The Future of Work: How New Technologies Are Transforming Tasks

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I. Executive Summary

Technology has long brought change to the nature of work, and to the skills required for the most desirable, best-paying jobs. But until recently, new technology – even robotics – has tended to mean automating repetitive or arduous tasks, while often leading to new types of tasks for workers.

The emergence of artificial intelligence (AI) and machine learning (ML) poses a new set of opportunities – and challenges – for work and workers. The tasks that can be done by machine learning are much broader in scope than previous generations of technology have made possible. The expanded scope will change the value employers place on tasks, and the types of skills most in demand.

As AI and machine learning transform businesses and reshape industries, the innovators of these technologies must consider not only the business implications, but also the societal impact. As a result, the MIT-IBM Watson AI Lab has engaged in a first-of-a-kind research that sheds new light on the reorganization of tasks within occupations by analyzing 170 million online job postings in the US between 2010 and 2017. There is no question that AI and related technologies will affect all jobs. The research reveals how tasks are transforming and what the implications are for employment and wages.

I.a. *Key Findings*

While all jobs will change as new technologies scale, few jobs will actually disappear. What is fundamentally changing is the way work gets done. Here is how:

1. Tasks are Shifting Between People and Machines – But the Change has been Small

   With strong employment growth and workforce transformation underway, overall demand for tasks is down between 2010 and 2017. Across more than 18,500 tasks, for each occupation, on average, workers were asked to perform 3.7 fewer tasks in 2017 than seven years earlier.

   When looking at the impact of AI and machine learning on tasks across seven years, the data show that among tasks that are more suitable for machine learning (e.g., scheduling, credential validation), workers, by occupation, were asked for perform 4.3 fewer tasks.

   Conversely, among tasks that are less suitable for machine learning (e.g., design, industry knowledge), workers, by occupation, were asked to perform 2.9 fewer tasks. This reflects a 46% larger decline in demand for tasks that are more likely to be suitable for machine learning, compared to those that are less likely.

In other words, tasks that are more likely to be done by AI or machine learning are disappearing from employers' job requirements more often than those more likely to be done by a worker.

The decreased task requirements are likely due to employers' seeking greater focus from workers and the early adoption of AI and machine learning, indicating a fundamental shift in the way work gets done. But the shift has been small, allowing time for workers and employers to adapt.

2. Tasks Increasing in Value Tend to Require Soft Skills

As technology reduces the cost of some tasks, the value of the remaining tasks increases. Tasks that require grounding in intellectual skill and insight as well as to some degree, physical flexibility, common sense, judgment, intuition, creativity, and spoken language have tended to increase in value.

Here are a few examples across wage ranges and occupations:

- In high-wage business and finance occupations, industry knowledge tasks are on the rise. The annual wages for industry knowledge tasks have increased in value between 2010 - 2017 by $6,387 on average, while the annual wages for manufacturing and production tasks have decreased in value by $5,218 per year, on average.
- In low-wage personal care and services occupations (hairstylists, recreational workers, fitness trainers, etc.), annual wages for design tasks – like presentation design or digital design – have increased between 2010 – 2017 by $12,000, on average among these workers.
- In fact, design tasks are increasing in value across all wage groups. Design tasks including graphic and visual design, industrial design, user interface, user experience, and presentation design have increased in value consistently across occupations and wage groups. In mid-wage sales occupations, the value of design tasks increases $8,522. And, in high-wage computer and mathematics occupations, the value of design tasks increases $6,011. Design tasks require innovative thinking, bringing together deep insight and experience.

3. High- and Low-Wage Jobs are Gaining Tasks and Earning More

Among the three tiers - low-wage jobs, mid-wage jobs and high-wage jobs - workers in the middle tier are being squeezed. Tasks have shifted out of mid-wage jobs into low- and high-wage jobs. For every five tasks shifted out of mid-wage jobs, four tasks move to low-wage jobs and one moved to a high-wage job.

As a result, wages are rising faster in the low- and high-wage tiers, than in the mid-wage tier. Low-wage workers gained an average of $600 in annual compensation more than mid-wage workers. High-wage workers gained an average of $1,200 in annual compensation more than mid-wage workers over the same period.

II. Economics Literature Review: Labor Market Context Across Recent Decades

The impact of technology on labor markets has long been an important issue for economic theory, empirics, and policy. With successive generations of technology, new challenges have arisen, and new effects have appeared. Most recently, the widespread use of robotics and the advent of artificial intelligence (AI) solutions have continued to stoke debate and generate new work.

In the current era, the widely misunderstood work of Frey and Osborne (2013) has received much popular attention. Frey and Osborne found that 47% of current American occupations fall into a "high risk" category. The risk measure is a relative metric, suggesting that compared with other occupations, the identified 47% are the most vulnerable to automation. This carefully caveated, theoretical upper bound of 47% has, unfortunately, been transformed in the business media into a firm forecast.

In fact, Frey and Osborne make no attempt to estimate how many occupations will be automated nor do they comment on whether such occupations will be automated in whole or in part. Quite rightly, they observe that the expected transformation of work will depend on such considerations as required business process and technology investment, regulatory concerns, political pressure, and social resistance.

II.a. *Technology and Global Labor Market Transformation*

The focus on economic and social transformation has also grown as a result of a series of papers by Acemoglu and Restrepo who seek to understand how new technologies displace and, sometimes, reinstate labor. Building on the notion developed most fully by Autor, Levy, and Murnane (2003), Acemoglu and Restrepo present a task-based framework, recognizing that occupations require a collection of tasks to be performed.

Acemoglu and Restrepo use the task-based framework to differentiate tasks performed by capital and those performed by labor. The view is that goods production and service delivery require tasks allocated to capital and labor.

Acemoglu and Restrepo (2019) write:

> New technologies not only increase the productivity of capital and labor at tasks they currently perform, but also impact the allocation of tasks to these factors of production - what we call the *task content of production*. Shifts in the task content of production can have major effects for how labor demand changes as well as for productivity. [See page 3]

Acemoglu and Restrepo find that past rapid wage growth and stable labor shares was a result of technological change that created new tasks for labor that counterbalanced the displacement effects of automation. They write: "some technologies displaced labor from automated tasks while others reinstated labor into new tasks". [See page 5]

Acemoglu and Restrepo also find slow wage growth over the most recent three decades was a consequence of weaker-than-usual productivity growth and significant shifts in the task content toward capital and away from labor.

Acemoglu and Restrepo look at US labor market performance over nearly 75 years and divide the seven and half decades into two periods. Looking at the evolution of aggregate wages paid - average wages and total employment - industry data provides a decomposition of changes in wages paid into (1) productivity growth, (2) composition and substitution effects, and (3) changes in the task content of production.

Technologies create productivity effects that contribute to labor demand. The composition effect results from the reallocation of activity across sectors with different labor intensities. The substitution effect captures the substitution between labor- and capital-intensive tasks within an industry in response to a change in task prices.

With the needed reallocation of activities, realization of the composition and substitution effects requires time. Brynjolfsson, Syverson, and Rock (2017a) argue benefits realization from general-purpose technologies is realized only with a lag and require the development and implementation of waves of complementary innovations.

In the first period, 1947 – 1987, wages paid per capita increased 2.5% per year. The rapid growth is largely explained by the 2.4% average annual productivity growth. The substitution and composition effects are small, as is the change in the task content of production. Despite limited task reconfiguration, there is considerable displacement and offsetting reinstatement. Over the period, the displacement effect reduced labor demand at about 0.48% per year, while the reinstatement effect increased labor demand by 0.47% per year.

The Acemoglu and Restrepo estimates suggest the 40 years early in the 75-year period were golden years. Rapid productivity growth was reflected in wage increases while limited task reconfiguration created a sustained period of stability in skill requirements. The skills workers acquired early in their careers held their importance and value over the long term. Further, the golden years were strengthened as the re-employment opportunities just about offset displacement. For workers losing opportunities, new opportunities appeared.

However, the 1987 – 2017 period looks very different. Wages paid grew at a very modest 1.33% per year and essentially stagnated after 2000. The 1.54% annual increase in productivity was the first factor contributing to the slowdown. A significant negative shift in the task content of production away from labor at 0.35% per year caused labor demand to decouple from productivity.

Compared with the 1947 – 1987 period, the change in task content in the 1987 – 2017 period was driven by a deceleration in the introduction of technologies reinstating labor. Displacement accelerated to 0.70% while reinstatement increased only by 0.35% per year.

The slower productivity growth, the shift in task content away from labor, and the deceleration in the introduction of technologies reinstating labor combined to slow average wage growth. In addition, real median US household income increased at an average annual rate of only 0.4% over the 30 years. The coincidence of these outcomes is also correlated with substantial decline in the net investment in US capital stock.

Figure 1 shows US nonresidential investment minus depreciation as a percent of the nonresidential capital stock over the period 1925 to 2017.[1]

After declining in the Great Depression, the rate of investment in physical and intellectual capital increased sharply and remained generally above 3% per year through the late 1980s. However, over the most recent 30 years, net additions to the capital stock has slowed again reaching a recent low during the 2008 – 2009 Great Recession. Viewed from a long-term perspective, perhaps it is not surprising that the introduction of technologies reinstating labor slowed as well.

Beyond the variability of capital stock additions, the available technology over the entire period was generally a rules-based technology that was ideally suited for robotics deployment, most often in the manufacturing sector.

In fact, Acemoglu and Restrepo (2018b) show, using a model in which robots compete against labor in the production of different tasks, robots likely reduced employment and wages. The impact of robots is distinct from the impact of Chinese and Mexican imports, the decline of routine jobs, offshoring, other types of IT capital, and the total capital stock. Acemoglu and Restrepo find that one more robot per thousand workers reduces the employment to population ratio by between 0.18 and 0.34 percentage points and wages by 0.25% and 0.5%.

Apparently, while net additions to the capital stock – both physical and intellectual capital – were slowing, the composition of additions was shifting with a more significant increase in robotics.

II.b. *Labor Market Polarization*

The bifurcated performance of the US labor market over the past 75 years, observed by Acemoglu and Restrepo, is also reflected in the share of jobs in each occupation. In a series of papers, Autor has developed the job polarization hypothesis which finds a decreasing share of employment among mid-skill occupations and a rising share of employment among low- and high-skill employment. See Autor (2015) and Autor (2019).

In the first four decades between 1940 and 1980, occupational change moved away from physically demanding work and toward skilled blue- and white-collar work. See Figure 2. Agricultural employment declined by almost four percentage points per decade while professional, technical, and managerial employment - the highest skill categories - grew by three percentage points per decade. Among the vast middle group of workers, service and skilled blue-

[1] The nonresidential capital stock, investment, and depreciation include equipment, structures and intellectual property products.

collar occupations were stable, clerical and sales occupations rose, and operative and laborer occupations fell sharply. See Autor (2015).

By contrast, over the most recent four decades, labor market polarization has become more obvious. Skilled blue-collar occupations shrank rapidly as did clerical and sales occupations. Operative and laborer jobs continued to decline. Personal services began absorbing an increasing share of non-college labor. However, the forces of polarization appear to have lessened. Figure 3 shows the small changes in occupational employment shares in 2000 – 2016 period. See Autor (2019).

Many forces were at work over the two four-decade phases of the most recent epoch. How such forces play out in the decades ahead depends, in part, on labor supply and, in part, on labor demand.

On the supply side, Autor (2019) suggests that location in urban versus non-urban areas could impact the outcome. The growth in skills non-college workers once achieved as they entered urban labor markets has become more difficult to gain. Thus, the slowing of non-college workers entry into urban labor markets might allow an upward wage adjustment of low-skill wages in high-skill labor markets. Conversely, aging of the non-urban labor force during the most recent four decades suggests rising wages for certain low-skill occupations - in-person care, transportation, repair, and other services.

For labor demand, the task content of goods production and service delivery will shape the demand for workers' skills. Acemoglu and Restrepo have shown the linkage between robotics and employment, largely in segments of the manufacturing sector. Other technologies, most prominently information and communications technology, have also impacted employment.

II.c. *Task Suitability for Machine Learning*

The advent of AI solutions will very likely shift the demand for labor skills. Brynjolfsson, Mitchell and Rock (2018) create a rubric for evaluating the potential for applying machine learning to the 2,069 work activities, 18,156 tasks, and 964 occupations in the O*NET database.

