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PRODUCTIVITY AND WAGES: WHAT WAS THE PRODUCTIVITY-WAGE LINK IN THE DIGITAL REVOLUTION OF THE PAST, AND WHAT MIGHT OCCUR IN THE AI REVOLUTION

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Productivity and Wages: What Was the Productivity-Wage Link in the Digital Revolution of the Past, and What Might Occur in the AI Revolution of the Future?
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ABSTRACT

Wages have been spreading out across workers over time – or in other words, the 90th/50th wage ratio has risen over time. A key question is, has the productivity distribution also spread out across worker skill levels over time? Using our calculations of productivity by skill level for the U.S., we show that the distributions of both wages and productivity have spread out over time, as the right tail lengthens for both. We add OECD countries, showing that the wage-productivity correlation exists, such that gains in aggregate productivity, or GDP per person, have resulted in higher wages for workers at the top and bottom of the wage distribution. However, across countries, those workers in the upper income ranks have seen their wages rise the most over time. The most likely international factor explaining these wage increases is the skill-biased technological change of the digital revolution. The new AI revolution that has just begun seems to be having a similar skill-biased effects on wages. But this current AI, called "supervised learning," is relatively similar to past technological change. The AI of the distant future will be "unsupervised learning," and it could eventually have an effect on the jobs of the most highly skilled.

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I. Introduction

It has been established that wage inequality has grown over time, or that wages are spreading out more across people over time. Is this because productivity levels are also becoming more unequally distributed across people? That is, is productivity rising faster at the top of the skill distribution than at the bottom of the skill distribution? Might rising inequality in productivity gains explain, in part, the rising inequality in pay?

We aim to answer these questions by looking at productivity and pay by skill group, and then looking at the implied correlation of these two measures over time. The measurement of productivity by skill group is challenging, because there is no direct data on it. It is also conceptually challenging – firms rarely measure the productivity of their workers for skilled jobs. Therefore, we have to work around the absence of direct measures.

Our approach to measuring productivity by skill level begins with the assumption that the average skill level of an industry is measured by the average educational level of that industry. We then link average education by industry to productivity by industry. As examples, consider two very different industries that represent our data points. One data point is for the software industry. Software has a very high average educational level. This industry also has a high productivity level, based on BLS data on output and employment by industry. Therefore, the software industry can be one of our data points, having an average educational level of 17 years, and a productivity level that is well above average. A second data point is for the retail trade industry. The average educational level in the industry is very low, at 11 years, and the productivity of the industry is also very low.

Thus, these two data points, from the software and retail trade industries, are illustrative of the relationship between productivity and skill levels over time which we examine for 40 3-digit industries that include manufacturing and other industries.[1] We already know, and confirm, that wage levels have risen fastest over time for workers in the highest-skilled groups. Taken together, using our constructed productivity and pay data, and their correlations across and within industries, we address the question, if wages are spreading out across skill groups, could this be caused, in part, by the spreading out of productivity gains? We don't have causal data,

[1] The software and retail industry example here is illustrative – the actual industry data that is available is for more aggregate industries than software.

but what do correlations reveal?

Before turning to our regressions utilizing productivity by skill level, we begin by updating the evidence on the linkage between productivity and pay in aggregate data at the country level. We show that across OECD countries and within them over time, there is a positive correlation between aggregate productivity increases and wage increases. This relation, while positive and strong, is neither perfect nor necessarily unitary in magnitude: there is not a one-for-one increase in productivity and then increase in pay. In some situations, productivity gains outstrip wage gains within a country over time, while in others cases the reverse is true. However, we conclude that there is a direct and unequivocal empirical correlation between wages and productivity when they are measured using aggregate annual data.

The key conclusions of the paper are as follows:

- Using economy-wide data, over a long span of time and across countries, aggregate productivity gains appear to be passed on as aggregate wage gains.

- A rising tide lifts all boats. High, middle and low wage earners experience growth in wages when productivity grows for the aggregate economy.

- The industries that have experienced the most rapid growth in productivity are those that use the most skilled and educated workers.

- Thus, educated, and thus skilled. workers have also enjoyed the most wage growth and productivity growth over time, which is consistent with productivity increases being the source of wage growth rather than primarily monopoly power, institutions, taxes, or other policies.

In sum, it is well known that the wage distribution has spread out more over time – the 90th percentile of wages has grown more than the 50th percentile of wages. This is also true of the productivity distribution. It has stretched out. Using our proxy for productivity by education level, productivity among more educated workers is higher and has grown more rapidly than productivity of less educated workers. This is consistent with growing wage dispersion, where the wages of highly educated workers have pulled away from wages of less educated workers.

The explanation that we offer, and the theoretical model, for the spreading out of productivity gains is that it may reflect non-neutral technological gains over time, as well as innovations in management practices that were introduced over time, in part due to their complementarity with rising computerization. However, in the last five years, the technological revolution is the rise of AI, or artificial intelligence. We provide evidence, from the recent research literature, on the impact that it is having on productivity, skill demand, and pay. Because AI is in a nascent phase of adoption by firms, we emphasize that in past technological revolutions it took time to introduce the technology and the organizational changes that made revolution powerful, so we end with some speculations as to where productivity and pay could go up in the future due to AI.

The outline of the paper is as follows. The first sections introduce the key question – the spreading out of productivity and pay – and then briefly review the literature. Next, we show figures that remind us that over the span of the last century, GDP and productivity have risen as the computer revolution occurred. Our theoretical framework, in Section V, is therefore one of technological changes.[2] The next two sections, VI and VII, introduce the data, and the links between wages and aggregate productivity growth. In sections VIII and IX, we re-visit the lag in pay that the middle class has experienced, and look at regressions of the effects of aggregate productivity growth on pay in the 10th and 90th deciles of the wage distribution.

Our key results regarding the spreading out of productivity and pay are in section X. In that section, we ask the question, if pay increases have been greater for higher income workers, is it also true that productivity increases have been greater for these workers? Section XI introduces what research economists now know about the effects of AI on the factors discussed in this paper, and the conclusion follows in section XII.

II. The Empirical Question for the Data

[2] Substantial sections of this paper, particularly starting with the section on the Theoretical Framework, include extracts from Lazear (2019). Some of these, such as the first two subsections of the Theoretical Framework, contain direct excerpts from Lazear (2019). Lazear died of pancreatic cancer on November 24, 2020. Shaw and Lazear had begun a large research project on productivity topics. Shaw is extending that work, and thus also publishing Lazear's work, by focusing this paper on some of the joint work they were doing. The third co-author is Grant Hayes, who was a full-time research assistant for Edward Lazear and is now a PhD student in the Chicago Booth Accounting group. The fourth co-author for this paper is James Jedras, who was a full-time research assistant for Edward Lazear and is now a PhD student in economics at Boston University. Much of the empirical work in this paper has been updated using current versions of data, updating the work contained in Lazear's (2019) paper.

The central empirical issue here is whether shifts in aggregate productivity that occurred in past decades were coupled with changes in the shape of the productivity distribution. It is well-documented that the wage distribution has spread out. Consider two extreme characterizations of the causes. First, growing monopsony power by employers and increased labor market exploitation of less skilled workers has driven their wages down. Note that the monopsony power and ability to exploit must fall only on the less skilled because during the same period, the wages of highly paid and highly educated workers (as discussed below) increased.[3] The second extreme alternative is that all labor markets are completely competitive and wages move directly with productivity. If the productivity of the highly skilled increases more when the economy's average productivity rises, then the wages of the highly skilled would diverge from wages of the less skilled over time. Determining the validity of the second explanation is the subject of this section.

Hypothetical Productivity distributions in Figure 1 illustrate the point. Initially, productivity is distributed as the solid curve with mean P. Over time, productivity grows, and the productivity distribution shifts from the solid to dotted curve with mean P'. Average productivity rises by P'-P but the dotted distribution is not simply a displacement of the solid distribution. The dotted distribution has a higher variance and a different shape. In particular, the productivity of high-productivity workers has grown by more than the productivity of low-productivity workers. The 90^{th} productivity percentile worker before the change had level productivity of P90 and the 10^{th} productivity percentile worker before the change had productivity level of P10. After the increase in productivity, the 90^{th} percentile worker has productivity P90' and the 10^{th} percentile worker has productivity P10'. In this example, the 90^{th} percentile worker's productivity has risen by more than P'-P while the productivity of the 10^{th} percentile worker has risen by less than P'- P. If workers were paid exactly in accordance with their productivity, then wages would spread out over time.

Evidence on the relation of wage increases at various deciles as a function of average productivity increases is interesting, but not directly relevant to the issue here.[4] For example, suppose it were found that the wage of the 10^{th} percentile grew less rapidly with aggregate productivity than did the wage of the 90^{th} percentile. This could be explained by the fact that

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[3] See for example Manning (2003) and Bhaskar et al. (2002) for a review of modern monopsony literature. Matsudaira (2014) explores monopsony power in the low-wage labor market.
[4] This is what is done in Stansbury and Summers (2017).

wages at the bottom are less responsive to productivity increases than wages at the top. Alternatively, it might simply reflect that productivity at the bottom grew less than average productivity and productivity at the top grew more than average productivity, while wage increases exactly matched the productivity increases of the specific worker or types. To disentangle these two explanations, measures of productivity changes by worker skill level are required. This is the aim of Section, using education as the proxy for skills.

III. The State of the Literature

The literature on productivity and growth began with growth models going back at least to the 1930s.[5] All growth models have as by products implications for factor shares and wages. A direct feature of the theoretical models is they provide a link between growth in aggregate output, growth in productivity (defined either as labor or total factor productivity) and growth in wages. The models generally assume that capital responds in a competitive way to changes in productivity, but that labor is determined exogenously by population growth. The benchmark case links wage growth to productivity growth in a one-to-one manner, but this is a consequence of both supply assumptions and assumptions about technological change (discussed in the theory section below).

There is a literature that examines explicitly, both empirically and theoretically, the link between wages and productivity using economy-wide data. For example, Karabarbounis and Neiman (2013) do this when they ask why the labor share of income has declined over time for 59 countries. The commonality of the decline across so many countries, including high income and low-income countries, creates a key puzzle as to what they have in common. The authors attribute about half of the decline in the labor share to the lowering price of investment. This is also important because it says that the quantity of capital is rising, not that the marginal capital investment yields more than in the past.

A comprehensive analysis by Stansbury and Summers (2017) focuses, like virtually most of the prior literature, on the relationship between wage growth at many income deciles and economy-wide productivity growth. Their primary conclusion is that aggregate productivity

[5] Harrod (1939) and Domar (1946, 1947) are the best known of the early ones. Solow's path-breaking work (1956) changed growth accounting and has served as the workhorse model to this day.

increases translate into pay growth at many points of the income distribution. The authors cannot reject the hypothesis that the pay increase for the median worker is one-for-one with the aggregate productivity gains. However, the relation of various deciles of the wage distribution to changes in aggregate productivity is non-monotonic. The highest coefficient of economy-wide productivity on pay is at the top 20th pay percentile and the lowest is at the bottom 30th percentile, although the latter is imprecisely estimated. We will expand on this question of aggregate productivity on pay, using extensive data on the 90th, 50th, and 10th percentiles across countries and over time within countries.

A few prior studies address the primary issue of our analysis, which is the relation of a particular worker's or worker-type's wage to that worker or worker-type's productivity rather than to aggregate productivity. Hellerstein, Newmark and Trosky (1999) use a matched US employer-employee dataset to examine the demographic structure of a firm and its productivity and conclude that with the exception of women, wage differences among groups mirror productivity differences. For three countries in sub-Saharan Africa, there one-to-one relationship is found in the most educated (Zimbabwe) and not in the least educated (Tanzania), where the positive relationship follows the theory below, that labor is imperfectly substituted across firms (VanBiesebroeck, 2011).

Dunne et al. (2004) use plant level data to determine variations in productivity and wages at the level of the establishment over time. They find that between-plant variations in both wages and productivity have increased during the last decades of the 20th century. Faggio, Salvanes and Van Reenen (2010) use UK data for manufacturing and non-manufacturing firms since the 1980s and conclude that productivity inequality across firms has increased more over time than the manufacturing data indicated. This resulted in an increase in pay inequality across firms and within industries. They conclude that increased productivity dispersion could be linked with new technologies

Complete equilibrium models of the labor market have also been used as explanatory tools. Lee and Wolpin (2006) address the fact that employment in the service sector grew dramatically relative to the goods sector while wages did not, ultimately estimating that the costs of mobility between sectors are large, so potential output and the implied productivity gains are lost due to a lack of mobility. Their 2010 paper goes further and finds that skill-biased technological change accounts for the bulk of the increased college wage premium and overall wage inequality. Hornbeck and Moretti (2018) find that when manufacturing productivity rises in an area from 1980 to 2000 it elevates the pay of those working in that area. The gains do not depend on a worker's education, but on where they live.

It is important to mention other relationships between productivity and wages in the time series evidence. Antràs, Gortari, and Itskhoki (2017) document that globalization increases inequality, and that rising inequality erodes about 20% of the performance gains from international trade. Card (2001) shows that higher unionization slows the growth in inequality, so collective bargaining is a factor. Much of prior literature has also been spent examining the effects of output-based compensation. Lemieux, Parent, and MacLeod (2007) find the share of performance pay jobs has increased across firms, explaining 24% of the growth in male wages over a roughly ten-year period.

Our analysis below differs from these prior studies that focus on changes over time, the use of industry data for large segments of the population, or the emphasis on international comparisons to determine which of the patterns are common across countries.[4] Some of our analysis repeats that which has gone before for comparison reasons, but most is related to explaining the spreading out of the wage distribution as it relates to education by matching it with the spreading out of the productivity distribution as it relates to education.

