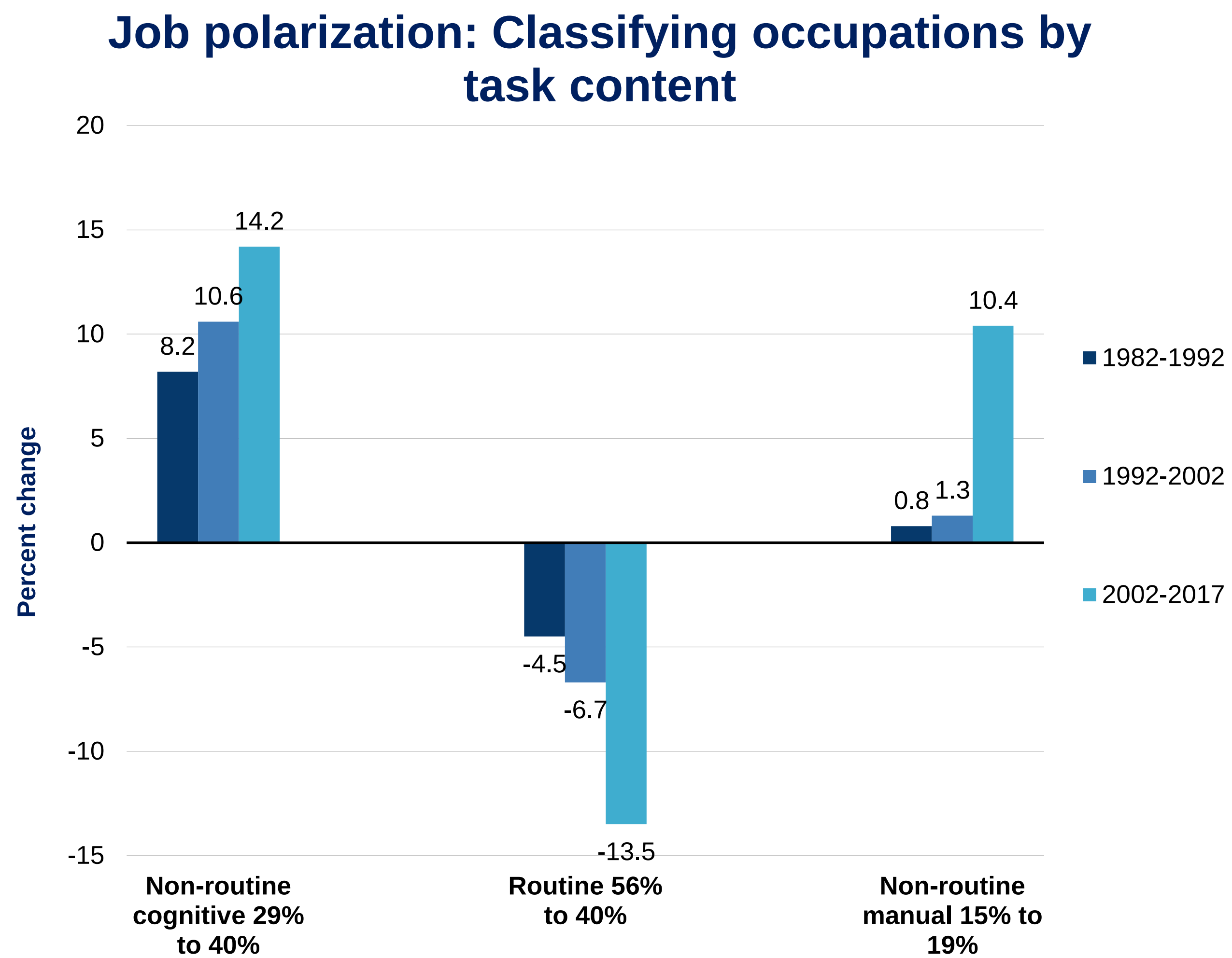
3. [3] Given the nature of this review, discussion will largely focus on the US economy and findings relating to the US labor market. However, it is important to note that job polarization, and its relation to the routine nature of middle-class jobs, has been widely documented across all industrialized economies. See, for instance, Green and Sand (2015) for analysis of Canada, Spitz-Oener (2006) for Germany, and Goos, Manning, and Salomons (2009) for Europe.

Figure 2: Job Polarization: Classifying Occupations by Task Content



Notes: Changes in employment share by occupation group.
Source: This figure is reproduced from Jaimovich and Siu (2018). See text for details.