With a measure called "suitability for machine learning" (SML) for labor inputs, the potential for task reorganization shows the limits and extent of possible demand shifts. The work finds (1) most occupations in most industries have at least some tasks that are SML; (2) few if any occupations have all tasks that are SML; and (3) unleashing machine learning potential will require significant redesign of the task content of occupations, as SML and non-SML tasks within occupations are unbundled and re-bundled. See Figure 4.

The future, of course, is unknown. Should capital accumulation – equipment, structures, and intellectual property – resume at rates similar to the 1945 – 1987 period, it's possible the quickening pace of accumulation will draw on new tools, new solutions and new technologies. If the resulting transformation of work is as profound as is often speculated, new data and new analytics will be necessary.

Should capital accumulation continue to stagnate at current rates, similar data and tools will be required to understand where the positive and negative labor market impacts are found. Interestingly enough, the tools of machine learning and AI provide an opportunity to probe for the needed insight.

The path to the future state remains uncertain. Having been stung by misunderstanding, exaggeration, and deep personal criticism, Frey has recently laid out his view of the transition in detail. Frey finds that new technologies take time to produce productivity and wage gains. In the long run, it is likely that the new technologies and the global business transformation that accompanies them will increase productivity, income and wealth. But, Frey asserts, the transformation is likely to boost inequality in the short run by pushing some workers into lower-paid jobs.

Unless the transformation and the deployment of the new technology is complete - scaled across business processes, sectors and geographies - investors, workers, and households will be worse off in the long run, giving rise to what Frey has called the "technology trap". See Frey 2019.

The technology will be trapped in limited deployment with the full productivity benefit not realized. While many worry there is too much AI technology, Frey is more concerned about a future with not enough. The incomplete technology transformation will trap workers in a permanently unequal income distribution.

Broad, global macroeconomic transformation has not only created new labor market requirements but has been associated with a new computing technology as well. The emerging tools of cloud computing, natural language processing, and others have not only transformed ways of working but also have provided new data sources and tools for understanding change.

Section II will describe a new data set built on US job posts over the period 2010 to 2017. The data set consists of two dimensions. Job posts are categorized by occupation and tasks likely to be performed in each occupation. The data produces insights aligned with existing stylized and known facts.

Section III will provide results and emerging insights. The data show the reorganization of employment, occupations and tasks. Looking ahead in anticipation of the broad availability of AI, particularly those based on machine learning, occupations and tasks are shown to be impacted differently. The data also provides an opportunity for task valuation. Over the 2010 – 2017 period, within occupations task valuation has shifted. Across high, mid, and low-wage groups, there are tasks that have been consistently more highly valued and are less likely to be automated. High- and low-wage occupations have gained competitive advantage – and thus, increased compensation - across a range of tasks while mid-wage occupations have lost competitive advantage, and thus compensation.

Section IV presents conclusions and next steps.

III. Data and Methodology Design: Occupations and Tasks

The potential deployment of AI solutions and tools creates the expectation that ways of working will change. As work is redesigned, it is useful to distinguish between skills and tasks. In the redesign, tasks will be reconsidered. Some will be eliminated, others will be automated, and still others will require different skill levels.

Task are designed and developed by employers, on the demand side of a labor market transaction. Tasks are intended to result in work activities that produce output or deliver services. Skills are the capabilities workers bring to the transaction to perform the required tasks and are provided by workers on the supply side. See Autor 2013, page 2.

This distinction between tasks and skills is important when tasks can be accomplished by workers with a range of skill levels, workers in differing locations, or substituting capital for labor. To the extent that buyer requirements change, and certain tasks need to be performed by workers with differing skill levels – higher or lower - the resulting shifts in market prices mandate reallocation of skills to tasks.

Workers are compensated with a wage for supplying skills. Most, but not all, occupations require workers to perform a number of tasks when engaged in an occupation. The wage earned, then, is the weighted average of the wage paid for performing a collection of tasks and providing a portfolio of skills. See Roy (1951) and Heckman and Scheinkman (1987).

With the advent of natural language processing, new data sources are now available that provide much more detail about tasks and required skills than traditional survey data. Provided by Burning Glass Technologies, 170 million job listings posted by employers have been ingested on the IBM Cloud and provide a detailed view of employers' demand for employees and tasks to be performed. See Nania, Bonella, Restuccia, and Taska (2019).[2] Watson Studio has been used as the data environment to build and train the models.

The job posts are available monthly and cover the period 2007 to 2018. The job posts' text is processed to create a structured data set characterizing each job listed.[3] Table 1 shows the resulting data elements for each post.

The Burning Glass skills taxonomy holds over 17,000 unique skills. The skills are organized into skill clusters, grouping similar skills used for a common purpose. Clusters are then organized into families. There are 572 skill clusters and 28 skill cluster families. Skills are identified using keyword searches with conditions. For example, the term orange can both refer to the fruit and

[2] The Burning Glass Technologies data has also been made available to other researchers. See: Börner, Scrivner, Gallant, Ma, Liu, Chewning, Wu, and Evans (2018); Deming and Kahn (2018); Deming and Noray (2019); and Hershein and Kahn (2019).

[3] Following the 2008 – 2009 Great Recession, the 2010 – 2017 was a period of recovery and expansion in the US economy. Hershbein and Kahn (2019) find requirements in job vacancy postings differentially increased in geographic areas impacted by the recession. Consistent with production restructuring toward routine-biased technologies, Hershbein and Kahn also find that effects are most pronounced in routine-cognitive occupations. Modestino, Shoag and Ballance (2019) find employers opportunistically raise education and experience requirements, within occupations, in response to increases in the supply of relevant job seekers.

the British telecommunications firm. So, rules are needed for disambiguation. For skill clusters and cluster families, k-means clustering algorithms and qualitative effort is required.

There is some ambiguity as to whether the content of job posts describe skills of workers or tasks workers are required to perform. Because firms do not know workers skills before hiring - ex ante - and because firms know with near certainty the tasks workers are to perform, in what follows the requirements will be referred to as tasks. Such a distinction is consistent with the theory that tasks are specified by employers on the demand side and skills are the capabilities workers bring on the supply side.[4,5]

There are two adjustments required to the data set. The Burning Glass job posts are not available for 2008 and 2009 and, in addition, the number of posts grew much faster than US job creation in the period following the Great Recession. See Figure 5.

The resulting data are represented in a three-dimensional array with dimensions for occupations, tasks and years. The data provide a novel opportunity to enumerate the tasks required for each occupation. With data on an annual basis, for the period 2010 – 2017, the occupation-task listing also provide data, as shown in Table 1, for wages, the industry of the employing firm and a number of additional characteristics.

Each cell in the data array is a count of mentions, m_{toy}, for each task t in each occupation o and year y. In addition, the count also provides mentions of each occupation o in each year y, a_{oy}. The calculation includes all listings for each month of each year.

If one assumes that the distribution of tasks demanded in a job listing reflects the distribution of tasks performed by workers in an occupation, the share of workers in each occupation that perform each task can be calculated.

The occupation-task share is:

$$OccTaskShare_{toy} = \frac{m_{toy}}{a_{oy}} \qquad (1)$$

As an external baseline, the Bureau of Labor Statistics (BLS) publishes annual statistics of the average hourly wage w_{oy} and number of employees E_{oy} in 964 SOC occupations.

Because the job listings are posted based on the current needs of employers and because online job posts have accounted for a much larger share of recruiting activity, the postings are not

[4] Because there are differences between the taxonomies, Burning Glass has not merged their skills taxonomy with the O*NET taxonomy of tasks. Some tasks in the O*NET taxonomy are not mentioned in Burning Glass postings, as they are assumptive of the position to be filled. Also, the O*NET technology tasks are not updated frequently while the Burning Glass data is updated monthly.

[5] Job postings do not always reflect workers' roles precisely. Especially in tight labor markets, the eventual responsibilities of workers might differ from intentions at hiring. In additions, postings can also reflect marginal rather than average occupational changes. The marginal changes can reflect replacement demand as well as net new demand.

necessarily representative of the US labor force. See Figure 5. However, using the BLS data the share of the labor force employed in each occupation can be calculated:

$$e_{oy} = \frac{E_{oy}}{\sum_o E_{oy}} \qquad (2)$$

Combining BLS statistics with Burning Glass data, the share of workers performing task *t* as part of occupation *o* in year *y* is:

$$\text{OccTaskEmp}_{toy} = e_{oy} \times \text{OccTaskShare}_{toy} \qquad (3)$$

With data for each year creating a time dimension, the primary dimensions are occupations and tasks with detail available by industry.[6] As Acemoglu and Restrepo (2019) hypothesize, labor demand is a function of composition effects across industries, substitution effects between the labor and capital task intensity, and the impact of technology on productivity. All impact and are impacted by changes in task prices.

With 2010 as the base year, occupations are ranked by wage, $w_{o,y=2010}$. See Autor (2015). Each bin contains occupations employing one third of the workforce:

$$\text{OccBin}_i,\ i \in \text{low, mid, high}$$

As expected, providing an important check, the data show the decline in mid-wage occupation employment share consistent with the job polarization hypothesis. See Figure 6. The changes in occupational employment share in Figure 6 show the continued slowing of share changes shown as the decades progress in Figure 3. Consistent with data presented by Autor and others, mid-wage occupations share declined by 1.0% over the seven years for a 0.1% average annual decline.

In addition, the average wage of a worker performing task *t* in year *y* can be calculated:

$$TaskWage_{ty} = \frac{\sum_{ty} w_{oy} * OccTaskEmp_{toy}}{\sum_{ty} OccTaskEmp_{toy}} \qquad (4)$$

Tasks are grouped into low-, mid-, and high-wage tasks to compare demand for tasks in those occupations has changed over the period 2010 to 2017

Tasks are ranked by the average wage in the base year,

$$TaskWage\ Rank_{t,y=2010} = \frac{RankTaskWage_{t,y=2010}}{Count\ of\ Occupations_{2010}} \qquad (5)$$

Figure 7 shows that the task employment share among the most highly compensated workers decreased over the period while the share of tasks provided by low- and mid-wage workers

[6] Table 1 shows additional detail available for each job post. The geographic dimension is not used due a concern that posts can originate from employers headquarter locations and therefore not reflect the geographic demand for labor. In addition, education and experience data will be the subject of future research.

increased. The finding of such a shift is similar to that of Beaudry, Green and Sand (2016) who find that in the decade of the 2000s high skilled workers moved down the occupational ladder and increasingly displaced lower-educated workers in less skill-intensive jobs.

As a further check of data validity, the expectation is that those tasks that are more highly compensated are performed by workers in more highly paid occupations. Figure 8 presents such a one-to-one alignment.

A similar check is shown in Figure 9 in which the highly valued tasks are consistent across occupations, independent of which skill group performs the task.

As is well-know, in recent years, wages for more highly skilled workers have been rising more rapidly. Not surprisingly, the data also show that highly valued tasks performed by highly skilled occupations have experienced the largest increases in real wages. See Figure 10.

So, the novel Occupation-Task data produces results well aligned with expected behavior and known stylized facts.

Finally, in Figure 11, the data show those tasks that experience the largest increase in demand – along the x-axis - saw the largest decrease in real wages – along the y-axis - over the period. Untangling the negative correlation shown is Figure 11 is, in part, the goal of Section III.

IV. Results

The occupation-task data matrix provides an annual view of the demand for tasks for each occupation. In addition, each occupation has a wage rate associated with it. The goal is to understand changes in the demand for tasks within and between low-, mid-, and high-wage occupations from 2010 to 2017.

Consistent with the job polarization hypothesis, shown in Figures 2 and 3, share of employment in the mid-wage occupations has declined overtime. The job polarization hypothesis advanced by Autor (2015) and Autor, Levy, and Murnane (2003) suggests the completion of tasks with substitution of computing power for worker effort. For a set of "routine tasks," there is a codification and automation that is possible. The tasks are labeled "routine" not because they are mundane, but because they can be reflected in a set of rules to be executed as conditions dictate.

Routine tasks are characteristic of many mid-wage occupations. Because core tasks of these occupations follow precise, well-understood procedures, they have been increasingly codified in software. The result has been an employment decline across clerical, administrative, support, production and operations tasks.