Fundamentally, the question here is, to what extent has the education wage premium risen over time and is the rise in the education productivity premium sufficient to account for that change?

It is important to conclude this brief literature review by pointing out that is has been widely accepted for 20 years that skill-biased technical change characterizes the effects of technological gains on pay. That is, there is rising demand for non-routine cognitive skills (Autor, Levy, and Murnane, 2003, and Autor and Dorn, 2013). This is also reflected in the rising rates rates of return to education over time. The general finding is that the skill differential has increased and explanations for that increase, based on either supply or demand, go back to Katz and Murphy (1992). Standard Bureau of Labor Statistics data from the CPS show that the college premium has grown over time. The ratio of the mean wage for college

[4] Additionally, some studies look at individual companies or sectors to try to assess the link between worker productivity and wages at a disaggregated level.

graduates to the mean wage for high school graduates has increased between 1987 and 2017, going from 1.77 to 1.90 for men and 1.77 to 1.97 for women.

IV. The Backdrop of Long-term Productivity Gains

Before turning to the theoretical model of why productivity grows over time or across people, it is valuable to see the episodes of productivity gains for US workers over the past 150 years. Manufacturing is the only industry with data over this long time period. As is shown in Figure 2, productivity surged as a result of the introduction of General Purpose Technologies (GPTs) including steam power, electricity, and then computerization. These surges in productivity imply that the level of productivity grew over the last 150 years. This graph reminds us that the rising productivity of the last 30 years was initiated by the GPT of computerization. This “technology shock” is the major technological change that we need for our simple production function model below, in which productivity gains are grounded in exogenous technological change.

The next point, evident in Figure 2 but displayed prominently in Figure 3, is that each new technologies get adopted very slowly. The solid red line in Figure 2 shows the very slow adoption, or a long S-curve of adoption, of the electrification of manufacturing plants converting from steam power. To use electricity, manufacturing plants had to be completely re-configured, and complementary changes of new skill development for workers were needed. The solid yellow line shows the fast adoption rate that occurred in industries using computerization in the late 1990s.[6] Thus, when we look to estimating the empirical relationships there can be long lags between productivity increases and wage increases over time.

Our regressions below show the correlation between productivity growth and wage growth over the period of the computer revolution, or we use the years 1989-2019. At the end of this paper, we will describe what we now know about AI adoption and its likely effect on productivity and wages in the last ten years, with brief speculation as to its future effects in the coming decades.

[6] Going outside of manufacturing to the household adoption of new technologies, it took 70 years for all US households to have landline phones (1900-1970) but only 20 years for cell phones (1970 to 1990) to be used in all households (Ritchie and Roser, (2017)).

V. Theoretical Framework

Three models of productivity are provided here, expanding on the point in the section above that we are focusing on the adoption of new technologies, which in the time frame of our data arises from the computer revolution of the last 30 years. Because computerization was a GPT, described above, our model applies later to the AI GPT introduced at the end of this paper.

The first two models, in subsections A and B, concern technological changes that are neutral and then non-neutral. The third model, in subsection C, raises the possibility that productivity gains over time are due to the introduction of new people management practices, that may be introduced due to computerization, and that also improved productivity over time or across people.

A. *Neutral technological change*

What does theory predict about the relation of wages to productivity? Let us begin with the simplest situation in which there is only one type of labor. Formally, define productivity by the average product of labor, or by

(1) Productivity ≡ Average Product of Labor = Q / L

where Q is output measured in dollars and L is the number of hours of labor employed to produce it. Also let the aggegate production function be given by

(2) $Q = A\, f(L, K)$

where A and f are time-specific and relate to technology, and where L and K denote labor and capital employed. Consider a neutral change in productivity which takes the form of a change in A. In competitive equilibrium, workers are paid their marginal product so the wage is determined by (2),

(3) $\text{Wage} = A f_L (L, K)$

Substituting (2) into (1) and differentiating with respect to A yields

$$\partial\text{Productivity} / \partial A = f(\ ) / L + [(L\ A\ f_L(\ )-Af(\ )\ ) / L^2]\ \partial L/\partial A + (Af_K(\ ) / L)\ \partial K/\partial A$$

or in proportionate terms, the change in productivity is

(4) $$[\ \partial\text{Productivity} / \partial A\ ] / Q = \{f(\ ) / L + [(L\ A\ f_L(\ )-Af(\ )\ ) / L^2]\ \partial L/\partial A + (Af_K(\ ) / L)\ \partial K/\partial A\} / [\ A\ f(\ ) / L\ ]$$

Analogously, the change in the wage is equal to the change in the marginal product or

$$\partial\ \text{Wage} / \partial\ A = f_L(\ ) + Af_{LL}(\ )\ \partial L/\partial A+Af_{LK}(\ )\ \partial K/\partial A$$

or in proportionate terms analogous to (4)

(5) $$[\partial\ \text{Wage} / \partial\ A\ ] / \text{Wage} = [f_L(\ ) + Af_{LL}(\ )\ \partial L/\partial A+Af_{LK}(\ )\ \partial K/\partial A\ ] / [A\ f_L(\ )]$$

Now assume that all firms are identical and that the supply of labor and capital are both fixed at the initial levels. Then $\partial L/\partial A = \partial K/\partial A = 0$ and average and marginal productivity move with A proportionately. Specifically, $[\partial\text{Productivity} / \partial A] / Q = [f(\ ) / L] / [\ A\ f(\ ) / L\ ] = 1/A$ and

$[\partial\ \text{Wage} / \partial\ A\ ] / \text{Wage} = f_L(\ ) / [A\ f_L(\ )] = 1/A$.

This model generates the prediction that productivity increases translate directly into equal wage increases. Using (4) and (5), a proportionate 1% increase in productivity translates into a 1% increase in wage. There are a number of assumptions, however, that are necessary for this to be true.

First, the productivity increase here is caused by a *neutral shift in technology*, parameterized as an increase in A. Not all technological change that induces productivity increases are neutral. Second, and more important, it was assumed that labor supply was fixed, or completely inelastic. For the empirical purposes below, when emphasizing technological change, the focus is on the demand side only. The expression in (5) is a statement about how the wage that firms are willing to pay at a given quantity of labor is affected by technology, not about how the equilibrium wage actually responds to increases in productivity. As is obvious, supply conditions are essential in determining the equilibrium effect of increases in productivity on the wage. To derive the result that both productivity and wage increased (proportionately) by 1/A, it was assumed that both labor and capital were fixed.

Consider the alternative case in which productivity rises, but wages do not. This occurs when the supply of labor is perfectly elastic. It is perfectly reasonable to assume that the supply of labor is very elastic across industries. In this case, all increases in productivity, which increase the demand for labor in accordance with (4), translate into increases in employment without any increase in the wage at all. All of the surplus generated by increases in productivity goes to producers: workers' wages do not rise.

This model produces hypotheses regarding the correlation between productivity and wages that we will find in the data. At the microeconomic level, using, for example industry productivity data, it is usually assumed that labor supply is elastic in the short run for each industry. Thus, there is no necessary positive correlation between productivity growth and wage growth. But at the country level, the reverse is likely to be true. For each country, in the short run, the elasticity of labor supply to the entire country is likely to be low. Labor supply increases can occur through higher population growth or rising worker participation rates. But neither population nor labor force participation rates are very responsive to wages, although the literature on the Earned Income Tax Credit shows some elasticity on the extensive margin, where higher wages affect the extensive margin of labor force participation.[5] Capital, on the other hand, is mobile across countries and supplied highly elastically, even if fixed in the short run to a particular firm.

In sum, at the country level which is the focus of empirical sections VII and IX, as a result of the inelasticity of labor supply, it might be appropriate to expect that most of country-wide productivity increases take the form of wage increases, rather than employment increases. However, those increases in aggregate productivity could also reflect additional capital, which raises the average product of labor and wages. Turning later to the industry level, as a result of

[5]See for example, Eissa and Liebman (1996), Meyer and Rosenbaum (2001), Eissa and Hoynes (2004).

the greater elasticity of labor supply to each industry, wage increases need not follow productivity increases. We will look for these results in the empirical section.

B. *Non-neutral technological change*

The neutral technological change model may be unrealistic – because there is more evidence for non-neutral technological change in the past.[7] In addition, when concluding this paper with evidence on the future impact of AI, it is non-neutral technological change that is most concerning for wages.

In 2003, Autor, Levy, and Murnane showed very convincingly that labor demand was shifting to the greater demand for non-routine cognitive skills.

Given our focus here on technology, an example is thought-provoking. We will consider the grocery business as it existed 70 years ago and the changes due to digitization that followed, and then re-consider the grocery business today and the changes that have occurred recently due to AI investments.

In the mid-1950s, early cash registers performed few tasks and were also costly. Prior to cash registers, in many stores checkout consisted of bringing items up to the cashier who knew most prices by heart, wrote them down (often on a brown paper bag used to package the items), and then added them up by hand to obtain the total. After the customer gave the money to the cashier, it was his job to subtract the amount owed from the amount given and to return the correct change. This was a skilled job. The clerk had to have a good memory, had to be facile in arithmetic, and had to exercise care when doing the calculations. Accuracy was particularly important because every checkout involved computation and customers would be very sensitive to errors. In those days, grocery clerks, many of whom were unionized, were skilled workers.

Today, because of digitization, the process of checking out goods in a grocery store is vastly different from that of earlier years. Most items carry a bar code, which is scanned. The register computes the tally, lists items purchased, and when cash is used, specifies the required change. The skills required to be a retail clerk today are far fewer than those that characterized the cashiers of an earlier age.

[7] In 2003, Autor, Levy, and Murnane showed very convincingly that labor demand was shifting to the greater demand for non-routine cognitive skills.

Digital cash register technology increased productivity in grocery stores, but this productivity gain was not passed to workers as wage increases.[8] Instead, technology caused workers to have only one skill level or job type, instead of two – before there were less-skilled shelf stockers and more skilled cashiers. The productivity of cashiers rose when the scanner was invented, because the number of items sold per hour of cashier time would be higher than it was earlier. The scanner is invented and transforms the technology so that now only one scanning system is needed per store and every worker can use that system. Now, because all workers are able to use the scanner, there is no distinction by worker type. High-skilled workers' wages are suppressed, because there are no longer high-skilled workers. The higher revenues per employee go to buying scanners, and the difference between the selling price of the scanner and its cost of production is a return to invention, which may over time be eliminated by competition from other scanner producers.

Conceptually, then, it is possible for wages to move with productivity or in extreme cases to move in the opposite direction, even if supply conditions are such that all changes in demand affect wages rather than employment. The failure to find a link between productivity and wages, or to find that it does not move 1-for-1, is not a statement about market failure or monopsonistic behavior by employers. It might simply reflect less than perfectly elastic labor supply or non-neutral changes in technology.

As a consequence, the issue of interest is inherently empirical. This also has implications for labor share because if labor supply is perfectly inelastic, then any failure to see wage increases that match (proportionately) productivity increases implies declining labor share.

Standard economic theory does have implications for what one might expect in competitive equilibrium. To the extent that one industry experiences an increase in productivity that is not enjoyed by other industries, there will be little or no wage effect, but there will be employment effects to the extent that workers are substitutable across industries. For example, electricians work in furniture factories, but also in hospitals, maintaining facilities in both. If there is a increase in productivity in health care without a corresponding increase in furniture, then electricians will move from furniture production to health care, but there will be no effect on wages of electricians in either industry as long as each makes up a small share of total

[8] Appendix A contains a formalization of that change in technology that characterizes the market equilibrium before and after the change.

electrician employment.

Suppose instead that the increase in productivity is one that is experienced not by one industry, but by all industries that use primarily highly skilled, educated workers. In the short run, the wages of educated workers will rise and employment will stay almost constant because of the inelasticity of the supply of skilled workers. In the long run, the proportion of educated workers in the economy will change, rising relative to those with less education. Wages are less affected in the long run because the supply curve is more elastic in the long run than in the short run, but employment of the highly educated should increase as a result of higher supply elasticity.

C. *Alternative microeconomic explanations for the rising growth and spread of productivity gains*

The above models are of the rising spread of productivity and wages across skills groups as a result of neutral technological change or non-neutral technological change. The firms adopting these technological changes are increasing the productivity of their workers.

An alternative source of productivity gains over time is improved management practices. From the 1980s onward, the human resource management practices of teamwork, incentive pay, and improved hiring were introduced into US manufacturing, thus increasing productivity and pay (Ed 19xx, Shaw, JOLE). Details on this link between performance and pay were evident in the steel industry in the 1980s. A set of these new management practices were introduced into integrated steel mills, making workers more productive, thus pay could continue to rise (Ichniowski, Shaw, and Prennushi, 1997).[9] These new management practices were aimed at using the minds and experiences of average employees to problem solve, thus making employees that were formerly unskilled into skilled employees and increasing their productivity and wages.

Similar changes continued in the 1990s and 2000s. In Lazear (2000), Safelite Glass introduced performance pay for its windshield installers and productivity and pay rose. While not stated in the paper, performance pay was introduced at that time because the firm began keeping computerized records of employee productivity. The technological change of

[9] These management practices were also introduced into minimills, where wages grew within and across mills (Boning, Ichniowski, and Shaw, 2007). A specific example is of the minimill firm Nucor Steel. Nucor minimills paid high performance pay wages in exchange for higher productivity from problem solving.

computerization was coupled with new performance pay. A second example of the impact of technological change is the computerization of the valve-making machines in the valve industry. Computer-run machinery increased productivity directly, and also indirectly, due to greater worker problem solving (Bartel, Ichniowski, and Shaw, 2007).