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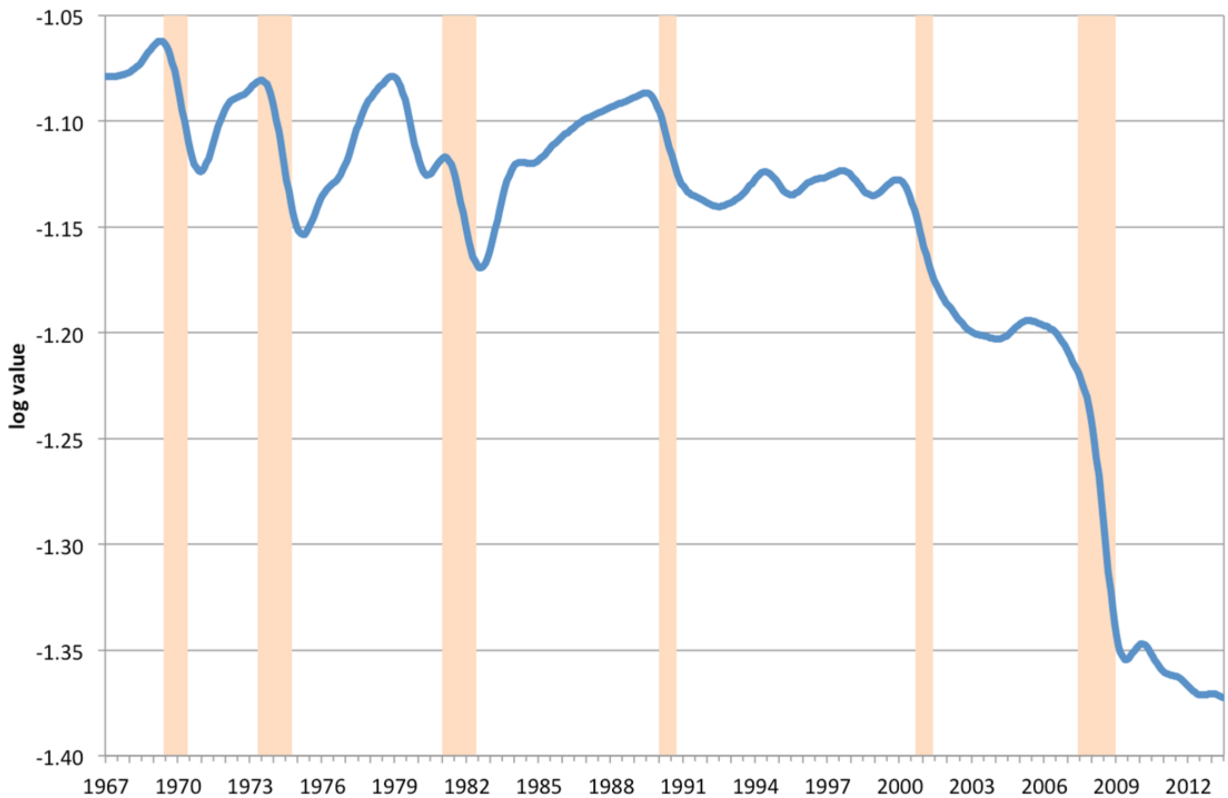
More recently, Jaimovich and Siu (2018) study the temporal nature of this hollowing out and the loss of middle-class jobs. Figure 2 presents the change in the share of total employment represented by the various occupation groups. Clearly, polarization represents diminished job opportunities in middle-wage, routine occupations. Jaimovich and Siu (2018) ask how this process has unfolded over time: whether the losses have been gradual or whether they are “bunched up” within certain time intervals. To do this, they use employment data at the monthly frequency delineated by occupational groups, from 1967 to 2017. This data comes from Employment and Earnings, a historical publication of the BLS, and more recently from the CPS.

Jaimovich and Siu (2018) find that losses are clustered around economic downturns. Specifically, of all the per capita employment losses in routine occupations experienced in the US, 88% occurred within a 12 month window of NBER-dated recessions. This is indicated in Figure 3. Since the late 1980s, when employment is lost in these routine occupations, they do not return. This is in contrast to what occurred before the job polarization era. Prior to the late 80s, job losses in routine occupations during downturns would quickly rebound following recessions.[4]

Figure 3: Routine Job Loss around NBER-dated Recessions



Notes: Logged per capita employment in routine occupations. This figure is reproduced from Jaimovich and Siu (2018). See text for details.

A natural question this raises is what happens to people who were previously employed in these middle-class jobs? Where do they go? Answering such questions and uncovering the response of individuals to the loss of middle-class job opportunities is challenging. This is because of a scarcity of panel data that is representative of the US population, and rich both in terms of time coverage and sample size.

Cortes (2016) is the first to do so, tracking prime-aged male household heads, 1976-2007, in the Panel Study of Income Dynamics (PSID), a longitudinal study following the same 9,000 US families since 1968. A key insight to the paper's approach is the fact that workers in routine occupations differ in their work ability (i.e., their productivity or wage-earning potential) and, hence, their occupational switching behavior. Given this, Cortes (2016) finds that both low- and high-ability routine workers are more likely to switch out of routine employment, as compared to those of middle-ability, since at least the 1990s. Moreover, among individuals that do switch out of routine jobs, the occupations they switch into are dependent on their work ability. High-ability routine workers are significantly more likely to move to (higher-paying) non-routine cognitive occupations; those with low ability are more likely to switch to non-routine manual occupations than those in the middle. These findings validate the predictions of textbook models of occupational choice based on comparative advantage. In addition, Cortes (2016) uses a novel identification strategy to obtain credible estimates of how occupational wages have changed over time. This is required since workers select into occupations based on unobserved ability.[5] Cortes (2016) confirms that, indeed, routine occupations have seen a significant fall in wages. The routine wage premium (relative to non-routine manual occupations) fell by 17% from 1976-2007, while the non-routine cognitive wage premium increased by 25%.