However, importantly, the scope for substitution is limited because there are many tasks that workers can understand tacitly and accomplish effortlessly but which cannot easily be reduced to rules. Certain tasks involving physical flexibility, common sense, judgment, intuition, creativity, and spoken language are capabilities that workers easily provide. But, formalizing these tasks has, in the past, been very difficult to codify and accomplish, in the absence of tacit understanding. See Autor (2015), p. 15.

IV. a. *Task Reorganization Among Workers*

In the context of job polarization, it is of interest to learn where the tasks that previously were provided by the mid-wage occupation workers have shifted. Figure 12 shows that over the 2010 – 2017 period, 2.2 percentage points of the tasks performed by the mid-wage occupation workers in 2010 were no longer performed by that segment in 2017.

A substantial portion of the mid-wage tasks that disappeared moved to low-wage workers while a somewhat smaller proportion moved to high-wage workers. With 77% of the tasks moving to low-wage workers, for every four tasks that shifted to low-wage workers, one task shifted to high-wage workers.

The figure also shows that the largest portion of all tasks are performed by the most highly paid workers – about 47% in 2017 - while the fewest tasks are performed by the lowest paid workers – about 25%. Mid-wage workers were performing 28% of tasks in 2017.

To provide more color to the task reorganization, Figure 13 provides a view of the tasks that were increasingly performed by low-wage and high-wage workers. Low-wage workers increased their focus on health care, environmental, public safety, administrative, supply chain, and logistics tasks.

By contrast, high wage workers increased their focus on design, information technology, legal, marketing, media, and writing.

In equation (3), the number of workers engaged in each occupation-task combination was calculated. However, the average number of tasks mentioned per listing increased from 2010 to 2017. Thus, in order to avoid the naïve conclusion that demand for all tasks increased over the time period, a normalization is needed. Thus, the focus will be on occupation-task mentions as a percent of all occupation-task mentions in a time period:

$$OccTaskEmpNorm_{toy} = \frac{OccTaskEmp_{toy}}{\sum OccTaskEmp_{toy}} \quad (6)$$

Equation (6) converts the units of equation (3) from counts of workers to percentages.

Next, 10 bins are created for tasks demanded for each occupation tercile. From equation (4), the tasks are ranked by task wage within the occupation tercile, and correspondingly, the proportion of workers summed in each decile.

$$binVal_{by} = \sum_{o \in bin_{b,y}} OccTaskEmpNorm_{toy} \quad (7)$$

Figures 14 - 16 correspond to the low-, mid-, and high-wage occupations, respectively. The values of bins $b \in (0 - 9)$ are plotted in the top panels of Figures 14 - 16, for 2010 and 2017. In the top panel the y-axis shows the proportion of workers engaged in the tasks in each of the bins, shown on the x-axis. Two years are shown; 2010 and 2017.

The middle panel of each figure plots the difference between the two years; 2010 and 2017. The y-axis shows the difference in the proportion of workers engaged in the tasks in each of the bins between the two years.

Thus, the difference presented in the middle panel expresses:

$$binVal_{b,y=2017} - binVal_{b,y=2010} \quad (8)$$

The bottom panel shows a decomposition of the difference into the extensive and intensive margins. The decomposition is calculated using a counterfactual that expresses the share of workers who would be performing each occupation-task combination in 2017 if the distribution of task in each occupation had held its 2010 distribution. For the decomposition, equations (3) and (6) are re-specified:

$$OccTaskEmp_{to,y=2017}^{counter} = e_{o,y=2017} * OccTaskShare_{to,y=2010} \quad (9)$$

Normalized for varying number of tasks per job listing in each year as in equation (6):

$$OccTaskEmpNorm_{toy}^{counter} = \frac{OccTaskEmp_{toy}^{counter}}{\sum OccTaskEmp_{toy}^{counter}} \quad (10)$$

In the bottom panel of Figure 14 - 16, combining equations (8) and (10), the "Intensive Margin" shows the change in tasks demanded resulting from changes within occupations, holding occupational employment steady:

$$binVal_{b,y=2017} - \sum_{o\in bin_b y=2017} OccTaskEmpNorm_{toy}^{counter} \quad (11)$$

and the "Extensive Margin" shows the impact of shifts in employment holding the distribution of tasks within each occupation constant:

$$\sum_{o\in bin_{b,y=2017}} OccTaskEmpNorm_{toy}^{counter} - binVal_{b,y=2010} \quad (12)$$

In Figure 14, among low-wage occupations, at the intensive margin, in 2017, there were proportionately fewer workers performing less well-compensated tasks – bins 0 to 3 – as tasks were distributed in 2010. There were proportionately more workers performing moderately compensated 2010 distributed tasks – tasks 4 to 6. And, the proportion of the most highly paid workers were unchanged from 2010 to 2017.

However, at the extensive margin, the change from 2010 to 2017 is solely the result of the occupational employment levels. From Figure 14 in 2017, there are more workers performing tasks that had been less well-compensated in 2010 – bin 0 to 3. There was little employment change, proportionately, over the remaining bins.

In low-wage occupations, tasks demanded shifted toward those with better pay (intensive margin). However, employment increased most for low-wage occupations with the least well-paid tasks (extensive margin).

In Figure 15, the shift is qualitatively similar for mid-wage occupations. At the intensive margin, in 2017, there were also fewer workers performing less well-compensated tasks.[7] At the extensive margin, in 2017, there are fewer workers performing all tasks than in 2010, a reflection of falling mid-wage employment.

Similar to the low wage tercile – Figure 14 – work drifted down in the mid-wage tercile – Figure 15. The shift seems to suggest an excess of low-wage and mid-wage workers who are, as a result, willing to take on the less well compensated tasks.

However, in Figure 16, the shift is qualitatively reversed. Among high-wage occupations, at the intensive margin, in 2017, there were fewer workers performing the more well-compensated tasks as distributed in 2010. The result at the intensive margin, shown in Figure 16, reflects the

[7] For both low- and mid-wage occupations, at the intensive margin, the 2017 fall off in demand for tasks among the least well-compensated occupations – decile zero for low-wage occupations and decile zero and one for mid-wage occupations shown in the bottom panel of Figures 14 and 15 – is somewhat less than other deciles.

shift initially shown in Figure 7, similar to that of the Beaudry, Green and Sand (2016) finding. At the extensive margin, in 2017, employment increased most for high-wage occupations with the most well-paid tasks as distributed in 2010. The seemingly disparate employment and tasks shifts shown in Figures 14 – 16 provide a conflicting view of work redistribution.

Employment has, proportionally, increased among the lowest compensated occupations in the low-wage tercile while employment has, proportionally, increased among the highest compensated occupations in the high-wage tercile. In the mid-wage tercile, there are, proportionately, fewer workers, a reflection of falling mid-wage employment.

However, task redistribution is strikingly different and could reflect the shift of tasks out of the mid-wage tercile shown in Figure 12. Tasks appear to have shifted from the low end of the mid-wage tercile to the high end of the low wage tercile. Conversely, other tasks seem to have clustered at the high end of the mid-wage tercile and at the low end of the high wage tercile.

There appears to be two disparate effects. The work redistribution and re-balancing would seem consistent with employment demand for increased low-cost, low-wage workers while also seeking high-skill, high-cost workers. In parallel with shifting labor demand, workforce transformation could be such that the tasks previously performed by mid-wage workers are now, in part, clustered among relatively highly compensated low-wage workers, perhaps providing interactive personal services.[8] Similarly, tasks also appear to have clustered among the relatively less well compensated high-wage workers. The clustering could suggest that more cognitive tasks clustered at the boundary of mid-wage and high-wage occupations.[9] Consistent with the Acemoglu and Restrepo (2019) finding that in the 1987 – 2017 period displacement accelerated while reinstatement lagged the earlier 1947 – 1987 period.

[8] Whether the task performed at the boundary of low- and mid-wage occupations are routine or non-routine is a less relevant distinction than in past eras. In a personal services environment, each request from a customer is unique, important to the customer and very often non-routine. From Autor, Levy and Murnane (2003), the routine versus non-routine difference evolved from the work of Herbert Simon and Peter Drucker in the 1950s. Six decades later the nature of economic activity has fundamentally changed.

[9] The clustering of tasks at the segment boundaries provides insight into one of the central conceptual challenges identified in Autor (2013), section 3.2.

IV. b. *Task Suitability for Machine Learning*

As observed earlier, Acemoglu and Restrepo (2019) develop the notion of the task content of production. New technologies not only increase the productivity of labor at tasks they perform, but also impact the allocation of tasks. Shifts in the task content of goods production and service delivery can have major effects for labor demand as well as on productivity.

As is well known, machine learning represents a new set of automation tools. As Brynjolfsson, Mitchell and Rock (2018) find, having created the SML rubric, most occupations in most industries have at least some tasks that are suitable for machine learning.

With a mapping between the O*NET taxonomy and the Burning Glass taxonomy, the SML rubic can be matched with the wage rate as specified in equation (4) and, thus, with wage terciles. Figure 17 shows the relationship between changes in the task shares over the 2010 to 2017 period and the SML score.[10] A negative and statistically significant relationship results. The tasks that have lost share over the seven years tend to be those tasks that are more suitable for machine learning.

From 2010 to 2017, the change in task share from equation (3) is -6.66 per 10,000 tasks. With more than 18,500 total tasks, the typical worker was asked to perform 3.7 fewer task in 2017 than in 2010.[11] Among tasks with a SML score below the median 3.075 – those less likely to be suitable for machine learning - workers were asked to perform 5.4 fewer tasks per 10,000 tasks over the seven years, which is 2.9 fewer tasks per worker. Conversely, among tasks with a SML score above the median – those more likely to be suitable for machine learning - workers were asked to perform 7.9 fewer tasks per 10,000 tasks over the seven years or 4.3 fewer tasks per worker, a 46% increase in task reduction.

Over the seven-year period, while the relationship between the change in task share and the SML score has been significant and negative, the task shifts have been small. It is hardly surprising with AI, cloud infrastructure, natural language processing, and other related technologies in early stages of deployment that the impact on the task content of production has been limited.

With data, shown in Table 2, that provide a view of tasks by wage tercile and an association of the suitability for machine learning with tasks, it is possible to examine the implications of task-replacing technological change for the demand for different types of tasks and for wages.

Autor (2013) observes that task-replacing technologies can reduce wages of a skill group even as it raises total output. Task-replacing technologies reorganize work such that workers shift focus to tasks where they have greater competitive advantage or are displaced. If workers are shifted to tasks for which they have lower comparative advantage, wages will shift down as well.

The reorganization of work does not imply that the displaced tasks are no longer required - in fact, just the opposite. As Autor observes:

[10] The relationship is estimated with approximately 14,000 data points that are binned in deciles, producing the relationship shown in Figure 18.
[11] The 3.7 fewer tasks per worker is $6.66 * 10^{-5} / 1.8 * 10^{-5}$.

> As the cost of performing routine tasks has declined by orders of magnitude, their use in production has grown explosively – think, for example, of the amount of processing power that goes into a single Google query. However, because these tasks are now performed by [information technology] capital rather than labor, the consequences for the earnings power of workers who previously held comparative advantage in these tasks are at best ambiguous. See Autor (2013), p.5, footnote 10.

The theoretical ambiguity of the consequences of task re-sorting for the earnings power of workers, of course, plays out in empirical reality.

Bringing together the task and SML data, as presented in Table 2, shows that the suitability for machine learning is high across all three wage terciles. Perhaps not surprisingly, there are a wide range of tasks, performed by both high- and mid-wage workers, that are suitable for machine learning. Tasks that are suitable for machine learning also impact low-wage workers, but to a slightly lesser extent.

In fact, at the aggregate level, there are some small differences – not statistical significantly – between the mid-wage occupations where tasks are more suitable for machine learning and the tasks performed by low- and high-wage workers.

While the deployment of machine learning solutions remain in an early phase, whether and to what extent such solutions substitute or complement tasks is to be determined. The data suggest, in contrast to robotics, substitution is not the default. As Acemoglu and Restrepo (2019) suggest, the task content of production can have productivity effects, as well as industry composition and substitution effects. However, if deployment is in the early stages of the "J-curve as suggested by Brynjolfsson, Syverson, and Rock (2017a) greater adoption is required to measure the labor impact.