These are examples of the time series introduction of new management practices, which could be considered a "technology shock" as they entered US manufacturing (Shaw, 2009, Bloom, N., R. Sadun, and J. Van Reenen, 2016). New management practices were often coupled with increasing digitization or mechanical technology shocks. Though there has been a burgeoning insider econometrics literature on the performance effects of management practices, the research papers rarely tell us why new management practices were introduced. Brynjolfsson and McAfee (2011) also make clear that rising computerization was coupled with new management practices.[10]

Using these empirical case studies, what are the implications for the link between the cross-worker productivity and pay increases over time? The above examples of new technologies and their performance effects within firms from the 1980s through 2000s show that pay and productivity rose for workers in the less skilled high-school educated skill range.

The rise in the pay and productivity of the less-educated would narrow the pay distribution over time if the pay and productivity of the better-educated were fixed. But new management practices also increased the productivity of one better educated group, the managers. The productivity of managers can be inferred from the productivity of their employees. In Lazear, Shaw, Stanton (2015), the lower-level managers, called "bosses," make their firms more productive because they make their workers more productive. The productivity of bosses was increasingly measured because the productivity of their workers was increasingly measured by computers. In Hoffman and Tedalis (2021), the best managers in a high-skilled company have workers with lower turnover. Though not stated in their paper, firms began to utilize "Engagement Surveys" in the last ten years that enabled their focus on managerial productivity (Shaw and Hayes, 2019). For the better educated at the top of the income distribution, improvements in software over the last 25 years likely contributed to rising managerial productivity. The introduction of ERP software, or Enterprise Resource Planning,

[10] See the literature review in Hoffman and Tedalis (2021) for the research literature on the impact of more management practices, such as hiring and promotions. See Chad Syverson's (2011) review of the microeconomic productivity literature, where there is more evidence of time series changes.

consolidated the software that was the backbone of firms. Skipping ahead to today, software for teamwork (such as Slack), and software for writing (such as Textio), and software for running HR departments (including LinkedIn) all make white collar jobs more productive. These products are increasingly run by AI technologies, which is a topic that we return to at the end of this chapter.

However, the real increase in pay for the highly educated is at the 90th percentile of pay is for executives. In Murphy and Jensen (2018), the authors state that "underlying the growth in pay for CEOs since the 1990s is an escalation in stock-option compensation from 1993-2001 coupled with a dramatic shift away from options toward restricted stock…In 1992, base salaries accounted for 41% of the $3.1 million median CEO pay package, while stock options accounted for 23%. By 2001, base salaries accounted for only 18% of the median $10.1 million CEO pay, while options accounted for more than half of pay." The drop in the importance of base pay for the very highly paid was the result of the shift to the performance pay of using stock options following President Clinton's cap of base pay at $1million in 1994.

Did executive pay rise drammaticially since 1994 because executives' productivity rose, so this is the productivity-wage connection that we are looking for at the top of the pay distribution? It depends on whether you believe that executives make their companies more productive due to their own greater performance pay, or if changes in the stock market over time had a bigger effect on managers' pay than did the talent and effort of executives.

More recently, the rising concentration of industries, and declining labor share for workers, may contribute to raising the productivity of the larger companies and the wages for those at the top of these companies. Autor, et.al. (2020) develop these ideas in their paper on the rise of superstar firms. Technological changes and globalization have increased the sales of the most productive firms in an industry, and these firms exhibit the fastest growth over time. It has been well-known for some time that there is a very large dispersion of productivity across firms within one industry (De Loecker and Syverson, forthcoming). An exploration into rising concentration and productivity of top firms is beyond the scope of this paper, but it is a possibility for the connection between pay and productivity at the top of the pay distribution.

The concluding points from this very limited review of microeconomic research on pay and performance are the following. Technology shocks, in management practices or machines, gave rise to productivity and pay increases for workers of all skill levels. There were gains for workers at the bottom and middle of the skill range and also for executives at the top. The data show clearly that the pay levels for the 90th percentile workers rose much faster than for all others. A conclusion as to whether this reflects much greater productivity, based on the microeconomic research evidence, depends on whether you conclude that executives have become much more productive over time. The rising share prices of their companies are correlated with their rising pay. It is a matter of interpretation as to whether this is due to rising performance. Over the last ten years, it is very clear that industries are becoming more concentrated and firm size is growing.[11] Thus, as executives run bigger and bigger multinational firms, their rising pay could reflect pay-for-performance.

The underlying causes of increased productivity in the 1980-2010 years were often the technology shocks of digitization – more computers and better computers. It is very well established that technological change over time has been "skill-biased," favoring the better skilled workers (Autor, Levy, Murnane, 2003). When we turn, at the end of this paper, to the introduction of AI in firms, we will again see cheaper data storage and faster computers are likely to contribute to a rising spread across people of productivity and pay.

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VI. Data

A number of data sources are used from the OECD, the Bureau of Labor Statistics, the Conference Board and the World Bank. They are described below and summary statistics are provided in Appendix C.

A. OECD

The Organization for Economic Co-Operation and Development (OECD) harmonizes data on wages and other relevant variables across its member countries and a few others.[12]

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[11] Juhn, McCue, Pierce and Shaw (2018).

[12] The OECD Income Distribution database (IDD) has been developed to benchmark and monitor countries' performance to measure income inequality and poverty. The OECD Employment and Labor Market Statistics database includes a range of annual labor market statistics and indicators from 1960 broken down by sex and age as well as information about part-time and short-time workers, job tenure, hours worked, unemployment duration, trade union, employment protection legislation, minimum wages, labor market programs for OECD countries and non-member economies. See OECD (2019), "Income Distribution", OECD Social and Welfare Statistics (database), https://doi.org/10.1787/data-00654-en (accessed on 04 February 2019) and OECD (2019), OECD Employment and Labour Market Statistics (database), https://doi.org/10.1787/data-00302-en (accessed on 04 February 2019).

There are wage data going back in some cases as far as 1973, but for the majority of countries, the data are complete back to 1990. Wage and productivity data are available for 33 countries back to 2000. These data allow both cross-country comparisons at a point in time and also analysis of the relation of wages to productivity within a country over time. They also permit an examination of the distribution of wage gains as they relate to average productivity as analyzed in Stansbury and Summers (2017). Specifically, information on the 10th and 90th percentile as well as median wage is available for most of the OECD countries.[13] The consistency of OECD data across countries and time periods makes the OECD data well suited to doing cross country comparisons. The data that form the basis of the OECD dataset used in this study come from the countries directly. For example, the OECD on the United States is taken from the Department of Labor Bureau of Labor Statistics (BLS). We verified this by downloading the BLS data and comparing it with the OECD numbers on the same series. A number of statistics are examined and the OECD data track the BLS data perfectly from the late 1990s on. Appendix B provides a detailed description of the data used for each variable and its source in the OECD data.

B. US Bureau of Labor Statistics Current Population Survey data on wages

Two sets of Bureau of Labor Statistics (BLS) data files are used for wages.[14] The first is the Annual Social and Economic Supplement (ASEC), which provides detailed information each year on approximately 75,000 households associated with the March CPS data. These data provide information on individuals, specifically their wages, demographic characteristics and the industries in which they are employed. The data are used primarily to compute average wages for each of the industries used in Section X. By merging the BLS ASEC data with the BLS

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[13] The OECD data set reports both the minimum wage and the ratio of the minimum-to-median, which allows the median wage to be calculated.

[14] The CPS is a monthly US household survey conducted jointly by the US Census Bureau and the Bureau of Labor Statistics. IPUMS-CPS is an integrated set of data from the Current Population Survey (CPS) from 1962 forward. IPUMS-CPS is microdata--it provides information about individual persons and households. To make cross-time comparisons using the CPS data more feasible, variables in IPUMS-CPS are harmonized. IPUMS-CPS also facilitates the study of long-term change by providing detailed documentation covering comparability issues for each variable and an interactive data extraction system. IPUMS-CPS consists of all substantive variables from the original CPS samples. See Steven Ruggles, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. IPUMS USA: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D010.V8.0.

productivity data, described in subsection C, it is possible to examine both wages and productivity over time at the industry level. These data are used for years in which industry-level productivity data are available.

The second set of files are taken from CPS outgoing rotation group of the monthly CPS data. The data, which cover 1989 through 2019, yield approximately 2.9 million observations of wage-earning workers, but since each individual is represented twice (one year apart), there are 1.45 million individual observations that are covered over the 30-year period.[15] These data provide detailed information on hourly wages, demographics, and education. They are used primarily to document trends in wages across skill levels.

C. US Bureau of Labor Statistics data on productivity

An important aspect of the analysis involves comparing the changes in the productivity of various educational groups with the changes in wages. It is virtually impossible to measure individual productivity except in some firm-based data where measures of output are readily available. Even in those cases, information on the firms rarely provide demographic characteristics of employees.[16] Consequently, it is useful here to compare productivity at the industry level and to match that with the educational and other demographic characteristics of those industries. The Division of Industry Productivity Studies (DIPS) in the Office of Productivity and Technology at the Bureau of Labor Statistics reports annual productivity measures by industry in "Labor Productivity and Costs by Industry and Measure." Three-digit industries based on the NAICS classification are used here. Both value added in absolute terms and a productivity index are contained in the dataset. For the purposes here, absolute value added was used, converted to 2019 dollars using CPI-U. The productivity measure, which is output-per-hour worked, is obtained by dividing real value added by the DIPS data series on total hours

[15] Every household that enters the CPS is interviewed each month for 4 months, ignored for 8 months, then interviewed again for 4 more months. New households enter each month, so one fourth the households are in an outgoing rotation each month. The data in the outgoing rotation groups are distinct from the ASEC data in the greater number of annual observations, but fewer variables available (for example detailed family questions are not covered in the survey). Weekly earnings are available. See Steven Ruggles, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. IPUMS USA: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D010.V8.0.

[16] See the growing literature in personnel economics on productivity, the most directly applicable being Lazear (2000), Fernie and Metcalf (1999), Shearer (2004), Bandiera, Barankay, and Rasul (2005), Lazear, Shaw and Stanton (2015), Bartel, Cardiff-Hicks, and Shaw (2017).

worked.[17]

Additionally, the Bureau of Labor Statistics collects data on aggregate productivity and on aggregate compensation in two separate data sources. The first, on productivity, is called "Nonfarm Business Sector: Real Output Per Hour of All Persons [OPHNFB]" and the second is called "Nonfarm Business Sector: Real Compensation Per Hour [COMPRNFB]." These are annual data and allow an examination of the relation of compensation to productivity over time. For the purposes here, 1951-2017 observations were used (some of which are based on data points back to 1947) to augment the industry-based productivity data with compensation information.[18]

D. The Conference Board

The Total Economy Database (TED) is a comprehensive database with annual data covering GDP, population, employment, hours, labor quality, capital services, labor productivity, and total factor productivity for 123 countries in the world. Data are mostly obtained from national accounts and are available for 68 countries. Most of the OECD tracked countries are in the Conference Board data of 68 countries. This Conference board data is used to augment the OECD analysis that relates wages to productivity across countries.[19]

E. The World Bank

Wage data are not available in the Conference Board dataset, but the World Bank provides net national income per capita for the countries in the Conference Board data. The correlation between World Bank income numbers and the OECD average wage numbers is very high for those countries of overlap. Income is expressed in 2010 US dollars.[20]

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[17] The source file can be downloaded from https://www.bls.gov/lpc/Tables.htm. For more description, see Bureau of Labor Statistics. (2019). *Labor Productivity and Cost by Industry and Measure*, https://www.bls.gov/lpc/Tables.htm.

[18] https://fred.stlouisfed.org/series/COMPRNFB.

[19] The Conference Board, https://www.conference-board.org/data/economydatabase/index.cfm?id=27762.

[20] https://data.worldbank.org/indicator/NY.ADJ.NNTY>PC>KD.

VII. Wages and Aggregate Productivity

The goal of this section is to demonstrate that there is a very robust positive relationship between wages and productivity at the aggregate economy-wide level. We start with the OECD and developing countries (subsections A and B) and then estimate the regressions for only the US (subsection C).

A. OECD wage regressions

The most obvious illustration of the correlation between wage levelsand productivity at the country level comes from our cross-country comparisons. OECD data on wages and productivity across countries make immediately apparent that the two are linked. Figure 4, which plots the cross-sectional 2017 average wage against labor productivity (the last year for which data are available), defined as output in US dollars per hour worked, reveals the close co-movement of wages with productivity. Countries like Switzerland, Norway, Denmark and Luxembourg all have both high productivity levels and high wages. At the other end, countries like Mexico, Chile, Latvia, Poland and Estonia have low productivity and low wages. The correlation coefficient between log wage and log productivity in 2017 is .84.

As discussed in the theory section, the ratio of marginal product to average product in country is given by

(6) $$\frac{A_i f_L()}{A_i f()/L_i} = \lambda_i$$

Under certain technologies, the ratio of marginal product to average product is a constant. If the ratio were invariant across countries, then assuming that the wage equals the marginal product and rearranging terms and taking logs yields

(7) $$ln\ (Wage_i) = ln\ \lambda + ln(Average\ Product\ of\ Labor_i)$$

for any country i.

Equation (7) forms the basis for much of the estimation below at the country level. This model forms the basic specification for Table 1. *The implied coefficient on the labor productivity in the regression (7) is 1*, but this requires a number of assumptions that are likely violated. Still, it is useful to examine this benchmark, albeit extreme, case.

Table 1, column (1) reports a regression of log annual wage on log annual productivity (defined as hourly productivity, times 1500) across 34 countries in 2017. The coefficient is 1.52, not 1, as implied by (7). Across countries, there is actually more than a one-for-one increase in wages with productivity. The difference from 1 is statistically significant.