An inherent difficulty of the PSID is that the sample size is small. For instance, the analysis of Cortes (2016) covers about 6000 people.[6] The Current Population Survey (CPS) on the other hand, being the main source of labor market statistics in the United States, samples approximately 60,000 individuals per month. This data, too, involves a longitudinal dimension because of its rotating sample design: households are interviewed for four consecutive months, leave the sample for eight months, then return for another four months of interview. But while the CPS is richer than the PSID in terms of the number of respondents, it suffers along the time dimension because of its very short panels.

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4. [4] Hence, the new nature of cyclical booms and busts and the onset of "jobless recoveries" is attributable to the polarization dynamics of per capita employment in routine occupations. See also Gaggl and Kaufman (2015) who corroborate these findings, using an entirely distinct methodology to classify occupations based on their business cycle characteristics.

5. [5] Given modeling assumptions, this selection issue is overcome using fixed effects for occupational spells, a measure that can only be obtained from longitudinal data.

6. [6] In addition, because it follows families/households that were included at its origin in 1968, it undersamples recent immigrants; see Moffitt et al. (2015).

Nonetheless, while little can be learned about individual-level experiences, the CPS allows us to track labor market transitions (in terms of occupational and employment status) for "synthetic cohorts" composed of those with similar demographic characteristics. This is the approach taken in Cortes et al. (2016). As is well known, the number of people employed in a routine occupation depends on two worker flows: inflows and outflows. The inflows are workers moving into routine employment from somewhere else (those employed in another occupation, the unemployed, or those previously not participating in the labor force); the outflows are those leaving routine employment for another destination. Cortes et al. (2016) find that since the late 1980s, the bulk of the disappearance in routine employment has come from changes in inflows, especially from unemployment and labor force non-participation. In terms of specific demographic characteristics, these changes are primarily due to those of the young—those in their 20s and early-30s.

In a highly related paper, Cortes, Jaimovich, and Siu (2017) further study the disproportionate effect the disappearance of routine jobs has had on certain demographic groups. The loss of middle-class, routine manual occupations (e.g. machine operators, production workers) has been most acute for young and prime-aged men with lower levels of education (those with no more than a high school diploma). For middle-class, routine cognitive occupations (e.g. secretaries, administrative support workers), the vast majority of the decline has been felt by young and prime-aged women with intermediate levels of education (a high school diploma and, perhaps, some non-degree post-secondary training). Moreover, these same demographic groups are key in understanding the fall in two key US statistics over the past 25-30 years: the labor force participation rate and employment-to-population ratio among the prime-aged population, a growing concern among economists and policymakers (see, for instance, Aaronson et al. (2014); Krueger (2017); and Abraham and Kearney (2019)). From an accounting sense, these groups account for all of the change observed since the late 1980s.[7] Moreover, though to a slightly lesser extent, they account for the rise of employment in low-wage, non-routine manual occupations.

This last point, of course, is closely related to the work of Autor and Dorn (2013) (hereafter AD), regarding the rise of employment in "service occupations" between 1980 and 2005. AD document that the growth in employment in low-wage occupations—the lower half of the U-shape in Figure 1—is entirely driven by jobs involved in the assisting or caring for others (e.g., food service workers, guards, cleaners, child care workers, and home health aides).

Using data from IPUMS, drawing from US decennial Censuses and 2005 American Community Survey (ACS), AD further their analysis by looking at spatial variation across geographic locations, specifically commuting zones (CZ). CZs in 1980 differ in the share of their workers employed in routine-intensive occupations. The larger is their share, the greater is the predicted growth in the CZs fraction of non-college educated workers employed in service occupations in 2005.[8] Moreover, places that were initially "more routine" also saw greater adoption of the PC in the private sector, as measured by the number of personal computers per employee at the firm level. This forms an important empirical basis for the narrative of technological change pushing less-educated workers out of middle-class jobs into lower-paying occupations. This is explored in detail in the following section.

Before further exploring the role of technology and automation on job polarization, one final point is worth making. The papers discussed above focus on employment changes between occupations; that is, job polarization is largely discussed as growth in certain occupations and decline in others. Implicitly, the view is that occupations are largely unchanged over time, in the nature of tasks they perform and the skills required to perform them; this is a point we return to in Section 5. Much less research has been done with respect to changes in the nature of work within occupations. Perhaps unsurprisingly, this is due to the relative lack of existing data that allows one to documents such change.

As an important exception, Spitz-Oener (2006) is the first to do so, using information from the Qualification and Career Survey in Germany. Using cross-sectional data from 30,000 respondents per survey, the paper tracks the activities these individuals perform on the job and their skill requirements, between 1979-99. Spitz-Oener (2006) finds that occupations require more complex (non-routine) skills over time, and that changes in skill requirements have been most pronounced in rapidly computerizing occupations. More recently, researchers have turned to textual analysis of job advertisements, to track firms' demand for skills and the changing nature of tasks performed under posted job titles. For instance, Atalay et al. (2019) construct a dataset of over 9 million newspaper job advertisements, 1950–2000, and use it to quantify the importance of within occupation task changes to widening earnings inequality; Hershbein and Kahn (2018) study skill demand using online job advertisements and find evidence of persistent "upskilling" in job requirements within occupations in response to the 2007 recession. Further research along this dimension would certainly be beneficial in understanding changes in job opportunities, and the skills required to perform those jobs, for middle-class workers.