IV. c. *Task Valuation*

How task-replacing technological change affects the relative earnings of workers across the wage segments depends on the nature of the technology in which capital substitutes for labor. In traditional rules-based robotic technology, the technology replaced routine tasks most often performed by mid-wage workers. The result was labor market polarization with increased employment shares in high-wage cognitive roles and low-wage manual roles with a hollowing out of mid-wage routine jobs.

Those tasks that are suitable for machine learning offer a different trade-off, between rising productivity and increasing wages versus job displacement, that was less often available with past technologies. The new machine learning technology can be expected to impact the labor market in a different fashion from the rules-based robotic technology.

As Acemoglu and Restrepo have suggested as some tasks are automated, other tasks continue to be performed by workers. Bessen has termed such shifts as "the 'reminder principle': as technology reduces costs or increases performance on one task in a process or one component in a product, the value of performance in the remaining tasks or components increases." See Bessen (2015) p. 45.

The ability of workers to bring greater skill to those tasks that are expected to create more market value than others is very likely to rewarded at a higher rate. The marginal value of tasks performed cannot be expected to be equal and, thus, workers cannot expect all tasks performed to contribute to compensation equally. In addition, the relative task remuneration can be expected to change over time. The values of interest are the increases in task wages from 2010 to 2017.

In equation (13), $Wage_{o,y=2010,2017}$ is the posted wage in individual job listings for a given occupation in 2010 and 2017. The right hand side includes a 2017 dummy, $Y_{y=2017}$, a vector of task cluster family dummies $Task_{to,y=2010,2017}$, and a vector of interaction terms $Task_{to,y=2010,2017}*Y_{y=2017}$. The coefficients of interest are on the interaction term, γ_t, expressing how much the expected wage changes when a listing is from 2017 and includes the given task. The equation is estimated for each occupation, individually.

$$Wage_{o,y=2010,2017} = \alpha_0 + \alpha_1 Y_{y=2017} + \sum_{to}\beta_{to} Task_{to,y=2010,2017} + \sum_{to}\gamma_{to} Task_{to,y=2010,2017} * Y_{y=2017} \quad (13)$$

The interpretation of the regression of wages on job tasks can be challenging. In theory, there is a value of γ_t for task performed by each occupation. Autor (2013) observes:

> The set of tasks that a worker performs on the job is an endogenous state variable that is simultaneously determined by the worker's stock of human capital and the contemporaneous productivity of the tasks that human capital could accomplish. This implies that task assignments are themselves a function of the current wage distribution…

Whether workers gain or lose competitive advantage is judged by shifts in the wage of the wage group relative to the wage of the task. As suggested by Autor, if the relative wage of the tasks in which the wage group holds comparative advantage declines [increases], the relative wage of the wage group should also decline [increase] – even if the group reallocated its labor to a different set of tasks. See Autor (2013), section 3.3.

The data presented here show that tasks have been reallocated from mid-wage workers to both low- and high-wage workers with a four to one ratio, suggesting high-wage workers do have a competitive advantage across a range of tasks.

Indeed, as Autor predicted, Figure 18 shows the γ_t values for the business and finance occupation in the high wage tercile. Those in business and finance occupations who can provide industry knowledge, customer care, and maintenance and repair skills have been compensated at a higher rate.

For example, the annual wages for industry knowledge tasks have increased in value between 2010 - 2017 by $6,387 on average. Conversely, while the annual wages for manufacturing and production tasks have decreased in value by $5,218 per year, on average.

The γ_t coefficients represented in Figure 18 are shown in column 3 of Table 2. The table presents the γ_t coefficients from the estimates of equation (13) that are significantly different from zero at the 1% level of significance. Across 11 occupations and 28 tasks, value shifts are both positive and negative.[12]

Table 3 shows that, for high-wage occupations, interesting results emerge. There is a subset of tasks that have been compensated at a higher rate across a range of occupations over the seven years. They are tasks such as: administration, design, education and training, heath care, industry knowledge, information technology, and personal care and services.

There is also a subset of tasks that have been compensated at a lower rate over the seven years. They are business; economics, policy, and social studies; and science and research. There are a remaining 17 tasks for which compensation changes have been mixed or showed little change.

Table 4 shows the shifting value of tasks for mid-wage occupations. Those tasks consistently compensated more highly are administration, agriculture and the outdoors, design, economics policy, and social studies, human resources, industry knowledge, sales, and supply chain and logistics. There are also tasks that have been compensated less well compensated. They are business, health care, information technology, legal, manufacturing and production, media and writing, and science and research. There are a remaining 13 tasks for which compensation changes have been mixed or showed little change.

Finally, Table 5 shows the shifting value of tasks required in low-wage occupations. Those tasks consistently compensated more highly are customer and client support, design, finance, and personal care and services. For example, in low-wage personal care and services occupations

[12] The estimation of equation (13) addresses the second of the two central conceptual challenges identified in Autor (2013), section 3.3.

(hairstylists, recreational workers, fitness trainers, etc.), annual wages for design tasks – like presentation design or digital design – have increased between 2010 – 2017 by $12,000, on average among these workers.

There are also tasks that have been less well compensated. They are business, human resources, and sales. There are a remaining 21 tasks for which compensation changes have been mixed or showed little change.

Across all three wage groups, there are tasks that have been consistently more highly valued and are less likely to be automated. They are administrative, design, industry knowledge, and personal care and services tasks. All require a substantial grounding in intellectual skill and insight. As Autor has observed, all involve, to some degree, physical flexibility, common sense, judgment, intuition, creativity, and spoken language.

Design tasks are increasing in value across all wage groups. Design tasks including graphic and visual design, industrial design, user interface, user experience, and presentation design have increased in value consistently across occupations and wage groups. In mid-wage sales occupations, the value of design tasks increases $8,522. And, in high-wage computer and mathematics occupations, the value of design tasks increases $6,011. Design tasks require innovative thinking, bringing together deep insight and experience.

The rising value of design and industry knowledge tasks could reflect the innovative and intellectual skills required to bring to together data, trends, and experience. Design, generally, and design thinking, specifically, often require deep insight and experience. Design thinking is intended to capture the needs and requirements of clients, markets and organizations and thus requires deep knowledge of a wide range of economic activity.

Among high-wage occupations, not surprisingly, education and training, health care, and information technology tasks are valued more highly. Among mid-wage occupations, even though capital equipment can improve productivity, tasks involving agriculture, horticulture and the outdoors; sales; supply chain; and logistics are unlikely to be fully automated and thus have benefited from increased value.

There are also tasks that experienced a decline in value over the period and could have been subject to capital substitution. They are business tasks across all three wage groups. Among mid-wage occupations, the tasks losing value are health care, information technology, legal, media and writing, and manufacturing and production.

In assessing shifting wage group competitive advantage, the relative wage of the tasks – as estimated in equation (13) - in which the wage group holds comparative advantage should be compared with the relative wage of the wage group. Equation (14) estimates the relative wage of the group.

$$Wage_{y=2010,2017} = \alpha_0 + \alpha_1 Y_{y=2017} + \sum_t \beta_t Task_{to,y=2010,2017} + \sum_t \gamma_t Task_{to,y=2010,2017} * Y_{y=2017} + \lambda_{L,y=2010,2017} Low * Y_{y=2017} + \lambda_{H,y=2010,2017} High * Y_{y=2017} \quad (14)$$

In contrast to equation (13), which is estimated separately for each of 11 occupations, equation (14) is estimated across the entire data set, comparing 2010 to 2017. Table 6 presents the results with the coefficients $\lambda_{L,y=2010,2017}$ and $\lambda_{H,y=2010,2017}$ the coefficients of interest. In each estimate both coefficients are positive and significantly different from zero. The coefficient estimates indicate that wages of both high- and low-wage occupations increased more than those of mid-wage occupations over the 2010 – 2017 period.

Finally, it is striking that low-wage occupations have seen larger wage increases than have mid-wage occupations. Figure 19 shows, across 747 occupations, there are more low-wage sub-occupations in which real wages increased over the 2010 – 2017 period than either high or mid-wage occupations. In addition, the percent of low-wage employment in the sub-occupations in which wages increased is also greater than either high or mid-wage occupations.[13]

The impact of the remixing of task wages on the occupational wage structure will depend on both the supply of available workers as well as the productivity of those workers. Occupations that are specialized in tasks that have declining market value, perhaps as a result of capital substitution, should see a reduction in both mean occupational wages – from equation (14) - and the variance of occupational wages – from equation (13) - and vice versa for tasks with rising wages.

The variance effect stems from the interaction between a falling task wage and distribution of task efficiencies within an occupation. Depending on the pace of technological change the distribution of task efficiencies can be fixed or can be rapidly evolving. As the market value of a given task falls, the range of wages paid to workers with differing productivities in that task can compress along with it. See Autor (2013).

To identify where high-wage workers have a comparative advantage relative to mid-wage workers in performing tasks, the positive $\lambda_{H,y=2010,2017}$ from Table 6 is matched with the positive coefficients in Table 2. The comparison shows high-wage occupations hold a competitive advantage in administrative, agriculture, horticulture, outdoor, analysis, design, education, training, industry knowledge, information technology, and personal care & services tasks.

Similarly, from Table 4, low-wage occupations hold a competitive advantage in customer & client support, design, finance, health care, and personal care & services tasks. Conversely, from Table 3, mid-wage occupations hold a competitive disadvantage in business, health care, information technology, legal, manufacturing & production, science, and research.

[13] Recent analysis from Levanon (2019) also reports gains among low-wage occupations: "After four decades of worsening, wage inequality has started shrinking. And in a twist, America's blue-collar workers are playing the biggest role in driving that reversal."

V. Conclusion: All Jobs Will Change

The US economy in the modern era has been marked by two distinct periods. The first from the 1940s to the 1980s was one of strong growth, rapidly rising productivity, strong wage and real income gains, and abundant career and work opportunities. Recent decades have brought just the opposite – slow growth, limited productivity advances, little wage and real income improvement, and stalled career and work opportunities.

Installation of novel and innovative technology, especially semiconductor-based information technology, marked the early period. The technology installation was correlated with, and indeed embodied in, a massive increase in installed physical and intellectual capital. The capital deployment slowdown and the technology maturation of recent decades has set the stage for the next global growth epoch – be it stronger or weaker than recent years.

Labor market transformation and alterations in ways of working have likewise responded to the underlying global trends. The early decades provided rapidly growing employment opportunities in which, when jobs were displaced, new jobs were installed at an equal or greater pace. Despite massive occupational transformation – the share of agricultural and labor workers fell notably – wage and real income gains were substantial.

In the more recent period - after 1980 - displaced jobs have exceeded newly installed jobs. Occupational transformation continued with gains in service, clerical, professional, and technical employment. Wages and real incomes stagnated.

However, much of the installed technology has been rules-based with robotics as a prime example. With the advent of artificial intelligence, machine learning, multi-cloud infrastructure, and natural language processing, fundamentally new technology applications are emerging that are resulting in still more business, economic and labor market transformation. Thus far, however, labor market transformation has been limited.

The new technology is not only impacting economic activity and ways of working but is also allowing for a substantially novel approach to understand labor market change. The ability of unstructured data, in the form of job posts, to be converted into structured data has opened new opportunities in labor market and talent analysis. The new data has allowed for the empirical implementation of parsing occupations into their required component tasks.

With new data available to assess the suitability of tasks for machine learning, the results show there are a small number of occupations with a high proportion of tasks suitable for machine learning. However, there are also a larger number of occupations with a small proportion of tasks suitable for machine learning. But this is a future statement about the extent of the transformation of work, which is only beginning to emerge today.

In the data, there is a weak but statistically significant, negative relationship between change in the share of tasks performed and those suitable for machine learning. Tasks losing share tend to be those most suited for machine learning. While the negative relationship is expected, the transformation has been occurring at a very slow pace over the past decade.

At a similarly slow pace, mid-wage occupations continue to lose employment share with low- and high-wage occupations continuing to gain share - job polarization. Mid-wage occupations have lost 1.0% of task requirements over the seven years, at an annual rate of 0.1%.