Figure 5 provides a different kind of evidence than that shown in Figure 4. Figure 4 relates the level of wages to the level of productivity across countries. Figure 5 looks very much like Figure 4, but the evidence is different using growth rates.

Figure 5 examines how the growth in productivity affects the growth in wages. The countries that have highest productivity levels in Figure 4 are different from the countries that have highest productivity and wage changes in Figure 5. In Figure 4, the highest wage countries are Denmark, Iceland, Luxembourg, Norway and Switzerland. They are also, without exception, high productivity countries; however, these highest wage, highest productivity countries in Figure 4 are not typically the countries that experienced the most rapid increases in productivity between 1997 and 2017 in Figure 5. The countries with the most rapid gains in both productivity and wages tended to be those that, like Poland and Lithuania, moved from command structures to market economies over the period. Thus, countries that are high productivity level and high wage level today are high because they experienced favorable wage growth in the past, but not necessarily in the recent past.

Columns (2) and (3) in Table 1 report a τ-differenced version of eq. (7). Annual productivity and wage data are available for 34 countries for most of the years between 1990 and 2019. In keeping with the long lags of technology shocks in Figure 3, column (2) reports the results of regressing the change in log wages over the past five years on the change in log productivity over the past five years both over time and across countries. The coefficient of wage changes on productivity changes is .72 in column (2), but not significantly different from 1, suggesting approximately a one-for-one increase in wages with productivity within the typical country (of the 34 OECD countries on which data are available) over time. The constant term should drop out and it is estimated to be zero with precision. Column (3) reports the same analysis, but does so using changes in log wages and log productivity over a within-country 20 year period rather than a 5 year period. The coefficient is slightly lower than for the five year difference shown in column (2), now equaling .68.

Columns (4) and (5) repeat the analysis of column (1) for wage levels, but do so over a long span of time rather than merely for 2017. Column (4) includes country fixed effects while column (5) excludes them. The wage levels regressions with country-fixed effects estimate the effects of productivity on wages by examining effect of the (average) within-country variation over time. This is akin to columns (2) and (3). Column (5), which excludes country-fixed effects, is more comparable in logic to column (1) and the estimates from the two columns (1) and (5) are close in magnitude. In column (4), which exploits only the within-country variation because of the country-fixed effects, the coefficient is close to those in columns (2) and (3).

Before reaching conclusions regarding these results, we next add developing countries to our regression estimates of equation (7).

B. Adding developing countries to the OECD wage regressions

The last two columns of Table 1 add developing countries by using World Bank data. The statistical analyses in columns (6) and (7) of Table 1 confirm that wages are closely related to productivity in the broader set of countries. Column (6) corresponds to column (1). The coefficient of 1.46 for the broader set of countries is virtually the same as the 1.52 obtained in column (1) even though 28 countries are added in column (6).

These results, in Figures 4 and 5 and Table 1, are important, in showing that across countries most people enjoy wage gains, even in the poorest countries, during periods when productivity is growing most rapidly. Taken together, there is little doubt of the close positive connection between wage levels and productivity levels in the OECD countries, but more ambiguity about whether a 1% increase in productivity generates a 1% increase in wages. Thus, we will test this later, in Table 5, using productivity changes and wage changes by skill level.

C. United States wage regressions, and other individual country regressions

Regression equation (7), estimated for wage levels and for its formulation in wage changes was estimated for 62 countries in Table 1; here we estimate it for the US only in Table 2 and then produce individual regressions for all other countries in Appendix Table D2.

Before turning to regressions, Figure 6 focuses on changes in hourly wages and productivity, using data from the Bureau of Labor Statistics databases over time in the United States.[21] Four-year moving averages are used to smooth the data. As is apparent, over the almost seven decade period, the average wage has risen during periods when productivity has risen, and has shown poor growth when productivity growth has been weak. It is also clear that wages have risen by a slightly smaller amount than productivity over the period, particularly in recent years, as evidenced by the gap between the two series.

Table 2 reports the results more formally for the US. Column (1) simply regresses the BLS compensation level index on the BLS output index for the period shown in Figure 6, namely for 1950-2019. The growth in wages as productivity rises is in columns (2) and (3). Column (2) fits the relationship shown in Figure 4 by taking changes in the four-year moving average of compensation and productivity. The coefficient on the change in 4-year moving average of productivity is .76, almost identical to that in the wage levels specification of column (1).

Shortening the period to 1990-2019 in column (3), which is the time period of lagging wage growth in Figure 5 for the US, a 1% change in productivity was associated with only a .60% increase in compensation growth.

Given these results for the US, we then run regression for each individual OECD country and some developing countries, asking if other countries each show a one-for-one relationship between productivity and pay. That is, to compare to the US results, we re-estimate equation (7), for each of the 62 individual countries of Table 1. Given the length of this table, it is in Appendix D. In all cases but two (Portugal and Venezuela), the relation between the average wage and productivity over time is positive and significant at conventional levels. The magnitudes of the coefficients vary widely across countries, in many cases being below one and in some cases being above one, but there does not appear to be any obvious pattern that would easily explain the sizes of the coefficients.[22]

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[21] Figure 6 and Table 2 switch to US Bureau of Labor Statistics data rather than OECD data. The US data is Nonfarm Business Sector: Real Output Per Hour of All Persons [OPHNFB], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/OPHNFB, July 1, 2019 and US Bureau of Labor Statistics, Nonfarm Business Sector: Real Compensation Per Hour [COMPRNFB], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/COMPRNFB, July 1, 2019.

[22] For example, Luxembourg and Norway, rich countries, as well as Latvia, Lithuania and Mexico, poor countries, all have coefficients above one. Wealthy Belgium, Finland, Germany, and Japan have low coefficients (well below one) as does less wealthy Poland. There are two obvious theoretical candidates for the differences, but we do not

An important conclusion from this subsection is that aggregate average wage growth has not kept up with productivity growth recently in the US, even though the average rate of productivity growth has trended down in the US in recent decades. This result leads us to think that for those people whose wages are in the middle of the wage distribution today, their wage growth may have lagged that of upper wage earners because their measured productivity growth is lower.

Having completed this analysis of aggregate wages and productivity at the country level, we look at the effects of aggregate productivity gains on the upper and lower tails of the employment income distributions. The focus is on wage income, as that is what should be determined by productivity, and it is well known that the upper tail income levels, at the 90th or 99th percentiles, have risen fast over time due to non-wage income growth.

VIII. The Position of the Middle Class? Looking at Wage Ratios

Before examining the effect of productivity on various parts of the skill distribution, it is useful to characterize more specifically what has happened to the wage distribution over time so that it is clear what changes in productivity need to be explained.

A. Displaying wage ratios, of median wages to the wage tails, over time

Figure 7 displays the spreading out of the wage distribution. Uncontroversial is that the 90th percentile has moved away from the median in the US. Over the last 35 years, the 90/50 ratio has risen from just below 2 to 2.4. Also noteworthy is that during the same period, the 50/10 ratio has risen, but to a lesser extent and not in the last twenty years. The median worker earns 2.1 times that of the 10th percentile. In the early 1980s, that ratio was below 2.

The wages for OECD countries do not exhibit the same pronounced pattern of increase in the pay of the 90th percentile that occurs in the US data. In Figure 8, the 90th/50th ratio rose in Europe, but only from 1.8 to above 1.9. Also well known, as shown in these Figures 7 and 8, is

explore them empirically. First is that the nature of technological change over time that generates productivity increases may differs across countries. The second possibility is that the coefficient varies with country-specific labor supply elasticities, which could conceivably differ across countries, even if the nature of technological change were invariant across countries.

that the level of the 90th /50th ratio is much higher in the US, at 2.4, than it is in Europe, at about 1.9. Because the goal of this paper is to relate wages to productivity, did the productivity of the highest skilled workers in the US rise at a much greater rate than that of the highest skilled for Europe? This question will not be answered in this paper, because we develop productivity measures by skill level only for the US, not for Europe.

B. Changes in the values of the wage ratios

The growth of relative wage ratios over time, shown in Figures 7 and 8 for the US and the average OECD country, are translated into numerical values in Table 3, for thirteen of the OECD countries. Table 3 reports the results on a country-by-country basis, comparing the base year of 1997 and the final year of 2015. All but two countries have witnessed increases in the 90/50 wage ratio over time and about half have also seen increases in the 50/10 ratio. The spread in the wage distribution is not only a US phenomenon, although the magnitudes of the 90/50 and 50/10 ratios in the US are higher than in other countries.[23]

IX. Wages in the Upper and Lower Tails as a Function of Aggregate Productivity

This section simply relates the change in wages at the 10th and 90th percentiles of the wage distribution to aggregate productivity measures, or the growth of GDP per person. These are important background results. They do not speak to the fundamental question, which is “do wages move with productivity and can the increased wage differentials be a reflection of increased disparity in productivity across the skill classes?” addressed next in section X.

Table 4 regresses changes in wages on changes in productivity, where the variables are five-year moving averages of the annual changes in the relevant variables. Because the specification is in changes, both year and country-fixed effects are excluded. The changes in wages, both at the 10th and 90th percentile, move with the change in average productivity, although not necessarily one-for-one. That is, GDP productivity growth is passed directly to the 90th percentile of wages, in columns (3) and (4), but the 10th percentile of wage earners benefit noticeably less. Previous sections showing that the earning of low wage workers have lagged

[23] The highest 90/10 ratio is in Israel at 7.22 in 2015.

high wage workers anticipated as GDP growth is passed to the low wage much less than the high wage.

The non-US countries in the OECD have coefficients that are significantly below one-for-one. Outside the US, there was little trend down in wages for the 10^{th} percentile, but at the same time, regression results suggest that increases in aggregate productivity gains are not passed on to workers as they are in the US.

Thus, aggregate productivity and wages are highly correlated over time and not just for the average worker, but for workers at both the low and high ends of the earnings distribution. However, low wage workers have benefited less form GDP productivity growth, reflecting the spreading out of the wage distributions. Furthermore, if anything, the association between wages and aggregate productivity at both extremes of the wage distribution is stronger in the United States (in columns 1 and 3) than in the typical other OECD country (in columns 2 and 4).

X. Productivity and Wages By Worker Skill Levels

Though late in this paper, this section X and the next section XI are the key sections of the paper. Earlier sections VII through IX were aimed at examining, as have other papers, the effect of increases in GDP-level productivity over time on pay increases in the two tails of the pay distribution, as the pay distribution has spread out across people. They asked, are economy-wide gains shared by all? They are, but much less for the low wage.

The fundamental question asked in this section is, has the pay distribution has spread out more over time across people because their personal productivity has spread out more over time? That is, if wages have grown more for the highly skilled, has productivity also grown more for the highly skilled?

To address this, we are going to use education as a proxy for skill, assuming the highly educated are more skilled. We know, from the research of others, that wages have risen more for the highly educated than the less educated (or, the return to education has risen over time). Has personal productivity also risen more for the highly educated than for the less educated? Might a rising wage gap across educational levels be explained, in part, by a rising productivity gap across educational levels?

As already mentioned, it is almost impossible to measure productivity comprehensively at the individual level. Although occasionally data are available on output by worker (e.g., Lazear (2000), Lazear, Shaw and Stanton (2015)), those data are rare, piecemeal, narrow and even less frequently combined with information on worker demographics, specifically education. It is possible, however, to examine productivity by industry and to compare industries that employ highly educated workers with those that employ less educated workers. That is the approach taken here.

As discussed in the data section, the BLS compiles detailed wage data by industry and demographic characteristics. Additionally, the BLS collects and computes productivity (value added, hours worked and productivity per hour worked) by NAICS industry that can be linked to the wage data. Three-digit level industries are used here. For most of the analysis, the period from 1989 through 2017 is used. The key variables are described and summarized in Appendix C. The statistics shown are the summaries across industry-year observations.

A. *Skill levels as determinants of productivity levels, across industries*

The heart of the analysis is an examination of three-digit industry data to infer productivity growth by skill level in order to explain wage growth by skill level. We start by looking at the determinants of productivity levels as a function of skill, and then turn in subsection B to the determinants of productivity growth rates as a function of skill. Education is used as the primary measure of skill.

Recall that theory tells us that there need not be a productivity pay correlation. As long as workers can move across industries, there is no reason to expect that productivity growth for an industry will be reflected in wage growth for that industry. When labor supply is more inelastic, then productivity improvements are shared with workers in the form of wage improvements.

Before turning to the results, note that by using education as the measure of skill, an individual's education level is more stable than the industry in which he or she works. Once education is completed, changes in educational level are rare, but movement between jobs in different industries and even occupations is common.[24] For that reason, it is reasonable to

[24] During the 1989-2017 period, the probability of changing jobs in any one year was .46. Almost half of those changes (.26 versus .46) were job changes where the individual also changed three-digit industry. Numbers calculated by Lisa Simon using Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren.

assume that different education groups cannot substitute perfectly for one another, thus implying that high school graduates, with the exception of current graduating cohorts, do not readily become college graduates even though a college graduate, even one who has worked for a decade, can move from the automobile industry to the steel industry. Appendix Table E1 shows that when education and other demographics (immutable characteristics) are held constant, the wage is not related to industry productivity.

The most important finding regarding the spreading out of the productivity distribution over time is summarized in Figure 9. We use data on the forty 3-digit industries for which complete productivity, wage and education data are available over the period 1989-2017. Industries are ranked by their skill level, or by their educational level. Figure 9 compares the productivity growth and wage growth, from 1989 to 2017, for the "low education in 1989" (blue bars) industries to the productivity growth and wage growth for the "high education in 1989" (red bars) industries.