Forces behind job polarization

What is causing these changes in the occupational distribution of employment? What is responsible for the changing nature of work being performed in the labor market? More specifically, what forces are behind job polarization and the loss of employment in middle-wage, routine-intensive occupations? As mentioned above, the economics profession is unanimous in identifying technological change and "automation" (in the form of industrial robotics and computing and information technology) as the primary factor.

Specifically, the non-routine tasks emphasized in both "lousy" and "lovely" jobs are not easily performed by machines. While computer controlled robotics have been very effective at performing the work of machinists and other workers on the "production line," they have been less effective at the tasks done, for instance, by landscapers and child care workers, in less controlled environments. And while information and communication technology are well equipped for the processing and organization of information, and data entry/retrieval— thus greatly simplifying the work of secretaries, typists, and travel agents—they have not yet replaced physicians and surgeons, senior managers, and policymakers in roles where discretion and decision-making are important. That is, non-routine labor input is not easily substitutable with modern technology, while routine labor is. Indeed, the phrase routine biased technical change (RBTC) appears frequently in papers addressing job polarization.

The role of automation has been considered along both theoretical and empirical lines. In this section we review the more empirically-oriented literature, and reserve discussion of theoretical work to Section 4. Discussion of other forces causing polarization is reserved for later in this section.

An early paper is Michaels, Natraj, and Reenen (2014) who study the role of information and communication technology (ICT) in job polarization. They do so using a detailed industry-level panel dataset for Japan, the US, and 9 industrialized European countries, 1980-2004. The key independent variable is a measure of industry-level ICT investment. They ask whether ICT investment has differentially affected demand for high-, middle-, and low-skilled labor, as reflected in these groups' share of total labor income.[9] Looking across countries, Michaels, Natraj, and Reenen (2014) find that ICT investment is positively correlated with changes in the high-skill group's share of labor income, negatively correlated with changes for the middle-skilled, and uncorrelated with changes for the low-skilled. More specifically, including variation across industries, the greater is the increase in ICT investment (at the industry-country level) the greater is the increase in the high-skilled labor's share, and the greater is the decrease in the middle-skill's share of labor income (with, again, insignificant effects on the least-skilled group).

Graetz and Michaels (2018) follows a similar research design to Michaels, Natraj, and Reenen (2014), but focusing specifically on industrial robotics. Such robots perform tasks (e.g., welding, painting, packaging) that were historically done by humans due to the need for agility and flexibility in movement in three-dimensional space. Using the same crosscountry industry panel data-set (EUKLEMS) of Michaels, Natraj, and Reenen (2014), they consider 15 European countries plus South Korea and the US, and given the focus of their study, place a particular emphasis on manufacturing industries, 1993-2007. In terms of motivation, industrial robotics are potentially impactful, given that the (quality-adjusted) price of robots has almost halved during this time period.

The main independent variable of Graetz and Michaels (2018) is the number of robots delivered to each industry, in each country and year, taken from the International Federation of Robotics (IFR). From this, they are able to construct a measure of "robot density" defined as the number of industrial robots per hour worked. Averaged across countries in sample, robot density increased by over 150%. Graetz-Michaels' main finding is that robot densification is associated with a statistically and economically significant increase in the productivity of labor. There are also positive and significant effects on mean hourly wages, but of an order of magnitude smaller than that found for labor productivity. This suggests very different benefits of this form of RBTC accruing to workers (as wages) relative to firm owners (who benefit from increased productivity). This interpretation is consistent with findings of Eden and Gaggl (2018) and Autor and Salomons (2018), that job polarization via automation is a potentially

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9. [9] High-skill refers to workers with a college degree; middle- and low-skill definitions are less consistently recorded across countries. It should be noted that the results cannot speak directly to changes in occupational demand, since there are no measures of occupation-level ICT investment (in addition to the lack of consistent occupational data across countries).

important factor in the decline of labor's share of national income, both in the US and a broader sample of industrialized countries.

Graetz and Michaels (2018) also find little to no effect on total hours worked; the idea that there is job loss without countervailing job creation is not supported in their data. But in terms of the share of hours worked by low-skilled workers, there are large (and in almost all cases, statistically significant) negative effects. This compares with the work of Acemoglu and Restrepo (2019) who also measure industrial robots using IFR data. By contrast, they consider variation across "local labor markets" within the US, as represented by commuting zones (CZs), in terms of a location's initial industrial composition and subsequent industry specific robot penetration. Acemoglu and Restrepo (2019) find negative labor market effects, translating to approximately 3-6 fewer workers for each new robot.