In US manufacturing sector industries, where mid-wage jobs are often found, employment increased by approximately 1.0M workers between 2010 and 2017. The recent increase followed a 30-year period of decline when employment fell from 19.5M to its current 12.9M. As a share of nonfarm payroll employment, manufacturing sector employment, between 1979 and 2010, fell 12.8 percentage points from its 1979 peak of 21.6%. Between 2010 and 2017, the manufacturing sector employment share fell by only an additional 0.3 percentage points.

With work shifting out of mid-wage occupations, over the 2010 to 2017 period, both low-wage and high-wage occupations have gained task requirements with low-wage occupations having gained more than high-wage occupations. Of the tasks that have shifted out of mid-wage occupations, four tasks have moved toward low-wage occupations for each task that moved to high-wage occupations.

However, the employment shifts and the task rebalancing have shown strikingly different effects.

Employment has increased among the lowest compensated occupations in the low-wage tercile while employment has also increased among the highest compensated occupations in the high-wage tercile. In the mid-wage tercile, there are, proportionately, fewer workers, a reflection of falling mid-wage employment. All consistent with the job polarization hypothesis.

Alternatively, task redistribution appears to have shifted from the low end of the mid-wage tercile to cluster at the high end of the low wage tercile. Conversely, other tasks seem to have clustered at the high end of the mid-wage tercile and at the low end of the high wage tercile.

Tasks required of workers, who are engaged in an occupation, are not valued equally. The ability of workers to bring greater skill to those tasks that are expected to create more market value than others is very likely rewarded at a higher rate. The marginal value of all tasks performed cannot be expected to be equal and, thus, workers cannot expect to be compensated equally for all tasks performed.

High- and low-wage occupations have gained competitive advantage across a range of tasks while mid-wage occupations have lost competitive advantage. The gains among low-wage occupations have resulted in low-wage occupations experiencing large wage gains over the 2010 p 2017 period, beginning to ameliorate income inequality differences of the last three decade.

Most occupations in most industries have at least some tasks that are suitable for machine learning. Few, if any, occupations have all tasks that are wholly suitable for machine learning. Unleashing machine learning potential will mean a continued redesign of the task content of occupations with tasks unbundled and re-bundled.

In contrast to traditional rules-based robotic technology, which has had a significant impact on mid-wage workers artificial intelligence and machine learning technology offer workers from all wage groups potential benefit as well as challenges. With deployment more often in the services industries, workers could potentially benefit from a trade-off between rising productivity and increasing wages versus job displacement. In the period ahead, the focus is shifting from production and clerical workers who have lost their jobs because of technology replacement to workers in all wage groups who will need to learn new skills, redesign their job roles, and focus on career advancement.

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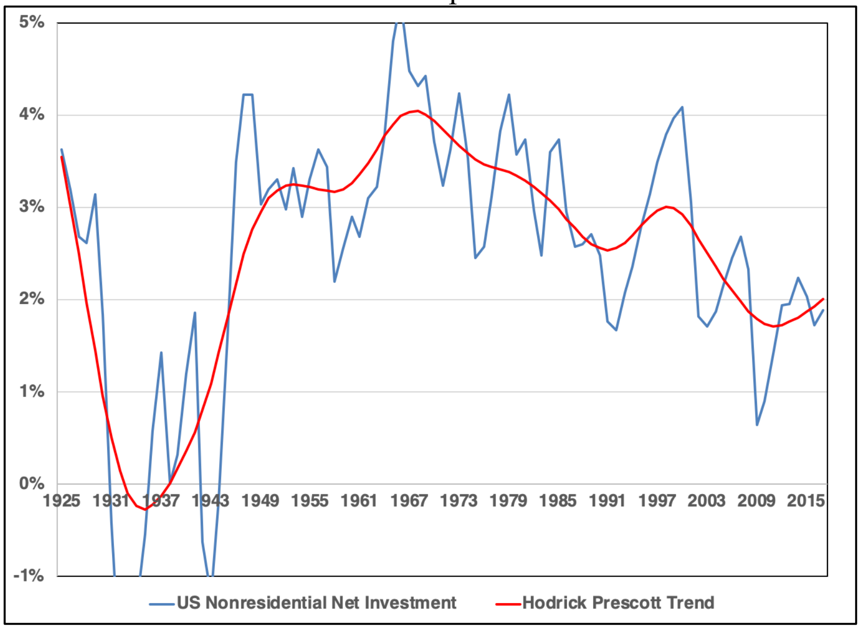
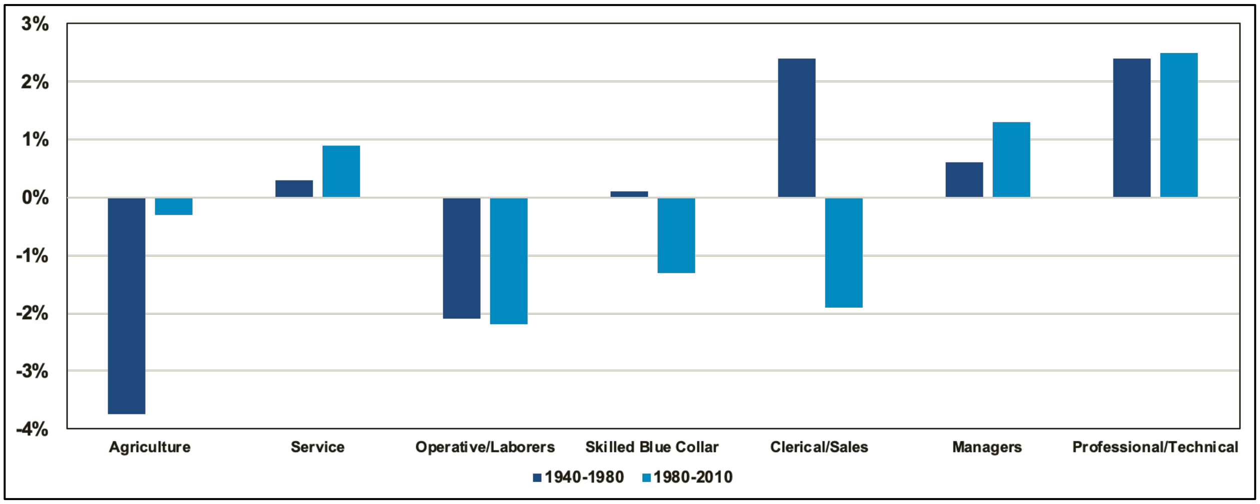
Figure 1
Nonresidential Net Investment as a
Percent of Capital Stock



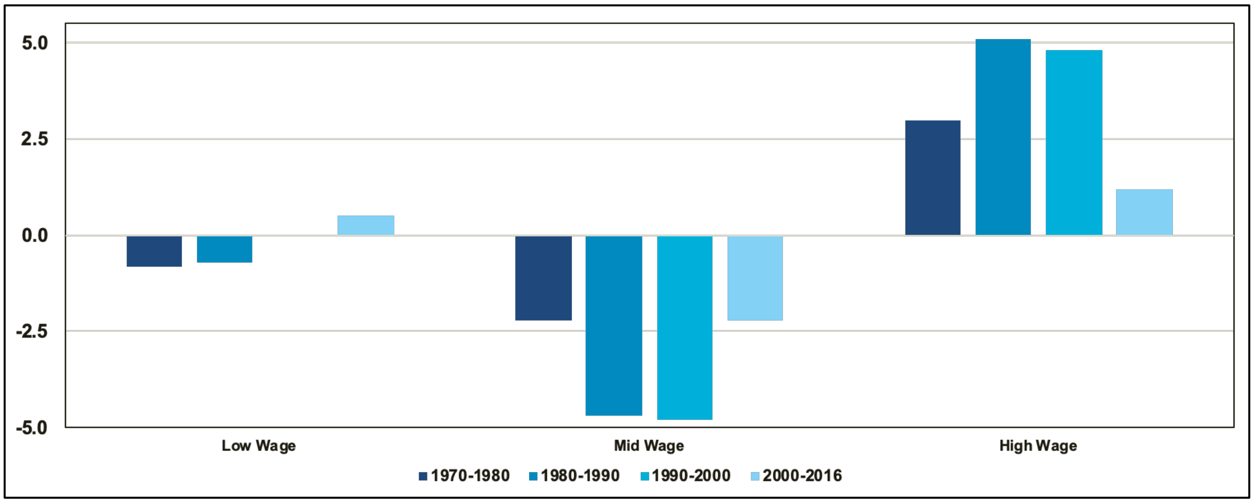
Source: IBM

Figure 2
Average Change per Decade in US Occupational Shares
1940-1980 and 1980-2010



Source: Autor (2015)

Figure 3
Changes in Occupational Shares
1970-2016



Source: Autor (2019)

Figure 4
Most occupations in most industries have at least some tasks that are Suitable for Machine Learning (SML)

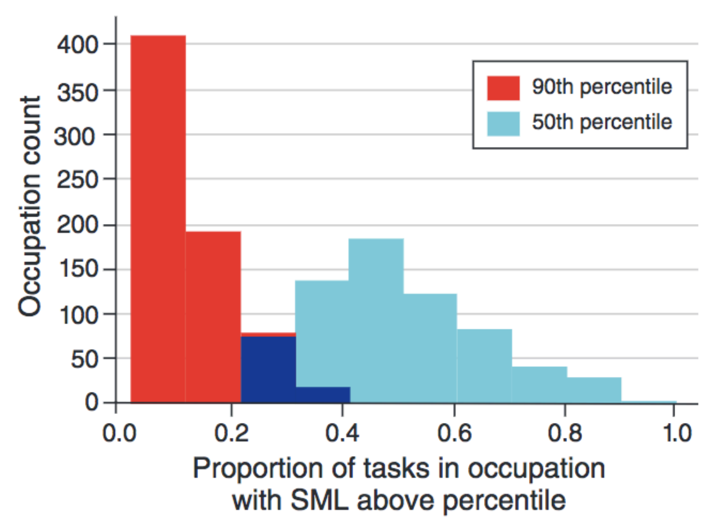
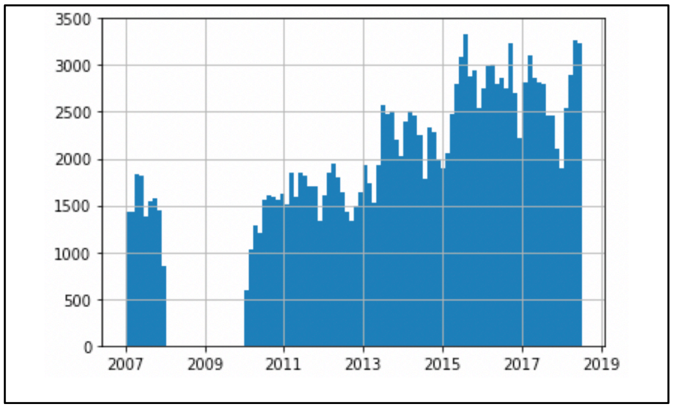


FIGURE 1. FREQUENCY COUNTS OF OCCUPATIONAL TASK PROPORTIONS ABOVE NINETIETH, SEVENTY-FIFTH, AND FIFTIETH PERCENTILES

Source: Brynjolfsson, Mitchell, and Rock (2018)