Productivity in the high-education industries grew by over .34 log points between 1989 and 2017, while productivity in the low-education industries grew only .20 log points during that same 30-year period (the two bars on the left side of Figure 9). The same pattern holds for wages, but not with the same force. Wages in high-education industries grew by .26 log points while those in the low-education industries half grew by .24 log points during the 1989-2017 period.

It's clear in Figure 9 that the difference in productivity growth between the two skill groups is more pronounced than the difference in wages. Productivity grew considerably more for the more highly educated. This simple comparison in Figure 9 suggests that differences in productivity growth rates between skill groups is more than sufficient to explain the greater wage growth that more educated workers enjoyed as compared with less educated workers.

Table 5 examines this productivity-wage correlation in a more detailed manner. As above for Figure 9, a variable that measures average education in each industry is calculated by matching the CPS-ASEC data with the BLS productivity data by industry. Instead of two skill groups, of highly educated and less education in Figure 9, in Table 5 the data now has 40 skill groups because there are 40 industries with mean educational levels attached to each industry.

"Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [1976-2018]." Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D030.V6.0.

The first basic fact that we seek to verify is whether worker productivity levels are higher in more highly educated industries. They are, as demonstrated by the regression in column (1). What is the size of the effect? The dependent variable, of log of industry output per hour as measured in dollars, is regressed on the average level of education (in years) within the industry. The regression is estimated across all industries and all years in which productivity and education levels are available (1353 observations). The coefficient on education, at .301, is positive, significant, and large. For our variable of education by industry, the standard deviation of average levels of education across industries is about .92 of an education year, and it ranges from 10.4 to 16.0. The column (1) regression implies that a one year increase in one industry's average level of education relative to another industry's education would increase productivity by .301 log points, or by 35%.

The next basic fact that we seek to verify is whether wage levels are higher in more highly educated industries. Column (2) does the same analysis as column (1), but the dependent variable is now the log wage instead of the log productivity. The coefficient on education, at .173 is still positive and significant. The effect of average industry education on the log wage is large and statistically significant with a coefficient of 0.17. Of course, there may be other factors that are correlated with education that affect industry pay.

What do we conclude by comparing productivity levels and wage levels across industries in columns (1) and (2)? The effect of education on productivity is about twice as large as its effect on wages. Thus, if these results are taken to be causal, the higher productivity levels for the better educated would over-explain the higher wage levels for the better educated, relative to the less educated. Thus, productivity gaps would more than explain wage gaps across skill groups.

B. Skill levels as determinants of productivity growth, across industries

Of more interest to the fundamental question addressed in this section is whether increases over time in the wage ratio of the highly to less educated workers can be explained by increases in the productivity of the highly to less educated workers. Columns (3) and (6) of Table 5 address changes in productivity across education groups. Column (3) reports that three-digit industries with higher levels of education in 1989 experienced significantly more productivity growth over the last three decades than those with lower levels of education. Column (6) performs the same analysis, but uses the industry's level of education at the end of the period in 2017, rather than the beginning in 1989, producing a coefficient of .16 log points. The conclusion is unchanged. Higher education industries experienced higher productivity growth rates during the period.

Columns (4) and (7) report the same regression results, but wages are the dependent variable rather than productivity. The same pattern holds, with higher education industries experiencing higher wage growth. At the end of the period, in 2017 in column (7), wage growth as a function of education has a significant coefficient of .07.[25]

Overall, productivity gains for the highly skilled across industries have been greater than the wage gains for the highly skilled. Regression results replicate the simple results in Figure 9.

These results tell us that the spreading out over time of the wage distribution across skill groups of workers is concurrent with the spreading out of the productivity distribution across skill groups. Given the magnitudes of the coefficients, if wages were a direct function of productivity, the wages of the highly educated would have risen even more over time. The overall conclusions regarding this productivity-pay link are in subsection D below.[26] Subsection C first uses data from the CPS outgoing rotation group to provide more reliable information on wage growth by educational category.

C. Productivity-based predictions of individuals' wage growth

The previous section establishes that wages and productivity have both increased over time more for educated workers, or more precisely, for workers in industries with higher average levels of education. In what follows, a productivity-based prediction of variation in wage change across educational groups is compared with actual wage change. The goal is to determine if

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[25] These results are only significant for end year 2017. It is somewhat surprising that the choice of year to measure industry education matters so much since the correlation between start year and end year education for the 40 industries is .78.

[26] Employment shifts across industries by skill level, as shown in columns (5) and (8) of Table 6, do not explain the differences in productivity growth and wage growth across industries. It is unsurprising that there is declining employment in some low-productivity growth industries, like apparel, but the most rapidly growing industries include building materials and garden equipment, miscellaneous retailers, and food and drinking places, are low-productivity growth, while computer and electronic product manufacturing saw large productivity gains and rapidly declining employment.

non-neutral changes in productivity across educational groups are sufficient to explain the observed spreading out of the wage distribution over time using individual-level CPS data. The CPS data has actual wages for every education level. Estimates from column (6) of Table 5 are used to forecast changes in productivity by educational group. Table 6 reports the results. Wages are based on the 153,815 individual level observations from the CPS outgoing rotation groups for 1989 and 2017.

Start with the high school educated. Consider a numerical example. In 1989, the average weekly wage for those with some high school or who graduated high school (but not beyond) was $735 in 2019 dollars (row 2, column (4)) or the average log wage was 6.40 (row 2, column (5)). In 2017, similarly schooled individuals earned on average $757 or an average log wage of 6.42 (row 6). Over the 28 year time period, the difference in log wages for the high-school educated group was .02 (column 6). The average level of education for that group of individuals was 11.79 years in 2017 (column 3). Thus, the regression in column (6) of Table 6 predicts that individuals with a high school level of schooling in 2017 would have experienced a change in log productivity of

$$-1.894 +(.161)(11.79),$$

which equals 0.00 (column 7). Productivity slightly under-predicts the actual change in wage for this education group because the group actually experienced an increase in log wage of .02 over the period.

Next, consider those in the group that had some college or graduated college. The actual growth of log wages for this group of individuals from 1989 to 2017 was .01 (in column 6). Productivity growth for this group, based on the regression of change in productivity on education in column (6) of Table 6, is predicted to be .46 log points during that period (in column 7). Thus, productivity is estimated to have increased substantially more for the group of some college or college graduates than the actual change in wages. Estimated productivity changes more than account for the change in wages experienced by this group over the 1989 to 2017 period.

Wages have spread out over time, but productivity has spread out even more. Generally, the least educated workers have experienced the poorest wage growth from 1989 to 2017. The change in log real wage for those without any high school was -.04 over the period while those with graduate education enjoyed gains of .07 in logs. The least educated workers have also experienced the poorest productivity growth, based on the industry-based estimates of productivity by education level. Overall, the differential growth in productivity across education levels exceeds the differential growth in wages. This is most easily seen in the columns 8 and 9 of Table 6. Column 8 reports the actual difference between wage growth for a given educational group and wage growth for one lower educational group. For example, wages for those with some graduate education grew by .07 log points between 1989 and 2017 (column 6). Wages for those with some college or college graduates grew by .01 log points during the same period. Thus, the difference between actual growth rates was .06 log points, shown in column 8, last row. Productivity for those with some college or college graduates was estimated to have grown by .46 log points while the productivity of those with graduate education was estimated to have grown by 1.00 log points (column 7). The difference between the two, shown in column 9, last row, is .55 (rounded). The fact that the numbers in the last column of Table 6 are all greater than those in the second to last column of Table 6 implies that the education-predicted productivity distribution has spread out more than the education-based wage distribution between 1989 and 2017. As shown in Figure 9, productivity changes more than account for the widening of skill wage premiums over time.

D. What has caused the spreading out of the productivity distribution?

The analysis in the last section implies that productivity has grown more rapidly for the more educated than for the less educated. Unfortunately, the analysis does not speak to the reason behind this difference. It is tempting to conclude that this reflects skilled-biased technological change, where the nature of technology is such that education and technology are complements. It is certainly possible that technology has affected the productivity of the highly educated by more than the less educated, but that is not the only possibility.

Trade is another. Changes in value added can be affected by changes in quantities or by changes in prices. If prices fall more rapidly in one industry than in another, then even absent technological change, value added will not rise uniformly across industries. Increased globalization during the 1989-2017 period, manifested in increased trade flows across countries, particularly between developed and developing countries, have surely changed prices in a non-uniform manner. If goods manufactured by less educated workers have seen a more pronounced declines in prices than have services produced by more educated workers as a consequence of increased trade, then productivity valued at the new lower prices will rise by less for the less educated than for the more educated.

A third possibility relates specifically to human capital. Suppose that educational establishments have improved in their ability to create human capital more at the college level than they have at the high school level. Because of improvements in college education, those who have completed college more recently will have acquired more human capital than those who completed college at an earlier time. This shows up as productivity growth for industries with college educated workers. During the same period, human capital production in high school may not have increased as rapidly or may have even decreased, meaning that those who completed only high school more recently will not have acquired more human capital than those who completed high school at an earlier time. This shows up as low productivity growth in industries with less educated workers.

Any of the three explanations are consistent with the results found throughout. The fact that other OECD countries experienced some of the same patterns in productivity and wages as found in the US suggests that the more country-specific institutional explanations are less likely. This also argues against changing quality of education at the college and high school level.

XI. Thinking about AI

We conclude by discussing what we know about artificial intelligence's (AI's) effects on productivity and wages. Though AI has only been booming for a few years since the advent of Big Data and highspeed computing, the technology is already incorporated into many firm processes and is thus already contributing to aggregate productivity growth today; it is much too important not to mention in the context of this paper. We then speculate briefly what these effects will be in the future, tying everything into the productivity and pay implications of the paper overall.

To quickly summarize, we consider AI's main role, currently, to be one of augmentation. In other words, the technology complements human performance and product quality by forming a relationship called "human-in-the-loop." In HIL, workers of various skill groups use AI tools in everyday work. Though it is true that AI has automated some jobs away and that the battle of automation versus augmentation will become fiercer as AI becomes the next General Purpose Technology, we believe that it's future effects are tied to HIL.

A. *What is AI?*

It is important to define a few simple AI concepts. The first is "machine learning", which is a subset of AI that has advanced considerably in recent years. The concept refers to the use of generic algorithms to learn and make predictions from a given set of data. There are two main fields within machine learning, and these are the key to understanding current and future productivity effects. seen two key ones are "supervised" and "unsupervised" learning.

Type of ML	Definition	Interpretation
Supervised	Input to output mappings	You know the output or have labeled the data
Unsupervised	Discovery of unknown patterns	You DON'T know the output or DON'T have labeled data

The current use of AI now is to make predictions[27], so let's frame these types from that perspective. A classic example of supervised learning is with image recognition, where an algorithm needs to predict whether an image is a cat or a blueberry muffin, which surprisingly look very similar. The model is "trained" by using images that are labelled with the correct answer, and then the model is used to predict the correct answer on new data it has never seen before. This is a simple task for humans, but prediction models need to be trained. For economists, this is a logit regression.

In unsupervised learning, the primary goal is to identify patterns in data that can be used to formulate predictions. Assume you want to separate pictures of cats by breed of the cat, so you give an algorithm a lot of pictures of different cats. The algorithm will begin to look at similarities and differences, like with fur color, and will then separate the pictures according to what it's learned. It was never told which cat is which breed. All it did was *cluster* cat images together. This trained model can then be used to formulate predictions with other similar data.

[27] Agrawal, Gans, and Goldfarb (2018).

Much of the economics literature has been studying the impact of Artificial Narrow Intelligence (ANI), which is an AI that can perform only one task. Our illustrative examples above classify as ANI. Artificial General Intelligence (AGI), a type of AI where algorithms can reason and perform anything humans do, is still far off. ANI is transforming businesses today, and with McKinsey projecting an additional $13 trillion in economic output by 2030 due to AI[28], and with the CEO of IBM saying that "every company will be an AI company,"[29] we focus on the impact of ANI in subsection B. But with research and AI job postings both increasing (Zhang et al. 2021), we consider both ANI and AGI in subsections C and D.

B. Review of ANI's Impact on Productivity and Pay

There are two ways in which AI can have an impact on productivity and pay. The one that is most talked about is AI's direct effects on people's jobs – on the productivity gains when AI <u>substitutes</u> for people by doing their task. The second is when AI augments or <u>complements</u> the tasks that people do.[30] We say that this augmentation results in a HIL relationship.

At this time, existing data sets do not measure the effects of AI on productivity for a wide range of occupations, so we begin with a quantitative case example to emphasize the skill and begin to draw some productivity implications. In forthcoming work from Jedras and Shaw (forthcoming), we model the implementation of an AI product in the home insurance industry. The AI company produces a product that uses image recognition to access wildfire risk to households and is used to predict when mitigating, or cutting brush that acts as wildfire fuel, will lower the overall property's risk. The predictive analytics makes underwriters better able to address risk (Table 7) and increase coverage efficiency. Now, they are able to train on less-routine cases. The benefit of AI also extends to the policyholder themselves (Table 8), as AI-enhanced risk classification leads to lower premiums. We also know through qualitative evidence that the number of underwriters and home inspectors employed – those employees that go inspect policyholder homes on their own – do not decline. Instead, there is a shifting in tasks

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[28] Bughin, J, et.al. (2018).

[29] Arvind Krishna, "IBM CEO Krishna: Every company will be an AI company,"ZDNet.com, May 5, 2020. https://www.zdnet.com/article/ibm-ceo-krishna-every-company-will-be-an-ai-company/

[30] Athey, et. al. (2020) refer to Replacement AI and Augmentation AI, as two key types when AI is functioning well in firms, when decision rights are given to the AI technology for Replacement, and decision rights given to the human for Augmentation.

or more focused work, thus raising productivity and efficiency for the insurance firms using AI.