Finally, Gaggl and Wright (2017) and Tuzel and Zhang (2019) consider the role of investment on the labor market and, specifically, occupational dynamics. Gaggl and Wright (2017)'s work exploits a unique natural experiment generated by UK tax policy: a 100 percent tax credit for investments in ICT that was made exclusively to small firms between 2000 and 2004, with a sharp discontinuity in the incentive to invest in ICT at the firm-size eligibility threshold. Given the nature of the policy, the estimated effects of ICT on labor market outcomes such as employment are arguably causal.[10] Gaggl and Wright (2017) find that ICT investment raises productivity, average weekly earnings and employment. However, the rise in earnings and employment is concentrated among workers engaged in non-routine, cognitive-intensive tasks; the opposite effect is found for routine cognitive work. They provide evidence that these divergent effects are due to the adoption of advanced management techniques, and changes in firms' organizational structure. Tuzel and Zhang (2019) use establishment-occupation level panel data from the US to study a federal tax incentive for equipment investment, and the differences across eligible and ineligible firms. Within an industry and size group, eligible firms increase equipment investment and highskilled employment in response to the stimulus plan. However, the overall employment effect is small

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10. [10] 10The nature of their results thus differs from other studies that simply correlate ICT and labor market changes. In such cases it could be argued, for instance, that variation in workforce characteristics (e.g. changing educational composition of workers) across countries, or that variation across more and less productive industries incentivize or cause differences in ICT investment or technological adoption.

because eligible firms significantly reduce the number of workers who perform routine tasks over a span of 2 to 3 years.[11]

A second, and perhaps more controversial, hypothesis is that the decline of middle-class job opportunities is due to forces of globalization and the increasingly free flow of goods and services across borders. With respect to the US labor market, globalization's effects are potentially manifest in two ways: (a) "offshoring", the trading of tasks at different stages of a production process with an increasing number of tasks performed internationally (see, for instance, Grossman and Rossi-Hansberg (2008)), and (b) the more familiar notion/channel of trade in finished goods with an increasing volume of manufactured goods produced internationally. In contrast to the case for automation, the empirical evidence for the role of globalization is less conclusive. We review relevant findings here, and note that further analysis along this dimension—especially work quantifying the comparative importance of automation versus globalization in accounting for declining fortunes for the middle-class—is warranted.

An early paper to address these issues is Goos, Manning, and Salomons (2014), who run a "horse-race" between RBTC and offshoring in accounting for employment dynamics in a sample of 16 European countries, during 1993–2010. The goal is to account for differences in employment growth observed at the occupation-industry-country level. The key to the Goos, Manning, and Salomons (2014) analysis is the measurement of variation in an occupation's intensity in performing routine tasks, as defined by AD, and well as its offshorability, as defined by Blinder and Krueger (2013)'s measure (using the Princeton Data Improvement Initiative dataset). While the two measures are naturally related, the correlation is far from perfect. As an example, while the tasks performed by office clerks are highly routine, they are hard to offshore; on the other hand, while engineering occupations are relatively non-routine, their tasks are highly offshorable. Moreover, Goos, Manning, and Salomons (2014) confirm that middle-class jobs in their sample countries are closely associated with "routineness."

Their key result is a clear negative correlation between an occupation's susceptibility to automation and its employment growth. The more routine an occupation is (at the industrycountry level),

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11. [11] 11Before proceeding, it is worth noting a further potential implication of automation and recent technological change: its role in accounting for the declining urban wage premium earned by non-college educated workers, the changing nature of work performed by the less educated, and increasing urban inequality. This is an area worthy of further research; see, for instance, Baum-Snow, Freedman, and Pavan (2018) and Autor (2019).

the slower is its employment growth; the effect is statistically significant and robust across regression specifications. By contrast, even in a simple reduced-form setting, the effect of an occupation's offshorability is near zero (with both regressors normalized for comparability of coefficient estimates) and statistically insignificant when routineness is included in the regression. As such, Goos, Manning, and Salomons (2014) conclude that the "horse race" is squarely "won" by the RBTC explanation.

Autor, Dorn, and Hanson (2015) consider a related question, disentangling the labor market implications of technology and trade (as opposed to offshoring), specifically import competition from China. Instead of studying occupation-industry-country variation, Autor, Dorn, and Hanson (2015) explore geographic differences across CZs. Disentangling these effects are possible because CZs are surprisingly distinct: "Chinese import-exposed" CZs are those specialized in labor-intensive manufacturing (furniture, toys, apparel); on the other hand, while "routine" CZs include some (auto) manufacturing intensive locations in the Midwest, they also include large metropolitan cities (e.g., New York, LA, Chicago) that are intensive in office/administrative support occupations in non-manufacturing industries. The analysis goes further to identify causal effects of technology and trade through an instrumental variables approach.[12]

Autor, Dorn, and Hanson (2015)'s primary results relate to the effect of technology and trade on a CZ's overall labor market, and not on middle-class workers or middle-class jobs per se. That said, the more China-exposed a locality is, the lower is employment and labor force participation growth; not surprisingly, this is driven by its consequences for manufacturing. Within manufacturing, negative effects are found for employment overall, but are magnified for the less-educated. In addition, the more trade-exposed a CZ is, the larger are the depressive effects on middle-class occupations outside of manufacturing. By contrast, there is no statistically significant evidence of overall employment effects stemming from exposure to automation. Instead, the negative effects are targeted in middle-class occupations. CZs that were initially more routine (and susceptible to automation) have experienced larger shifts in occupational composition—out of routine (production and clerical) occupations into non-routine

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12. [12] 12To see the importance of this, consider the case of trade exposure, as both labor market and trade outcomes may be correlated with unobserved shocks to US product demand.

work. Moreover, these changes are broad-based, not limited to the manufacturing sector, and are most evident outside of manufacturing.