Figure 5
Dates of Burning Glass Job Posts
Publication

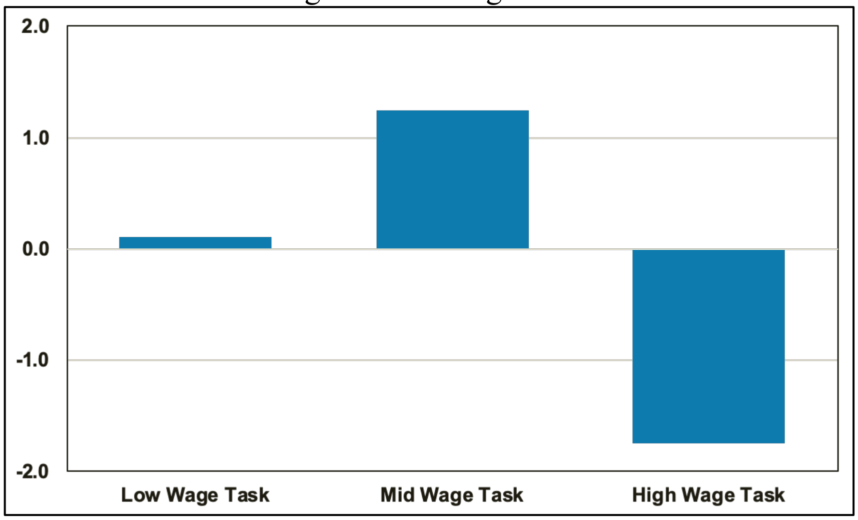


Source: Burning Glass

Figure 6
Occupational Employment Share
Percentage Point Change, 2010-2017

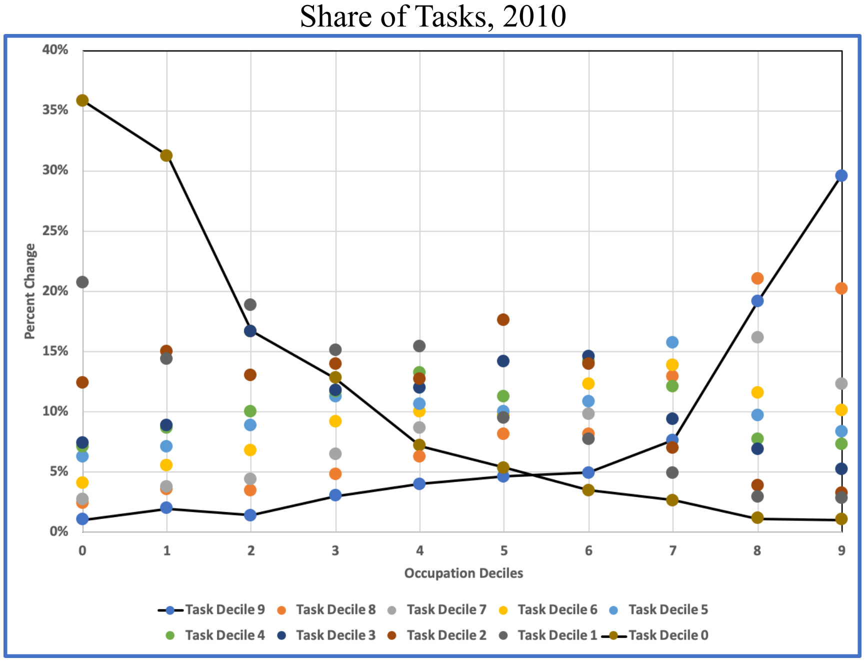
Source: IBM

Figure 7
Task Employment Share
Percentage Point Change 2010-2017



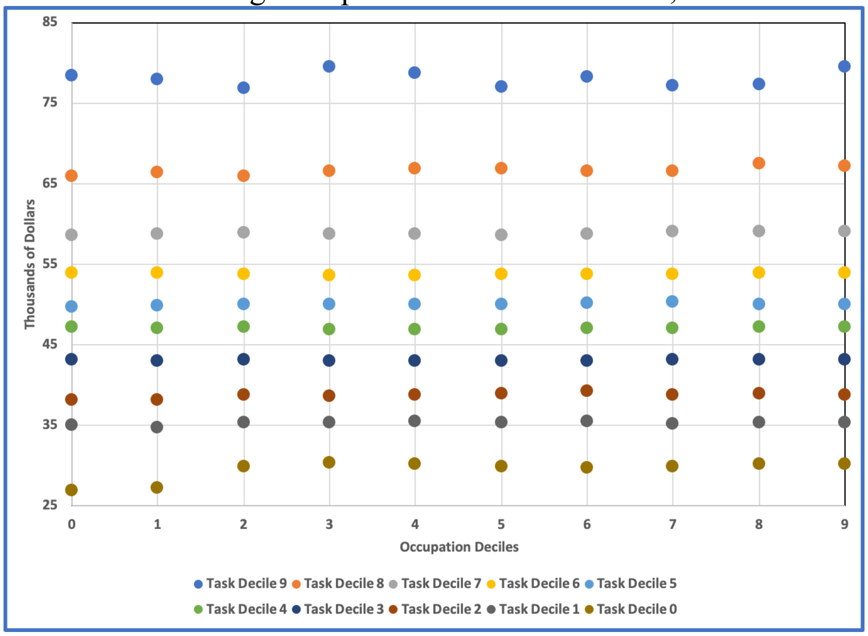
Source: IBM

Figure 8
Task Share
Share of Tasks, 2010



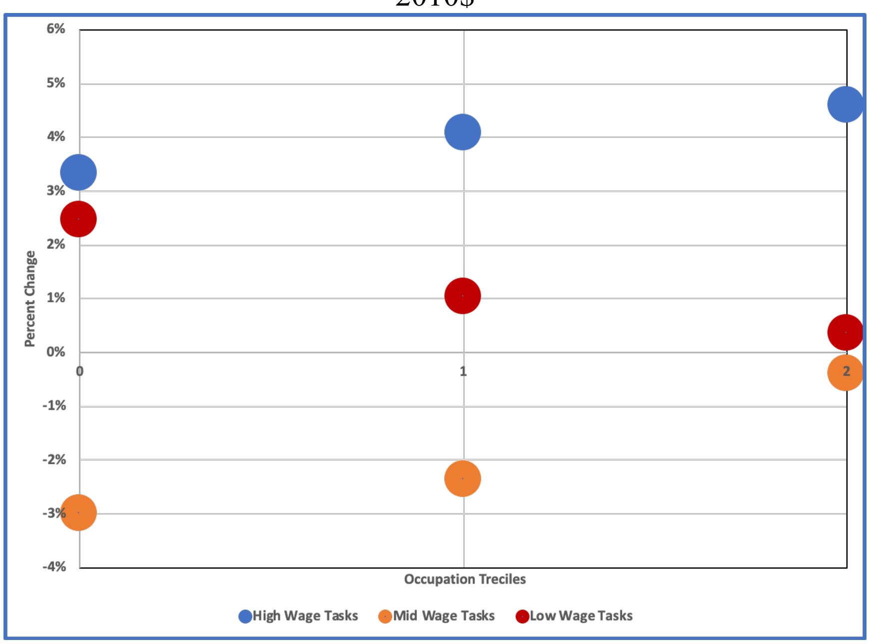
Source: IBM

Figure 9
Task Wage
Average Wage of Workers
Performing Occupation-Task Combination, 2010



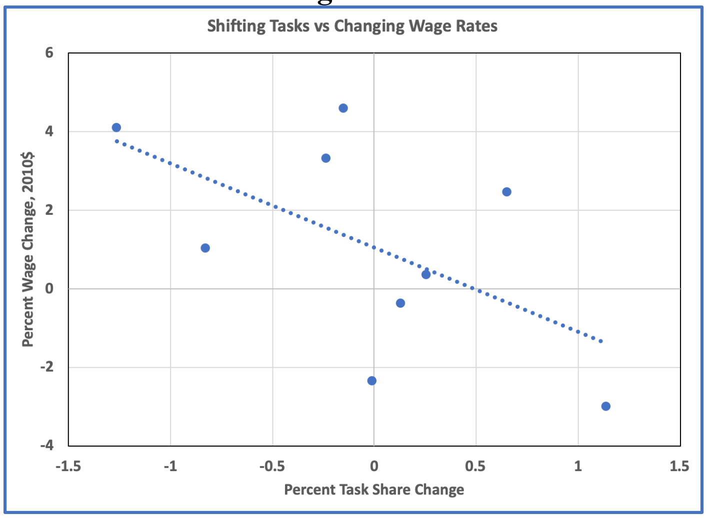
Source: IBM

Figure 10
Wage Changes
2010 – 2017
2010$



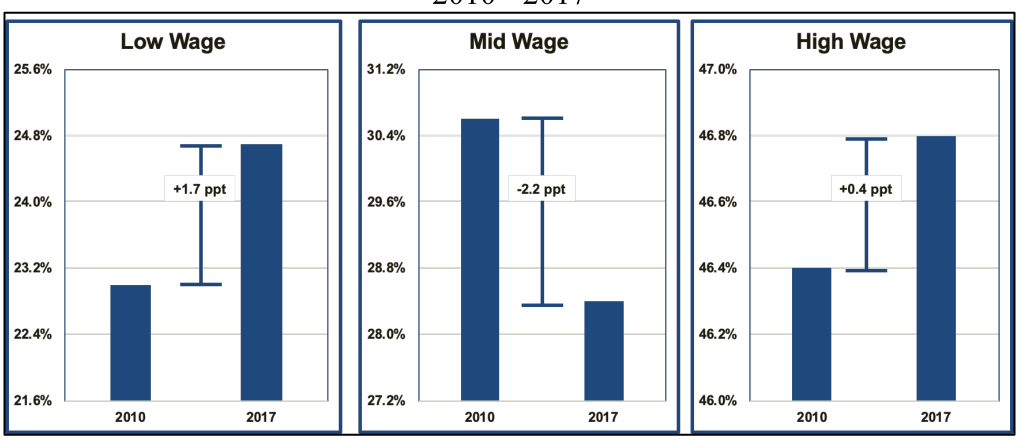
Source: IBM

Figure 11



Source: IBM

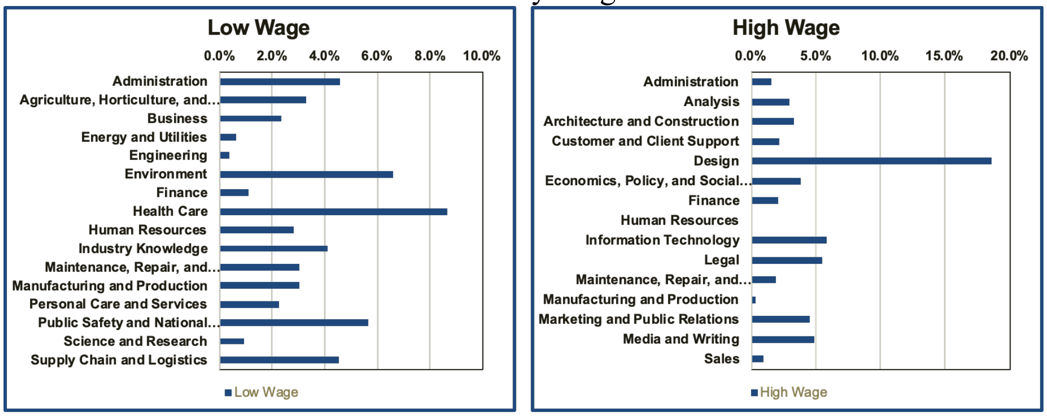
Figure 12
Task Changes by Occupation Wage Tercile
2010 - 2017