We are suggesting the opposite to mass AI substitution through that work. Instead of significant substitution, we are seeing rising productivity for workers. Information from the Annual Business Survey (ABS), a survey subset of the U.S. Census Bureau, confirms the case above. In the most recent year for data available, businesses were asked how incorporating and using AI affected their employment numbers and the skills of their employees. Table 9 shows very few firms reported causal detriments from AI. In fact, AI increased the number of workers employed and their skills much more, per their responses.[31] We thus know that productivity is rising for skilled workers, thus enabling steady real wage growth over time.

Part of our knowledge has been gleaned from cases that we have written for an AI MBA class taught by Shaw. Two of these cases reveal insights along the same lines as above. In the first, Synapse Technology Corporation developed an AI algorithm to use image recognition to predict when traveler luggage going through X-ray scanners contained contraband.[32] Using a labelled dataset of guns and bombs, the AI became more productive at recognizing hidden contraband than trained airport security personnel. The algorithm did not decrease labor demand, however – instead, employees are still needed to search bags and use interpersonal skills with travelers.

In the second case, Focal Systems uses AI to make grocery stores more productivity.[33] Placing cameras on grocery store shelves, they developed an AI algorithm to predict when items needed to be restocked and/or ordered in advance. The productivity of shelf stockers increased since they are timely alerted, and the productivity of managers also rises since the algorithm is essentially predicting the customer demand function. And there was no change in labor demand, but there was an increase in need for interpersonal skills to help customers. The combination of -prediction and more personalized service leads to higher product quality for the consumer.

While these cases are qualitative, they illuminate a few major points that were also found in our wildfire insurance case and the ABS data. ANI augmentation in a HIL relationship leads to increased productivity and product quality, leading to skill restructurings but not mass layoffs.

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[31] Shaw is also ongoing work studying the legal profession, where AI is augmenting the laborious legal case research that entry-level lawyers spent time on. Now, those new lawyers are spending their newfound time training on more complex cases and are not being fired.

[32] Synapse Technologies GSB E-763 case by Jedras and Shaw (2021a), written for Shaw's Stanford GSB class on "The Business of AI: Lessons from Entrepreneurs, Executives, and Investors."

[33] Focal Systems GSB E-764 by Jedras and Shaw (2021b)

AI can lead to increased demand, since rising output or growing firms have increased derived demands for labor. Our cases are of businesses selling their new AI products in the B2B market since productivity and product quality for their customer firms are rising. The skill restructurings themselves are mainly on the middle-skilled, though low-skilled and higher-skilled are affected as well.

Other papers also find much of the same conclusions we did, though there are some differences. A lot of recent literature has also looked at various skill domains. Namely, Gruber et al. (2020) examine the implementation of AI in a Medicare telephone enrollment service, finding that though the productivity of all agents increased, lower-skilled workers benefitted the most. Grennan and Michaely (2020) find a greater emphasis on soft skills for financial analysts using AI, though they also find that churn increased and pay decreased for those who stayed. Cao et al. (2020) investigate firms reporting their asset performance, showing that AI is being used to monitor and analyze financial documents and calls. Employees become more confident, more productive, and use their social skills more. Cowgill (2020) also shows that AI improves hiring processes with greater acceptance rates and higher employee productivity. Overall, these papers find increasing use of AI, increasing productivity, skill restructurings, and increased product quality when humans and AI work together.

Moving beyond examples, the fact that AI tools provide predictions, which are a fundamental part of human decision-making, implies that is applications may not be bound by industry or task in the future. Academic focus so far has been on labor demand and, occasionally, wages. Brynjolfsson, Mitchell, and Rock (2018), for example, use O*Net data on tasks by occupation to show that machine learning will affect virtually all occupations, resulting in job losses and a re-bundling of tasks. However, they conclude that as the content of tasks in occupations change, the occupations continue to exist. Acemoglu et al. (2022) similarly develop a measure of firm-level exposure to AI and show an increase in demand for AI workers with some substitution occurring for AI-exposed occupations, but because AI adds to overall demand for workers, there is no overall wage effects. [34] Webb (2020) also finds that some higher skilled jobs, like chemical engineers and optometrists, are affected by AI. He predicts that inequality

[34] Deming & Kahn (2017) also use Burning Glass data to document that cognitive and social skill requirements in jobs are complementary to each other across firms and industries, which is a change that is occurring as AI enters firms though they do not measure AI. And Acemoglu and Restrepo (2020) takes the task-based approach to modelling technology, with implications for AI.

will decrease for a large range of jobs from the 10^{th} to the 90^{th} percentiles, but it will increase from the 90^{th} to the 99^{th} percentiles.

Much of the work, both from us and others, takes current implications and then attempts to predict the future. Doing so can intertwine reasonings. So, we take the next section to summarize current implications, from which we will then touch on future trends.

C. Current Implications, a Summary

The case studies and literature cited above point to several main implications. We mentioned a few already, especially in the HIL context, but here is what we see.

First, as has been true of past General Purpose Technologies, the effects of AI right now are mostly on middle-skilled jobs, such as the airport security workers who are trained to scan bags and grocery managers overlooking a store. AI does affect all skill groups though, like low-skilled stockers or some high-skilled financial analysts, just not so much as middle-skilled jobs built around digitalization. More importantly, though automation is certainly taking place, much of ANI today complements human performance and is thus not eliminating jobs en masse. We call the resulting working relationship of humans using complementing AI tools HIL.

Second, because of complementarity and HIL, productivity and product quality are rising. Whether occupational taskings change, with an increased emphasis on soft skills, or workers are just better informed with predictive analytics, performance increases and results improve. Cases and literature all point to this. It will, however, take time for productivity to show up in the aggregate GDP numbers. We recall Robert Solow's famous quote in 1987: The productivity increase is everywhere, but in the numbers.[35]

Third, the technological revolution of AI is raising the output demand for many firms, which trickles down to many skill groups in principle. This is economic growth due to AI. The question is whether the economic growth is falling differentially. We know from Humlum and Meyer (2020) that earnings premiums for AI producers are rising, but they do not find the same for AI users. Aghion et al. (2017) find that R&D intensive firms pay more on average than their

[35] More specifically, Solow said in 1987, "You can see the computer age everywhere but in the productivity statistics". https://en.wikipedia.org/wiki/Productivity_paradox. Robert Solow, "We'd better watch out", New York Times Book Review, July 12, 1987, page 36.

counterpart firms, with lower-skilled workers benefitting more than higher-skilled workers due to complementarities between the two skill groups. So, economic growth due to AI is happening, with skill premiums rising as seen in Autor, Levy, and Murnane (2003) and Deming and Kahn (2020), though lower-skilled workers can also benefit.

For current trends, we see that productivity and performance are rising due to AI-induced economic growth, without the large and immediate unemployment effects. Because it will take time for the productivity effects to emerge in the data, it is hard to definitively say how pay and productivity are linked in this ongoing technological change. However, wage premiums and polarization are beginning to emerge, like the specialization conclusions addressed earlier in the paper.

D. Future Trends

We speculate that the complementary effects of ANI on productivity and product quality will increase as AI is integrated more into the workplace. An obvious point is that skill premiums for AI producers will rise as the field becomes more specialized. This would result in an extension of the spreading out of the right tail of productivity and pay, or in the inequality of pay. Perhaps another obvious point is that due to data requirements, large firms are posed to benefit more from acquisition or development of AI products, thus increasing the right tail's spread and ultimately changing the structure of the economy. An important point we raise though is that specialized interpersonal skills, required for HIL relationships and increased product quality, are omitted from productivity data. The derived demand for more soft skilled workers may cut down on the obvious effect. Knowledge diffusion could also deter more inequality.

This reality is contingent on AGI not being a reality for the foreseeable future. Even with AGI though, there are bound to be bottlenecks. As Aghion, Jones, and Jones (2019) posit, AI can lead to quick and more advanced growth, there may be a subset of cognitive skills that are needed to solve problems that AI can't. Benzell and Brynjolfsson (2019) call this factor "genius." So, even in the face of AGI, humans will still be needed, though the "genius" factor may raise important questions about the productivity and pay link for lower- and middle-skilled groups.

So, where do we stand on the inequality of productivity increases and wage increases in the future – will AI continue the trend of rising wage inequality, and might AI be associated with rising productivity inequality across skill groups? Akin to Jones (2002), Ai is an example of the growth of output due to the “ideas” production function, but idea generation or use is likely to be with the highly skilled. There would thus seem to be a relative decline in wages for the less to middle skilled. However, if these same workers shift to using interpersonal skills to satisfy HIL, they will be in demand and may see less significant wage decline.

Over the long run, the US economy will run at full employment, so the effects of AI are distributional. When AI does the job of workers, and is better at doing that job, we need re-training.

XII. Conclusion

Across countries and within countries over time, there is compelling evidence that productivity and wages are linked. Aggregate productivity and wages rise together in the data within countries over time, though theory does not imply that this correlation must appear, since it depends on the elasticity of labor supply of people to firms.

Looking across people, we also find that increases in aggregate productivity, or in GDP per person, increase wages for those earners at the lowest and at the highest parts of the wage distribution, or at the 10th and 90th percentiles of pay. This implies that increases in aggregate productivity are shared by earners at all skill levels, and this applies across countries.

If increases in aggregate productivity are passed on as higher wages for all skill levels, from the high-school educated to post-graduate skill level, does this mean that productivity rose for each of these skill groups over time? That is, does higher pay for all skill groups reflect higher productivity over time for all skill groups? This question is the cornerstone of this paper.

This is a difficult question to answer, because firms, or statistical agencies, do not measure productivity by skill level, such as education. Therefore, we construct a variable that serves as an approximation for personal productivity by educational level. We use US data on productivity by 3-digit industry and match it to the average educational level in each 3-digit industry, to get a “productivity by skill level” variable. This variable depends on the notion that industries with very high average educational levels may have the most productive workers, because they are so highly educated. Using this variable, U.S. regression results show that there a high implicit correlation between the rise over time of wages by skill level and the rise of productivity by skill level.

What do we conclude from these regressions? We know that wages have spread out over time, rising more at the 90th percentile than at the 50th percentile of pay. Has productivity also spread out over time? Our productivity regression results imply that it has: productivity has risen faster over time for the highly educated than for the least educated, who work in industries that have experienced the least productivity growth.

Thus, wages have spread out over time and productivity has spread out over time. Or, the main conclusion is that changes in productivity at different educational levels are more than sufficient to account for changes in the wage distribution. Our results, of non-neutral productivity growth across educational groups, is another way of affirming the rising premium for a college education shown by others. It could reflect a number of possible causes, which include skill-biased technological change, trade patterns that have altered prices in a non-neutral fashion, the rising concentration of industries, the falling labor share, and changes in human capital production technologies that favor tertiary over primary and secondary education.

Wages have spread out across people over time for 15 of 17 countries for 1989-2019, so there is commonality in the pattern of correlation between productivity and, suggesting global rather than institutional factors are at work. Therefore, the most obvious candidate is the often discussed skill-biased nature of technological change, benefiting highly skilled workers.

The skill-biased technical change of the last three decades reflects the “computer revolution.” Or, the technological change driving the wedge between the pay of the highly skilled and the less skilled has been the computer revolution, which took time to alter the workplace, as firms changed workflows and products. The new revolution is the AI revolution, and researchers have just begun to show that it is having similar skill-biased effects as past technologies. But over the last 150 years, the extent of skill-biased technical change has itself grown with new technologies, and thus AI is replacing the tasks of those who are more educated than did past revolutions. However, even for the middle-skilled whose routine tasks are disappearing, some will not lose their jobs, but will instead be expected to use more social or interpersonal skills in working with other employees and customers. And lastly, the type of AI now in use in some firms is basic ANI; the AGI that is most feared, is many years away to true adoption.

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Table 1
Wages and Productivity, Across Countries, over 1990-2019
OECD Data for 34 Countries Over Time (cols. (1)-(5)), and World Bank Data for 28 Additional Countries (cols (6)-(7))

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	2017 Log of Annual Wage 34 countries (2017 USD)	1990-2019 Change in Log of Annual Wage t-5 to t	1990-2019 Change in Log of Annual Wage t-20 to t	1990-2019 Log of Annual Wage in year t (2017 USD)	1990-2019 Log of Annual Wage in year t (2017 USD)	2017 Log of Annual Wage in year t (2018 USD)	1970-2019 Log of Annual Wage in year t (2018 USD)
Log Annual Productivity in 2017 (Output-per-hour times 1500; OECD)	1.517*** (.169)						
Change in Log of Annual Productivity between t-5 and t (OECD)		.716*** (.147)					
Change in Log of Annual Productivity between t-20 and t (OECD)			.682*** (.158)				
Log Annual Productivity in year t (Output-per-hour times 1500; OECD)				0.755*** (0.0731)	1.440*** (0.116)		)
Log Annual Productivity in year t (Output-per-hour times 1500; The Conference Board)						1.455*** (0.0705	
Constant	-6.654*** (1.909)	0.003 (.011)	.024 (.049)	9.253*** (0.815)	1.618 (1.314)	4.686*** (0.263)	5.992*** (0.094)
R-squared	.715	.329	.487	.989	.719	0.944	0.996

1.078*** (0.0306)

N	34	757	252	927	927	62	2,655
Years	2017	1990-2019	1990-2019	1990-2019	1990-2019	2017	1970-2019
Notes:	One observation per country	Clustered at country level	Clustered at country level	Clustered at country level, country fixed effects included	Clustered at country level	One observation per country	Clustered at country level, country fixed effects included

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table 1 analyzes the relationship between wages and productivity across several countries by estimating regression equation (7) from the model. Column (1) outlines a regression relationship between log annualized wage and log annualized productivity, just for the year 2017. Columns (2) and (3) outline time-differenced equations, where column (2) uses 5-year periods and column (3) uses 20-year periods. The years for columns (2) and (3) are 1990-2019. Columns (4) and (5) are akin to column (1) but extend the analysis to the 1990-2019 time period. Column (4) also introduces country fixed effects. Columns (6) and (7) extend the analysis of column (1) and column (4), respectively, to more countries by using World Bank and The Conference Board data.