It is important to note that while Autor, Dorn, and Hanson (2015) find effects for both technology and trade, the nature of the analysis is not able to quantify their relative roles for the decline of middle-class job opportunities. That is, “horse race” exercises that could shed light on statements attributing X% of routine job loss to automation versus Y % to globalization factors would likely require more (quantitative-)theoretical elements. As we are unaware of such work, this is an area where more research is warranted. That being said, given that manufacturing is small relative to the aggregate labor market (representing less than 20% of total employment even in the 1980s), attributing a large role for trade would require important spillovers, complementarities, and other general equilibrium effects.

In line with Goos, Manning, and Salomons (2014), other papers find less evidence for globalization factors in job polarization. Michaels, Natraj, and Reenen (2014) also study the importance of globalization by including empirical measures of offshoring and trade exposure to their regression analysis. They find that while ICT/automation effects are robust and statistically significant, globalization measures are not (or at best marginally significant) whenever ICT is included in their specifications.

Finally, in a recent paper Cortes and Morris (2019) consider occupational employment change and offshoring of jobs from the US to Mexico. If domestic jobs (for e.g., of welders or assemblers in automotive manufacturing) are being “shipped” or offshored to the cheaper labor market, occupations that are shrinking in the US would be growing south of the border, and thus negatively correlated. Cortes and Morris (2019) consider data at a detailed occupational level, matching occupational code descriptions in the two countries. Contrary to what one might expect, they find that the change in the employment share of different occupations is strongly positively correlated across the two countries. This is particularly true for routine manual occupations, like machine operators and other production occupations in auto manufacturing, which are on the decline in both countries. The occupations that exhibit the strongest growth in Mexico tend to be occupations that are also growing in the US. These results suggest that common shocks, namely the development of routine-task replacing technologies, are more likely to be the main driver of the observed changes in the occupational employment structure in both countries.[13]

Policy Evaluation

In this section, we turn to discussion of welfare analysis and policy evaluation. In particular, how have advances in automation and IT affected the middle class? What types of policy interventions are most likely to be effective to ensure that gains from technological progress and globalization are shared among all members of society?[14]

Answering such questions requires input from economic theory; that is, the findings of empirically-oriented work, on their own, are insufficient to speak comprehensively to these issues. Quantitative economic modeling allows one to gauge, for instance, the extent to which a typical middle-class, high-school educated individual has become worse off as compared to his/her college educated counterpart. Moreover, theory is needed to perform counterfactual analysis of various policy proposals—to evaluate their employment and welfare effects, to account for their financing/budgetary implications, and forecast their effects on aggregate economic growth and inequality. At the very least, this type of macroeconomic analysis makes clear how variation in underlying assumptions (for instance, regarding the distribution of capital ownership, or the underlying pace of technological change) impact the policy conclusions that might be drawn. This area of research—quantitative, policyoriented models of the consequences of polarization for the middle class—deserves much greater attention.

It is worth noting that the early work of Autor, Katz, and Kearney (2006) (AKK), while known for its empirical contribution, presented a stylized model of the labor market to rationalize its findings. This framework contains the basic building blocks of the small number of papers that have followed. In their

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13. [13] 3Finally, note that while our discussion has focused on the polarization of employment, an important related literature has studied the polarization of wages; see Firpo, Fortin, and Lemieux (2018) who document the role of de-unionization for increasing top-end inequality, and decreasing inequality at the low end.

14. [14] 4Again, it is worth emphasizing the value of research quantifying the relative impact of globalization and technology on middle-class job opportunities and prosperity. The ability of domestic, national policy to affect these macroeconomic forces obviously differs. Moreover, such work would speak to the merit of various policy proposals, for instance trade restrictions versus “robot taxation.”

model there are: three occupations, (nonroutine) cognitive, (non-routine) manual, and routine (combining cognitive and manual); and two types of workers: high- and low-skilled. Low-skill workers make an occupational choice, and supply their labor in either a routine manual job. The high-skilled simply work/supply labor in the cognitive job. In terms of labor demand, workers are put to use to produce aggregate output, via a production function that features different elasticities of substitution across labor in the three distinct occupations.

AKK's model is not meant to be quantitative, so it cannot provide an estimate of how much of job polarization is due to technological change, or how specific policy measures might reduce inequality. Nonetheless, the model predicts that automation (in the form of physical capital that perfectly substitutes with routine labor in production) drives lowskilled workers out of the routine, and into the manual occupation. Moreover, it increases wage inequality between the high- and the low-skilled. Unfortunately, the model doesn't allow for changes in employment and labor force participation; this is an important omission from a policy perspective given the link between job polarization and falling labor force participation, as discussed above. In addition, the dynamics of automation are taken as given, so the model cannot speak to the efficacy of policies like a "robot tax" meant to slow the adoption of labor-replacing technologies and/or redistribute resources toward the middle-class.[15]

As noted above, a number of features of AKK's analysis are the building blocks of subsequent work—specifically, the idea that automation is embodied in physical capital (machinery, equipment, and software) that substitutes for work performed in routine occupations, and the idea that labor in high-, middle-, and low-paying occupations (cognitive, routine, and manual occupations, respectively) feature differing elasticities of substitution (to automation capital, and to each other) in the production process.