Source: IBM

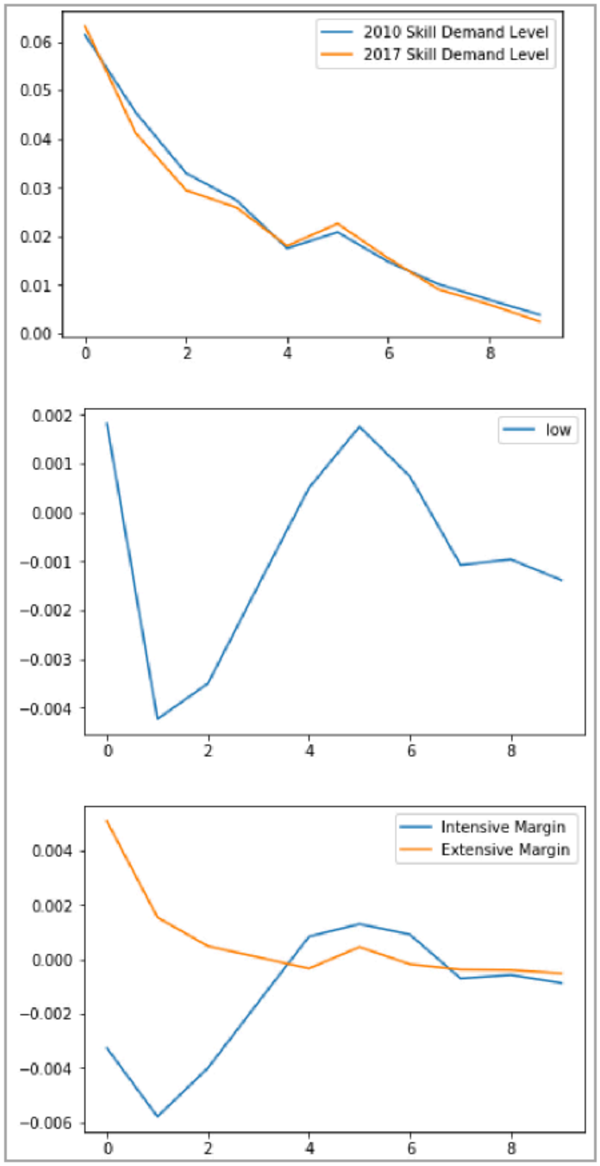
Figure 13

Task Increases by Wage Tercile



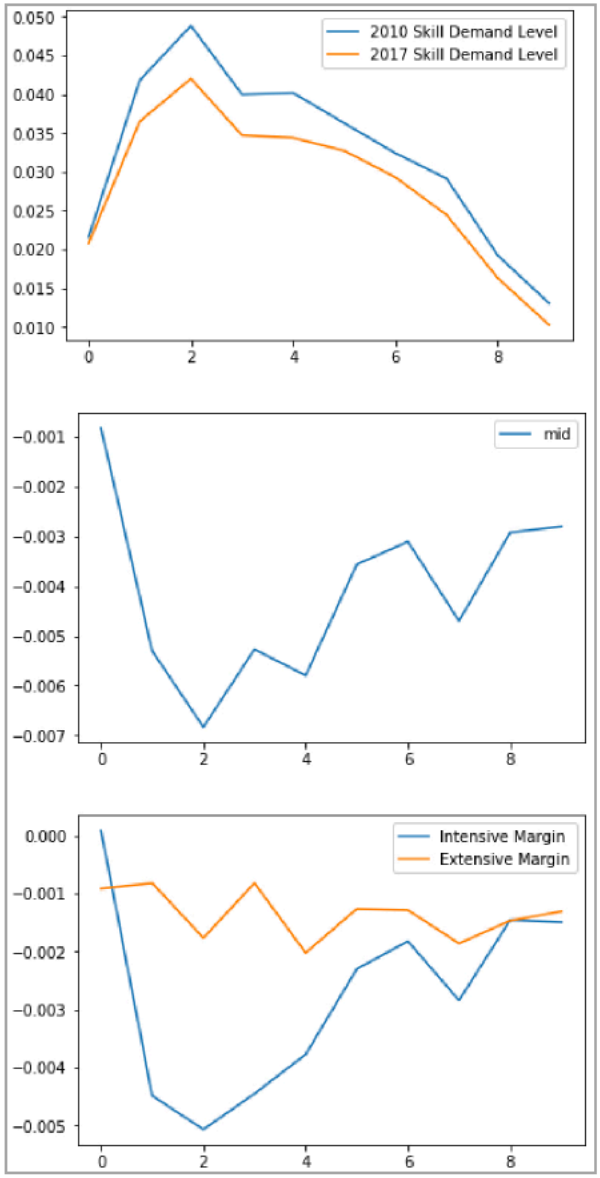
Source: IBM

Figure 14
Low-Wage Occupation Tasks Demanded



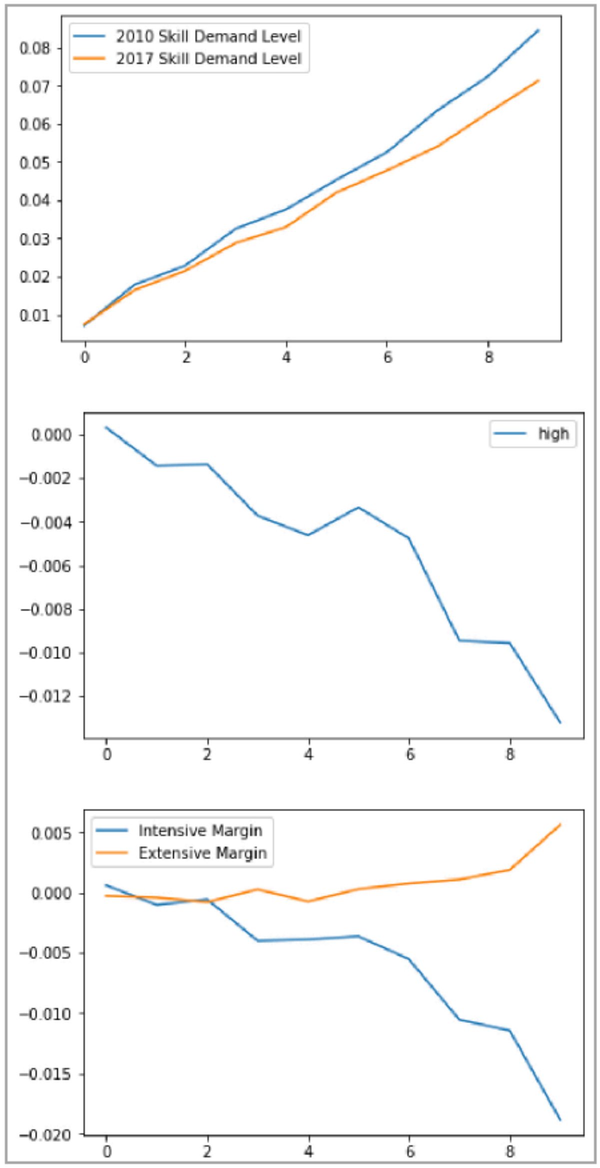
Source: IBM

Figure 15
Mid-wage Occupation Tasks Demanded



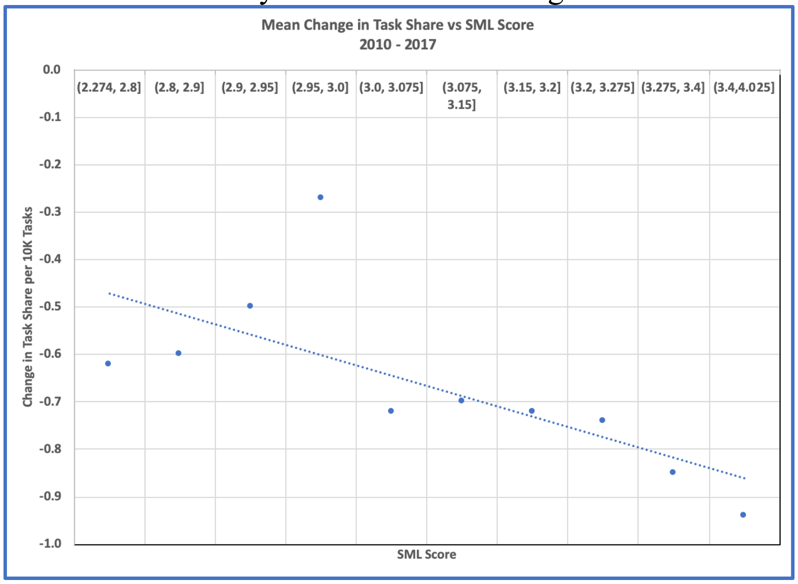
Source: IBM

Figure 16
High-Wage Occupation Tasks Demanded



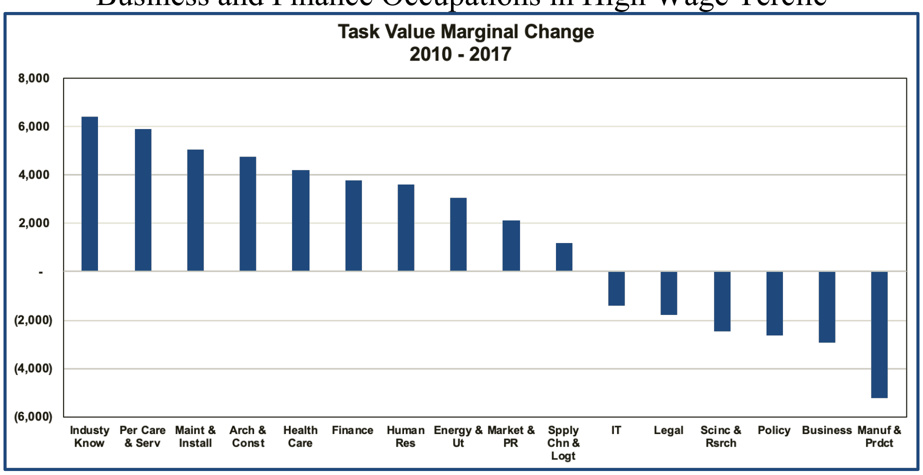
Source: IBM

Figure 17
Change in Tasks Demanded and
Suitability for Machine Learning Scores



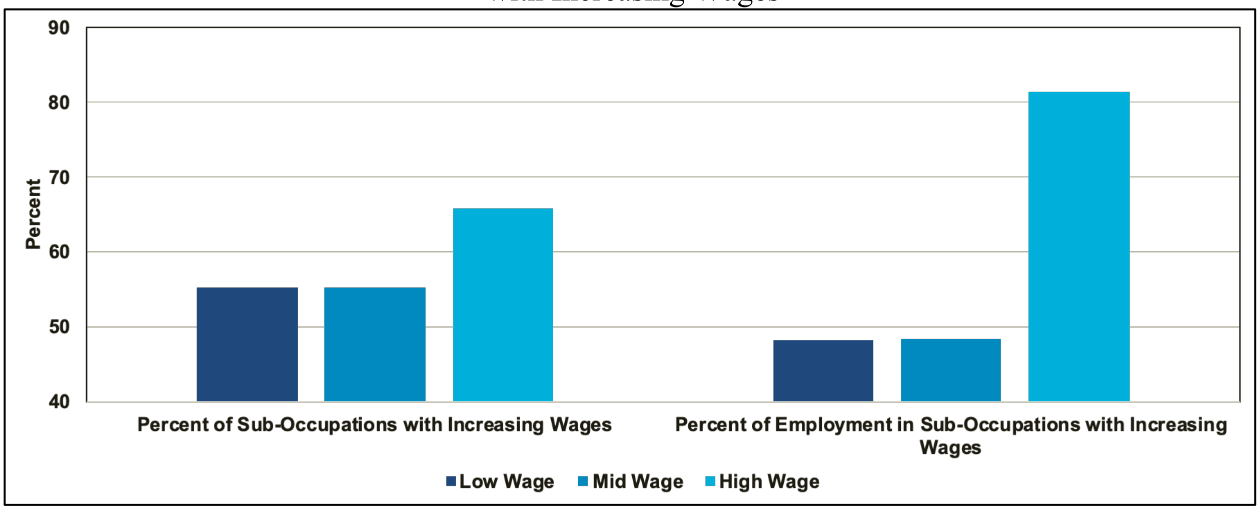
Source: IBM

Figure 18
Business and Finance Occupations in High Wage Tercile



Source: IBM

Figure 19
Percent of Sub-Occupations and Employment in Sub-Occupations
with Increasing Wages



Source: IBM

Table 1

Features Extracted from Text

MAIN TABLE	**Geography Variables**	49. Salary Type
Posting Identifiers	25. City	50. Job Hours
1. BGT Job ID	26. State	51. Tax Term
2. Job ID	27. County	52. Internship
3. Job Date	28. FIPSState	
Occupation and Industry Identifiers	29. FIPSCounty	**OTHER TABLES**
4. Clean Job Title	30. FIPS	**Skills Data**
5. Canon Job Title	31. Latitude	Skill
6. Occupation Family	32. Longitude	Skill Cluster
7. Occupation Family Name	33. Best-fit MSA (see description below)	Skill Cluster Family
8. SOC	34. Best-fit MSA Name	Is Specialized Skill?
9. SOC Name	35. Best-fit MSA Type	Is Baseline Skill?
10. ONET	36. MSA (2013 delineations)	Is Software Skill?
11. ONET Name	37. MSA Name (2013 delineations)	**Major and Certifications**
12. BGT Occupation (BGTOcc) Code	**Credentials & Requirements**	Standard Major
13. BGTOcc Name	38. Min Years of Education	CIP Code
14. Primary BGTOcc Group Name	39. Degree Name (Min Education)	Certification
15. Secondary BGTOcc Group Name	40. Max Years of Education	
16. Primary Career Area Name	41. Degree Name (Max Education)	
17. Secondary Career Area Name	42. Min Years of Experience	
18. Employer	43. Max Years of Experience	
19. NAICS Sector (NAICS 2-digits)	**Salary and Job Type**	
20. NAICS Sector Name	44. Min Annual Salary	
21. NAICS 3-digits	45. Max Annual Salary	
22. NAICS 4-digits	46. Min Hourly Salary	
23. NAICS 5-digits	47. Max Hourly Salary	
24. NAICS 6-digits	48. Pay Frequency	