Source: The wage data are from the OECD Employment and Labour Market Statistics database. The OECD productivity data are from the OECD Compendium of Productivity Indicators. The Conference Board productivity data are from the Total Economy Database. All data were originally accessed on 04 February 2019 and updated on 15 November 2021.

Table 2
United States Regression Results: Real Compensation and Productivity, 1950-2019 Bureau of Labor Statistics Data

VARIABLES	(1) 1950-2019 Compensation Levels Index BLS	(2) 1950-2019 Change in Four Year Moving Average of Non-farm Compensation Index BLS	(3) 1990-2019 Change in Four Year Moving Average Non-farm of Compensation Index BLS
Nonfarm Output Index BLS	0.788*** (0.0256)		
Change in Four Year Moving Average of Nonfarm Output Index BLS		0.758*** (0.084)	0.596*** (0.153)
Constant	27.625*** (1.730)	-0.0009 (0.00195)	-0.0017 (0.0030)
Years	1950-2019	1950-2019	1990-2019
Observations	73	69	30
R-squared	0.949	0.400	0.391

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table 2 focuses on the relationship between compensation and productivity for just the United States, while Table 1 looked at several countries. Column (1) regresses a BLS nonfarm compensation index (2012=100) against a BLS nonfarm output index (2012=100). Column (2) smooths out the indexes by creating four-year averages, calculating annual changes, and then regressing. Column (3) then restricts the time period from (2), making it only from 1990 to 2019.

Source: The output index is from the U.S. Bureau of Labor Statistics, "Nonfarm Business Sector: Real Output Per Hour of All Persons," and retrieved from FRED (https://fred.stlouisfed.org/series/OPHNFB). The compensation index is from the U.S. Bureau of Labor Statistics, "Nonfarm Business Sector: Real Compensation Per Hour," and retrieved from FRED (https://fred.stlouisfed.org/series/COMPRNFB). The data were accessed on 15 November 2021.

Table 3
Changes in 90/50 and 50/10 Wage Ratios Over Time and Across Countries

Country	90/50 in 2015	90/50 in 1997	Difference	50/10 in 2015	50/10 in 1997	Difference
Australia	1.95	1.81	0.14	1.68	1.61	0.07
Canada	1.91	1.76	0.15	1.94	2	-0.06
Czech Republic	1.85	1.72	0.13	1.93	1.79	0.14
Finland	1.77	1.69	0.08	1.44	1.41	0.03
Germany	1.9	1.75	0.15	1.85	1.67	0.18
Hungary	2.27	2.17	0.1	1.64	1.92	-0.28
Japan	1.85	1.85	0	1.59	1.63	-0.04
Korea	2.39	2.09	0.3	1.92	2	-0.08
New Zealand	1.89	1.7	0.19	1.57	1.59	-0.02
Norway	1.65	1.54	0.11	1.68	1.38	0.30
Sweden	1.58	1.5	0.08	1.32	1.25	0.07
United Kingdom	1.96	1.86	0.1	1.78	1.84	-0.07
United States	2.4	2.2	0.2	2.1	2.1	0

Not all OECD countries are reported. Only those with 1997 data points are included.

Source: The data are from the OECD Employment and Labour Market Statistics database. The data were originally accessed on 04 February 2019 and then updated on 15 November 2021.

Table 4

Relation of Changes in Wages to Changes in Productivity for 10th and 90th Percentiles

VARIABLES	(1) Annual change in log 10th percentile wage 5-yr moving avg	(2) Annual change in log 10th percentile wage 5-yr moving avg	(3) Annual change in log 90th percentile wage 5-yr moving avg	(4) Annual change in log 90th percentile wage 5-yr moving avg
Annual change in log productivity (5-yr moving avg)	0.704**	0.615***	0.919***	0.824***
	(0.349)	(0.127)	(0.222)	(0.124)
Constant	-0.0135**	-0.000117	-0.00901**	-0.00183
	(0.00585)	(0.00274)	(0.00403)	(0.00207)
Observations	40	204	40	204
R-squared	0.150	0.177	0.335	0.333
Notes	United States 1973-2017	All countries excluding the United States Unbalanced Panel	United States 1973-2017	All countries excluding the United States Unbalanced Panel

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses.

Table 5 goes beyond Table 4 and relates changes in wages to changes in productivity. Columns (1) and (3) are clustered by year, while columns (2) and (4) are clustered by country-year.

Source: The decile wage data are from the OECD Employment and Labour Market Statistics database. The productivity data are from the OECD Compendium of Productivity Indicators.

Table 5
Productivity, Wages and Employment United States 3-Digit Industry

VARIABLES	(1) Log Productivity	(2) Log Real Wage	(3) Change in Log Productivity (1989-2017)	(4) Change in Log Real Wage (1989-2017)	(5) Change in Log Employment (1989-2017)	(6) Change in Log Productivity (1989-2017)	(7) Change in Log Real Wage (1989-2017)	(8) Change in Log Employment (1989-2017)
industry average education current year	0.301**	0.173***						
	(0.113)	(0.0321)						
industry average education in 1989			0.141**	0.0155	0.316**			
			(0.0626)	(0.0400)	(0.127)			
industry average education in 2017						0.161***	0.0729**	0.111 (0.122)
						(0.0541)	(0.0341)	
Constant	0.964	8.417***	-1.461*	0.0574	-4.096**	-1.894**	-0.734	-1.715
	(1.430)	(0.427)	(0.770)	(0.491)	(1.556)	(0.730)	(0.460)	(1.642)
Observations	1353	3,036	40	40	40	40	40	40
R-squared	0.127	0.274	0.118	0.004	0.141	0.189	0.107	0.021

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses, clustered at industry level in column (1) and (2). Unit of analysis is a 3-digit industry. There is one observation per industry that measures the difference during period, 1989-2017, using merged data from the following two BLS sources: (1) The wage, education, and employment data are from the CPS-ASEC (Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [dataset]. Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D030.V6.0) (2) The productivity data are from the Bureau of Labor Statistics, Major Sector Productivity and Costs data file (https://www.bls.gov/lpc/data.htm). Naturalized metrics of industry output per hour are regressed on average levels of education.

Table 6
Actual and Productivity Predicted Changes in Log Wages, 1989-2017

1	2	3	4	5	6	7	8	9
year	education group	education in years (average within category)	mean real wage	mean log real wage	change in mean log real wage 1989-2017	change in log real product-ivity 1989-2017	difference in change in mean log real wage from one lower group	difference in change in mean log real productivity from one lower group
1989	Less than high school	6.48	615.26	6.25				
1989	Some high school or hs grad	11.65	735.24	6.40				
1989	Some college or college Grad	14.68	1032.01	6.74				
1989	Graduate education	18.00	1500.35	7.15				
2017	Less than high school	5.40	572.88	6.21	-0.04	-1.02		
2017	Some high school or hs grad	11.79	756.73	6.42	0.02	0.00	0.06	1.03
2017	Some college or college Grad	14.60	1069.74	6.75	0.01	0.46	-0.01	0.45
2017	Graduate education	18.00	1605.51	7.22	0.07	1.00	0.06	0.55

Estimates from column (6) of table 5 are used to forecast changes in productivity by educational group. Wages are based on 153,815 individual level observations from the CPS outgoing rotation groups for 1989 and 2017.

Source: Actual change in wages come from Bureau of Labor Statistics CPS outgoing rotation group data (Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [dataset]. Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D030.V6.0). Change in log productivity is estimated using Bureau of Labor Statistics productivity data matched with Bureau of Labor Statistics ASEC data to obtain estimated productivity change by education level.

Table 7
Poisson Regressions of Fire Claim Count

VARIABLES	(1) Fire Claim Count no FE	(2) Fire Claim Count ZIP FE
Current Risk Rating	0.122***	0.0622***
	(0.00934)	(0.00984)
Zone 1 – Coverage	0.522***	0.0778
	(0.108)	(0.110)
Zone 2 – Coverage	0.229*	0.310**
	(0.122)	(0.124)
Zone 3 – Coverage	1.450***	0.473***
	(0.120)	(0.136)
Can Mitigate, Current Year	-0.130***	-0.0434*
	(0.0226)	(0.0233)
Wildland Proximity	-0.0236***	-0.00363
	(0.00196)	(0.00587)
2015	0.794	1.111
	(1.002)	(1.000)
2016	2.556**	2.829***
	(1.000)	(0.999)
2017	2.601***	2.868***
	(1.000)	(0.999)
2018	2.625***	2.897***
	(1.000)	(0.999)
2019	1.254	1.572
	(1.003)	(1.002)
2020	0.952	1.272
	(1.004)	(1.003)
Constant	-8.072***	
	(1.000)	
Observations	1,706,976	1,592,671
Number of ZIP Codes		1,156

Table 8
Earned Premium Regressions

VARIABLES	(1) No ZIP Year	(2) Just ZIP Year	(3) All	(4) Can Mitigate, Current Year
Current Risk Rating	66.34***		43.58***	48.00***
	(0.564)		(0.517)	(0.563)
Can Mitigate Dummy, Year Before	-14.19***		-28.91***	-7.841***
	(1.428)		(1.250)	(1.430)
Can Mitigate Dummy, Current Year				-41.48***
				(1.543)
Fire Claim Count, Current Year	523.8***		368.0***	367.6***
	(12.95)		(11.32)	(11.31)
Fire Claim Count, Year Before	538.5***		408.9***	408.5***
	(13.95)		(12.36)	(12.35)
Total (no Fire) Claim Count, Current Year	260.0***		144.6***	144.6***
	(2.679)		(2.399)	(2.398)
Total (no Fire) Claim Count, Year Before	136.8***		42.92***	42.90***
	(2.910)		(2.681)	(2.680)
2015		293.0***		
		(12.14)		
2016		291.3***	505.9***	506.1***
		(12.14)	(8.479)	(8.478)
2017		323.6***	532.0***	532.5***
		(12.14)	(8.471)	(8.470)
2018		171.6***	379.5***	379.6***
		(12.15)	(8.475)	(8.474)
2019		237.7***	435.3***	435.6***
		(12.23)	(8.617)	(8.616)
2020		-215.3***	-13.73	-13.62
		(12.20)	(8.548)	(8.547)
Constant	772.8***	758.1***	430.5***	427.1***
	(1.363)	(12.09)	(8.484)	(8.486)
Observations	1,194,916	1,694,330	1,188,567	1,188,567
R-squared	0.036	0.292	0.300	0.300

Table 9
Causal Effects of AI, Number of Firms
Panel A: Number of Workers

Question	Number of Firms
Increased numbers of workers employed	4,613
Did not change number of workers employed	14,363
Decreased number of workers employed	813
Total reporting	19,789

Panel B: Skill Level of STEM Workers

Question	Number of Firms
Increased STEM skills of workers employed	7,805
Did not change STEM skills of workers employed	8,044
Decreased STEM skills of workers employed	359
Not applicable, no STEM skilled employees	3,582
Total reporting	19,789

Panel C: Skill Level of General Workers

Question	Number of Firms
Increased skill level of workers	8,763
Did not change skill level of workers	10,615
Decreased skill level of workers	NA
Total reporting	19,789

Source: Annual Business Survey (2019)