Two recent examples adopt these features and extends the analysis to endogenize the accumulation of capital, so that the pace of automation advance is not simply taken as given. Eden and Gaggl (2018) demonstrate that measured changes in the price of information and communication technology, and its consequent adoption in production, accounts for over half of the recent decline in the share of US national income (GDP) accruing to labor (as opposed to payments to owners of capital) and,

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15. [15] See the recent work of Guerreiro, Rebelo, and Teles (2017), for theoretical analysis of robot taxation and inequality in a "Mirrleesean" setting, when the skill level of workers cannot be observed and non-routine workers may have the incentive to misreport their work ability.

more specifically, the share of national income that is paid to routine (as opposed to non-routine) labor. vom Lehn (2019) demonstrates that such a model, when calibrated to match employment dynamics of the 1980s and 90s, overpredicts the extent of polarization experienced since the turn of the century; this corroborates the findings of Beaudry, Green, and Sand (2016) who show that the increasing demand for high-skilled labor in cognitive occupations has slowed since 2000, to the point where it is no longer keeping up with the increasing supply of college-educated workers. vom Lehn (2019) finds that an extended version of the basic model—so that the implementation of automation technology is intensive in the employment high-skilled workers (as engineers or technical specialists)—is potentially successful in matching recent employment dynamics.

While important in quantifying the role of technological progress in ICT and equipment and software, these examples are not well-suited for the analysis of welfare impacts, inequality, and policy. First, as with the model of AKK, all workers are assumed to be employed with no difficulty in finding acceptable work opportunities; as such there is no scope for considering unemployment, or changes in labor force participation. Secondly, all workers are assumed to belong to one large, "unified family," so that the gains from routine-labor saving technology are equally shared by all. A meaningful model for redistributive policy analysis must obviously allow for both winners and losers from job polarization and automation.

The recent work of Jaimovich et al. (2019) represents one of the few comprehensive analyses to date. Their model takes elements of Eden and Gaggl (2018) and vom Lehn (2019), but includes an empirically realistic distribution of income, with high-skilled individuals also being the owners of capital and firms, while low-skilled individuals earn labor income and receive government transfers. In addition, individuals are not simply assumed to work, and may find themselves employed (either in a routine or non-routine occupation), unemployed, or out of the labor force. And importantly, all government insurance and redistribution programs (e.g., unemployment insurance, and recently discussed proposals for "universal basic income") must be financed through progressive labor and capital/profit taxation. Jaimovich et al. (2019) use this flexible and quantitatively relevant model as a laboratory to evaluate a number of policies aimed at aiding the middle class.

One experiment they consider is the introduction of universal basic income (UBI): every individual in the economy receives an equal lump-sum government transfer (financed through greater taxation). This diminishes the incentives to work, participate in the labor force and, in equilibrium, the incentives for investment and job creation. The quantitatively obvious effect of UBI is to redistribute income from high- to low-skilled individuals (who are employed in routine jobs, manual jobs, or out of the labor force). Jaimovich et al. (2019) find that the program has small effects on labor force participation and the likelihood of working, and larger effects on GDP (which falls) and distortionary taxation (which rises). By contrast, policy experiments found to have much greater impact on the likelihood of working include increases in unemployment insurance benefits, employment subsidies, and reduced labor income taxes on low-skilled workers.

Another policy experiment of Jaimovich et al. (2019) worth mentioning, given the conference theme, is a large-scale retraining program for middle-class workers who have been displaced from the labor force by advances in automation (with an emphasis on augmenting skills relevant to expanding employment in manual occupations); the policy counterfactual is “enacted” up to the point where the labor force participation rate is returned to the level observed prior to the late 1980s. The key finding from this experiment is that the fiscal burden of such a program would not be unusually great. This retraining would result in an increase of GDP of approximately 1%, while the “treated population” would amount to 3% of the population. Thus, as long as the cost of retraining amounts to less than 1/3 of per capita GDP, per participant, the program has a positive return. Whether such a large-scale retraining program is feasible, what it would consist of in terms of content and implementation, and if improving the skills of such a wide segment of society is possible is an open question, and research along these lines is of first order importance.[16]

A secondary lesson of this experiment is that there can be unexpected winners and losers from any well-intentioned policy. Among the low-skilled, for example, many naturally benefit given that retraining is targeted to them, allowing for reentry to the labor force. However, some individuals would also be negatively affected: these would be low-skilled individuals who do not exit the labor force and remain employed in the face of automation. But given that a non-negligible fraction of the population has

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16. [16] See, for instance, the review of active labor market programs by Card, Kluve, and Weber (2018). They find that training programs generally exhibit small employment effects in the short-run that turn positive only in the long-run, with larger effect for the long-term unemployed, e.g. those with low labor force attachment. It is again worth noting that the scalability of policies considered in observational studies and previous randomized control trials is unknown, and understanding their equilibrium or “macroeconomic” effects would require quantitative theoretical analysis, such as described here.

been retrained and become more productive, this increase in the supply of employable workers "crowds out" and "displace" a segment of the low-skilled from the labor force, rendering them worse off.