Source: IBM

Table 2
Suitability for Machine Learning Index
For Tasks by Wage Tercile

Task	High Wage Mean SML Score	Mid Wage Mean SML Score	Low Wage Mean SML Score
Administration	3.148	3.292	3.388
Agriculture, Horticulture, and the Outdoors	3.013	2.926	2.912
Analysis	3.097	3.251	3.415
Architecture and Construction	3.016	2.911	2.888
Business	3.050	3.139	3.166
Customer and Client Support	3.185	3.311	3.323
Design	3.066	3.231	3.178
Economics, Policy, and Social Studies	3.029	3.028	0.000
Education and Training	3.051	3.109	3.115
Energy and Utilities	3.025	3.062	0.000
Engineering	3.094	3.090	3.216
Environment	3.054	3.052	2.894
Finance	3.129	3.320	3.347
Health Care	3.076	3.083	3.132
Human Resources	3.020	3.072	3.062
Industry Knowledge	3.093	3.152	3.198
Information Technology	3.110	3.186	3.193
Legal	3.023	3.134	3.180
Maintenance, Repair, and Installation	3.069	3.035	3.073
Manufacturing and Production	3.042	3.073	3.109
Marketing and Public Relations	3.074	3.274	3.196
Media and Writing	3.063	3.081	3.102
Personal Care and Services	3.010	2.987	3.067
Public Safety and National Security	2.989	3.130	2.891
Religion	0.000	2.940	0.000
Sales	3.158	3.303	3.190
Science and Research	3.056	3.179	3.123
Supply Chain and Logistics	3.058	3.090	3.182
Average	2.957	3.123	2.805

Source: IBM

Table 3
High Wage Occupations

Occupations (Across)	Architecture and Engineering Occupations	Arts, Design, Entertainment, Sports, and Media Occupations	Business and Financial Operations Occupations	Community and Social Service Occupations	Computer and Mathematical Occupations	Construction and Extraction Occupations	Education, Training, and Library Occupations	Healthcare Practitioners and Technical Occupations	Legal Occupations	Life, Physical, and Social Science Occupations	Management Occupations
Task (Down)											
Administration	3584	2937	4388	---	4418	---	1828	7023	10901	---	5636
Agriculture, Horticulture, and the Outdoors	5368	---	---	---	---	---	16404	---	---	3506	(7033)
Analysis	2854	(5666)	---	---	2546	---	3833	---	---	4850	---
Architecture and Construction	1796	(10747)	4734	---	---	(1006)	---	---	---	8042	7633
Business	---	(3531)	(2923)	(3258)	(1505)	(2838)	(10098)	(2543)	---	---	5174
Customer and Client Support	---	5005	---	2478	(6498)	(2998)	---	(5938)	6830	---	(1816)
Design	3035	3991	---	---	6011	5375	(4183)	16222	---	---	---
Economics, Policy, and Social Studies	(9419)	---	(2655)	(7605)	(4955)	---	(2481)	(5861)	---	(3495)	---
Education and Training	4207	2152		1573	---	---	---	(2013)	---	3245	2823
Energy and Utilities	---	---	3051	---	---	---	---	---	---	---	---
Engineering	---	---	---	---	---	(4176)	---	---	---	---	(4061)
Environment	(2610)	---	---	---	---	---	(8310)	---	---	(1739)	2103
Finance	(1441)	(2268)	3769	---	(4592)	---	---	2719	(5211)	(2889)	3448
Health Care	(2466)	2365	4208	3260	1555	(4677)	(1348)	5368	---	---	6309
Human Resources	---	---	3609	---	---	---	---	(3025)	5323	---	3199
Industry Knowledge	4433	(2634)	6387	---	4414	2724	9166	---	4239	(2321)	6709
Information Technology	2787	4665	(1393)	---	14146	2505	2370	(2504)	8686	---	2542
Legal	---	---	(1767)	---	---	---	---	---	(4060)	---	(4711)
Maintenance, Repair, and Installation	3171	---	5034	---	(1892)		(5413)	---	---	---	3846
Manufacturing and Production	4434	---	(5218)	---		(3402)	---	---	---	---	---
Marketing and Public Relations	---	(3090)	2112	---	7009	(5195)	2699	(10332)	---	---	(6905)
Media and Writing	---	1624	---	---	(2808)	---	(4632)	---	5302	3431	---
Personal Care and Services	---	---	5878	---	(5520)	6012	7609	12685	---	5646	8380
Public Safety and National Security	3345	(21113)		---	3807		10759	(5913)		(4074)	
Religion	---	---	---	(7236)	---	---	---	---	---	---	---
Sales	---	2411	---	---	---	(7568)	---	4254	(5368)	(6261)	(1080)
Science and Research	(2906)		(2449)	---	(1913)		---	---	(9897)	(5034)	---
Supply Chain and Logistics	---	3438	1174	7862	(6531)	(2068)	6515	(2627)	---	2804	(2567)

Source: IBM

Table 4
Mid-Wage Occupations

Occupations (Across)	Installation, Maintenance, and Repair Occupations	Office and Administrative Support Occupations	Production Occupations	Protective Service Occupations	Sales and Related Occupations
Tasks (Down)					
Administration	2486	1516	---	(4713)	4501
Agriculture, Horticulture, and the Outdoors	3767	4454	---	8208	6574
Analysis	3309	(1578)	---	(4302)	---
Architecture and Construction	---	---	---	6714	8635
Business	---	(580)	(2586)	---	(10088)
Customer and Client Support	3146	(265)		3201	---
Design	13251	2347	4837	13029	8522
Economics, Policy, and Social Studies	6037	(3729)	19031	---	8082
Education and Training	(7345)	(1406)	---	4356	6588
Energy and Utilities	(6436)	---	(2059)	12603	---
Engineering	---	9279	---	---	3166
Environment		(1916)	---	---	15622
Finance	2176	2991	---	(2164)	---
Health Care	(4517)	(403)	(2716)	---	8735
Human Resources	3353	1388	2376	6166	---
Industry Knowledge	1251	2114	---	---	1552
Information Technology	(5423)		1096	(3450)	(1594)
Legal	(7310)	(3412)	---	3159	(9858)
Maintenance, Repair, and Installation	4598	2757	1567	(6107)	
Manufacturing and Production	(1317)	(3479)	---	(10176)	(29102)
Marketing and Public Relations	---	(2625)	---	---	---
Media and Writing	(3898)	3747	(5130)	---	(2380)
Personal Care and Services	(4870)	2095	---	---	4758
Public Safety and National Security	---	---	---	(1628)	---
Religion	---	---	---	---	---
Sales	5260	1057	(1810)	4460	3435
Science and Research	(3218)	(2382)	(2441)	3618	---
Supply Chain and Logistics	(1861)	1034	(1619)	2279	6200

Source: IBM

Table 5
Low-Wage Occupations

Occupation (Across)	Building and Grounds Cleaning and Maintenance Occupations	Farming, Fishing, and Forestry Occupations	Food Preparation and Serving Related Occupations	Healthcare Support Occupations	Personal Care and Service Occupations	Transportation and Material Moving Occupations
Task (Down)						
Administration	5147	---	---	---	(2090)	(12438)
Agriculture, Horticulture, and the Outdoors	---	---	---	---	---	(9174)
Analysis	---	---	---	---	---	(8464)
Architecture and Construction	(7661)	---	9239	---	10105	---
Business	(5429)	---	(2271)	2121		(3797)
Customer and Client Support	(4456)	---	1470	3159	3701	(2403)
Design	40076	---	16777	9820	11767	10660
Economics, Policy, and Social Studies	---	---	19110	---	---	10747
Education and Training	(22354)	---	---	---	1741	---
Energy and Utilities	---	---	---	---	---	21471
Engineering	---	---	(11333)	---	---	(34036)
Environment	(5434)	---		---	---	(12421)
Finance	7666	---	2924	4007	---	4465
Health Care	3173	(9746)		2134	2891	(6876)
Human Resources	3738	(13904)	(2280)	---	---	(22883)
Industry Knowledge	(17737)	---	---	---	---	(9631)
Information Technology	(11178)	9305	(5215)	---	3596	---
Legal	---	---	---	---	---	---
Maintenance, Repair, and Installation	(13925)	5166	---	---	---	(7267)
Manufacturing and Production	3327	7591	(6175)	---	---	(5242)
Marketing and Public Relations	6796	---	---	---	(8242)	(6188)
Media and Writing	10349			6164		(5971)
Personal Care and Services	(4957)	---	1579	1805	(1431)	8265
Public Safety and National Security	---	---	---	---	---	(6299)
Regilion	---	---	---	---	---	---
Sales	(29003)	---	---	---	(8372)	(5617)
Science and Research		---	---	3792	---	6591
Supply Chain and Logistics	(6094)	---	2129	(2943)	---	6550

Source: IBM

Table 6
Estimates of Equation (14)

	(1)	(2)	(3)		(1)	(2)	(3)
LowY	576.81	1,607.58	597.69				
HighY	1,053.53	2,263.42	1,185.02				
Tasks				***Task*Y***			
Administration	----	(14,660.00)	(17,220.00)	AdministrationY	----	----	3,857.17
Agriculture, Horticulture, and the Outdoors	----	(10,200.00)	(12,270.00)	Agriculture, Horticulture, and the OutdoorsY	----	----	3,086.86
Analysis	----	8,762.81	7,888.74	AnalysisY	----	----	1,227.36
Architecture and Construction	----	925.56	(661.89)	Architecture and ConstructionY	----	----	2,303.17
Business	----	10,540.00	12,670.00	BusinessY	----	----	(3,358.43)
Customer and Client Support	----	(13,760.00)	(13,630.00)	Customer and Client SupportY	----	----	(79.54)
Design	----	2,394.34	(1,217.81)	DesignY	----	----	6,270.75
Economics, Policy, and Social Studies	----	1,981.05	3,673.38	Economics, Policy, and Social StudiesY	----	----	(2,078.26)
Education and Training	----	(2,209.27)	(2,884.77)	Education and TrainingY	----	----	1,197.95
Energy and Utilities	----	9,482.13	7,047.29	Energy and UtilitiesY	----	----	3,306.86
Engineering	----	11,090.00	11,960.00	EngineeringY	----	----	(1,227.81)
Environment	----	2,118.04	1,373.43	EnvironmentY	----	----	1,047.05
Finance	----	3,106.42	3,402.02	FinanceY	----	----	(234.96)
Health Care	----	4,563.43	199.15	Health CareY	----	----	6,680.49
Human Resources	----	(149.20)	162.75	Human ResourcesY	----	----	(453.74)
Industry Knowledge	----	843.09	(1,524.31)	Industry KnowledgeY	----	----	4,324.80
Information Technology	----	7,502.87	9,159.12	Information TechnologyY	----	----	(2,507.19)
Legal	----	794.37	2,531.96	LegalY	----	----	(2,606.17)
Maintenance, Repair, and Installation	----	(9,968.68)	(11,370.00)	Maintenance, Repair, and InstallationY	----	----	2,213.50
Manufacturing and Production	----	(4,967.56)	(4,655.76)	Manufacturing and ProductionY	----	----	(666.32)
Marketing and Public Relations	----	(5.02)	2,682.11	Marketing and Public RelationsY	----	----	(4,074.64)
Media and Writing	----	(1,600.42)	(1,592.39)	Media and WritingY	----	----	136.33
Personal Care and Services	----	(15,260.00)	(17,270.00)	Personal Care and ServicesY	----	----	3,753.41
Public Safety and National Security	----	(4,681.76)	(3,199.12)	Public Safety and National SecurityY	----	----	(2,088.76)
Religion	----	(63.47)	1,034.09	ReligionY	----	----	(4,891.87)
Sales	----	7,365.31	8,344.81	SalesY	----	----	(1,734.68)
Science and Research	----	(529.25)	2,151.19	Science and ResearchY	----	----	(3,974.91)
Supply Chain and Logistics	----	(2,383.50)	(5,931.60)	Supply Chain and LogisticsY	----	----	4,764.07

Coefficient estimates not significantly different from zero

Source: IBM