Finally, it is worth noting that the papers discussed in this section make an important simplifying assumption: the number and types of tasks performed in an economy are fixed and unchanging; workers work in one of three occupations: cognitive, routine, or manual (with automation technology capable of performing routine tasks). But in reality, as technology advances, the tasks performed in an economy expands, and this forms an important basis of the economic growth process. In a recent paper, Acemoglu and Restrepo (2018) provide a theoretical framework to articulate this. In their model, technological change is "directed," with innovation activities being devoted either to the automation of tasks previously performed by (low-skilled) workers, or the creation of new tasks in which workers (as opposed to machines) have the comparative advantage. Employment in these newly created tasks are assumed to be filled by high-skilled workers, as new tasks are "complex," or non-routine, in their nature. As such, this introduces an element that further contributes to the widening of inequality due to technological progress: while automation reduces the returns to low-skill work, newly created work opportunities benefit only the high-skilled (at least until new tasks can become "standardized" and performed equally well by all workers). The inclusion of the factors introduced by Acemoglu and Restrepo (2018) into a framework for quantitative policy analysis is a fruitful avenue of future research.

Final Comments

In this paper, we have documented how progress in automation technologies (industrial robotics, computing, ICT) has affected the middle-class labor market. In the near future, the pace of such change is unlikely to diminish, and progress in areas such as advanced robotics and artificial intelligence will have important labor market consequences (Brynjolfsson and McAfee (2014)). There is already much discussion of the impact of autonomous vehicles for transportation and material moving occupations (e.g., forklift operators, taxi drivers), and machine learning techniques in the fields of clinical pathology and radiology. Indeed, general interest in this topic has likely been heightened by reports predicting the "future of work" and declining opportunities in specific jobs or occupations (see, for instance, Frey and Osborne (2013), Arntz, Gregory, and Zierahn (2016), Nedelkoska and Quintini (2018)). These forecasts vary in severity, with earlier work relatively more alarmist and recent work less so. To help rationalize these differences, a key distinction is worth remembering: it is not occupations or jobs that are automated, but tasks.

Hence, in such discussions it is important to recognize the comparative advantages that human labor possess relative to machines in the multitude of tasks that are performed in daily economic life. One such domain is in human interaction. A story in Wired magazine provides context: "Take a robot called Tug, for instance. No, Tug can't talk philosophy with you ... But Tug is a pioneer. Because in hospitals around the world, this robot is helping nurses and doctors care for patients by autonomously delivering food and drugs, shouldering the burden of time-consuming mundanity."[17]Since robots can replace nursing assistants and registered nurses in the delivery of medication, it is possible that such jobs opportunities may shrink. But because these healthcare occupations perform a variety of tasks, it is equally likely or more likely that the nature of these occupations will evolve to place greater emphasis on tasks such as emotional support, counseling, and (perhaps) discussing philosophy. Indeed, work by Borghans, Ter Weel, and Weinberg (2014) and Deming (2017) have documented the disproportionate growth of employment in occupations requiring high levels of social interaction in recent decades. In addition, Cortes, Jaimovich, and Siu (2019) show how the return to interpersonal and social skills in occupational wages have increased significantly since 1980. As discussed above, economic progress involves the creation and adoption of new tasks to be performed by human labor (as robots take over the mundane), requiring workers to adapt and seize upon their comparative advantage.

The impact of automation on labor market opportunities depends on this interplay between these creative and destructive forces. A concrete example can be found in the BLS Occupational Outlook Handbook (OOH). As discussed above, employment in the occupation "secretaries and administrative assistants" has been in decline; the OOH predicts that between 2018 and 2028, employment will continue to decline by 7% (despite overall growth in the US population and economy). But a number of highly related, more specialized occupations are predicted to grow much faster than average over the next decade—for example, medical assistants (by 23%), paralegals and legal assistants (12%), and medical records and health information technicians (11%). All of these are middle-wage occupations, provide

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[17] see "Tug, the Busy Little Robot Nurse, Will See You Now," by Matt Simon, November 10, 2017.

administrative support in office settings, and have entry-level education requirements less than a bachelor's degree. This simultaneous decline and growth of employment opportunities in largely similar occupations has meant, as described by Holzer (2015), a "tale of two middles," emphasizing the need for new education, training, and retraining policies and practices.

As stated in Section 4, identifying these educational and training programs are of utmost importance. As well, further work on the importance and acquisition of interpersonal skills would be valuable to proposals regarding skill acquisition and human capital formation. And as stated at the close of Section 2, understanding how the changing demand for skills (along its many various dimensions) within growing occupations is critical. Finally, as discussed in Sections 3 and 4, greater work is needed to further our understanding of the relative importance of globalization versus automation in employment dynamics, and the development of empirically valid, macroeconomic models of automation for policy analysis. Such advances would substantially aid policymakers in addressing the future of middle-class labor market opportunities.

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