Figure 1

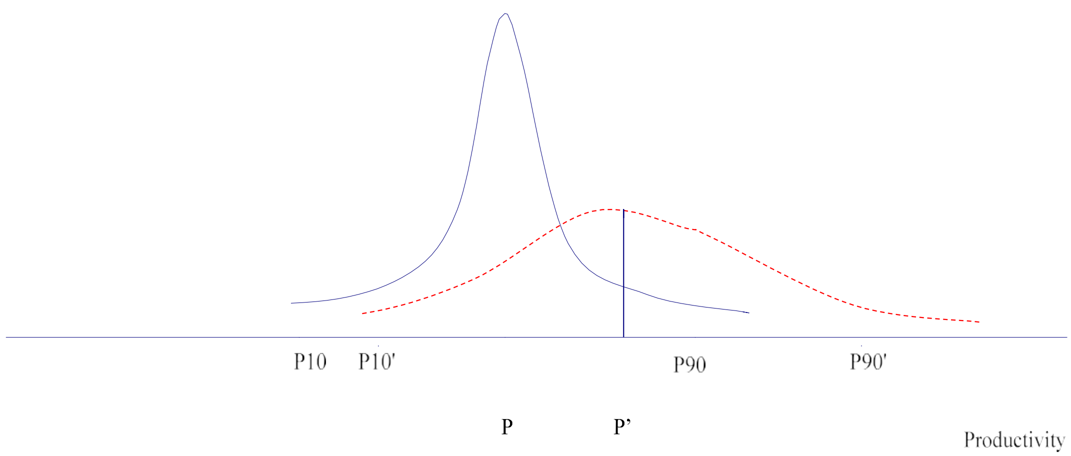
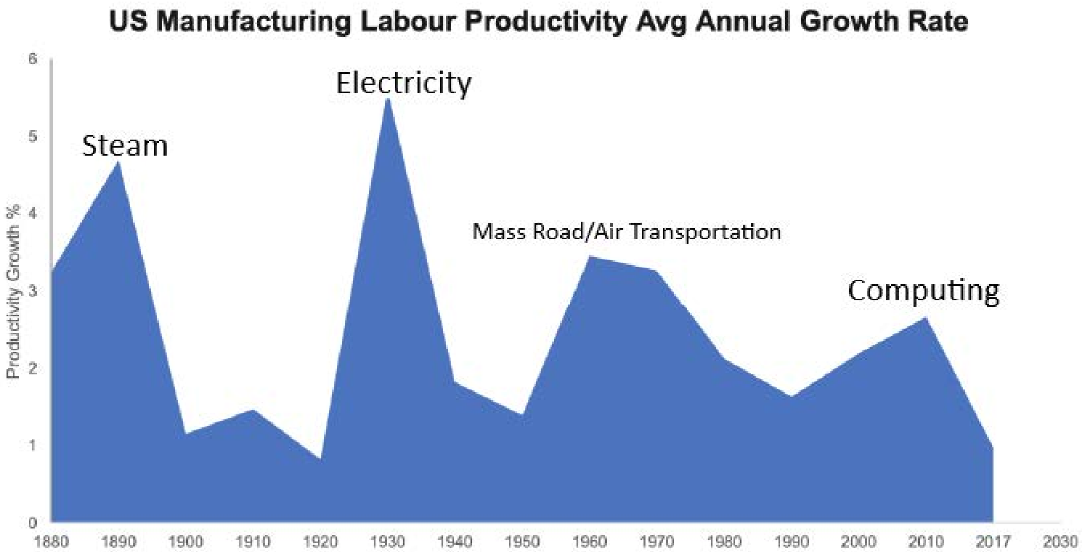
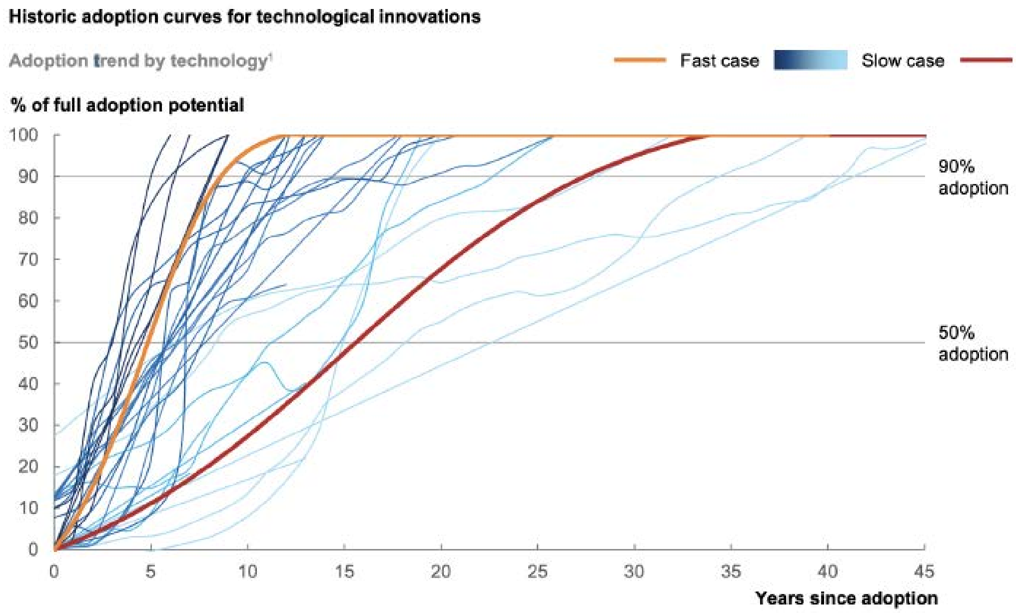


Figure 2



Source: David, Paul (1989) "Computer and Dynamo: The Modern Productivity Paradox in a Not-Too Distant Mirror", OECD International Seminar on Science, Technology and Economic Growth. BLS Data (2018).

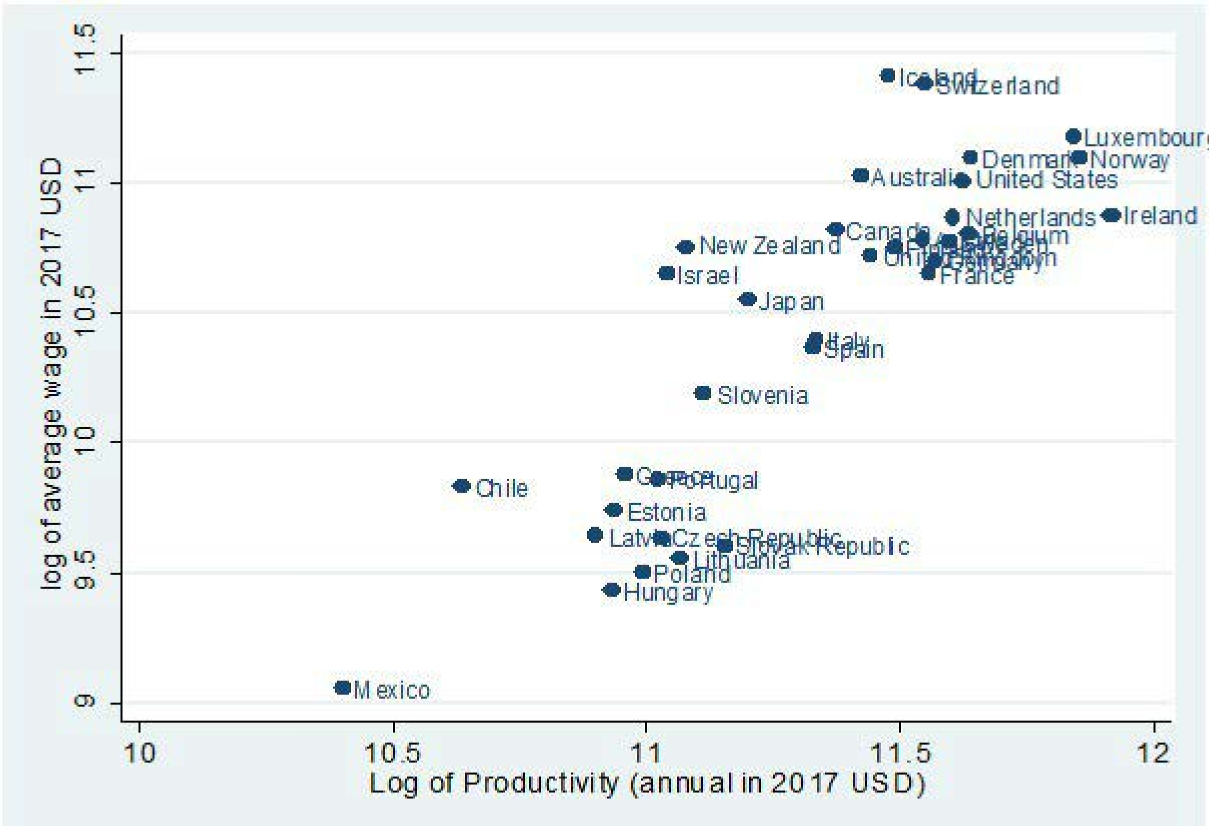
Figure 3
Adoption Rates for New Technologies, 1950-2010



1 Technologies considered include airbags, antilock braking systems, cellphones, cloud CRM, cloud ERP, cloud SCM, color TVs, copper production through leaching, dishwashers, electronic stability control, embolic coils, Facebook, instrument landing systems, laparoscopic surgery, Lithium-ion cell batteries, microwaves, MRI, online air booking, P2P remote mobile payment, pacemakers, PCs, smartphones, stents, TVs, and VCRs.

Figure 4
Cross-Country Comparison of Wages and Productivity in 2017

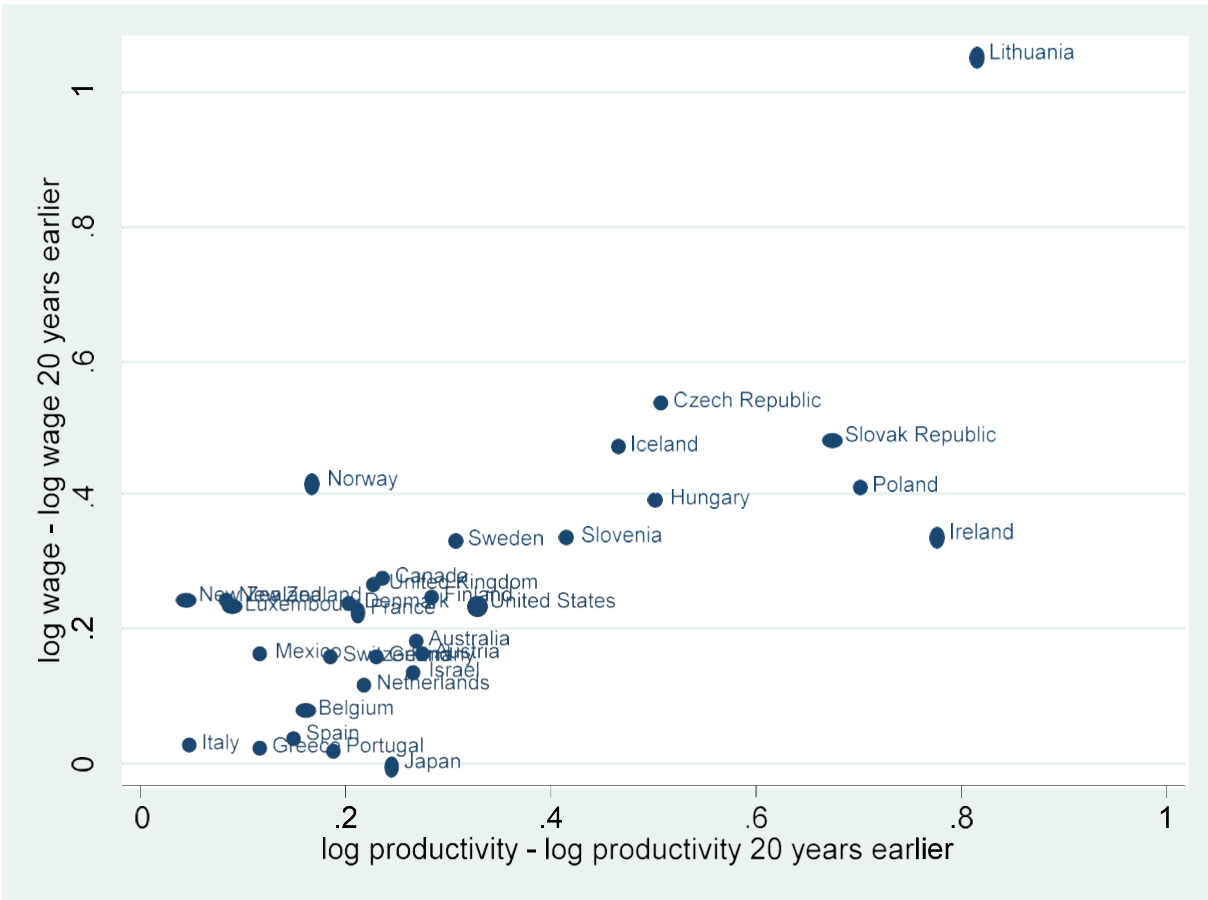
Horizontal axis is the log of productivity in 2017 USD, annualized (which means times 1500). Vertical axis is the log of annual wages in 2017 USD.



Source: The wage data are from the OECD Employment and Labour Market Statistics database. The productivity data are from the OECD Compendium of Productivity Indicators.

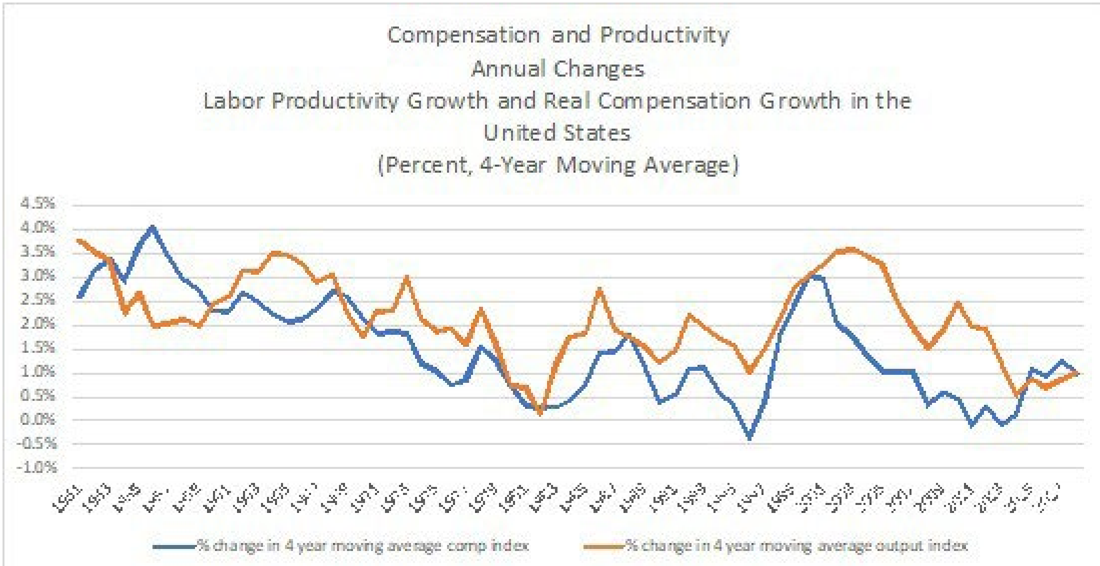
Figure 5
Cross-Country Comparison of Productivity Growth and Wage Growth 1997-2017

Horizontal axis is the proportionate change in within-country productivity (annualized in 2017 USD). Vertical axis is the proportionate change in within-country wage.



Source: The wage data are from the OECD Employment and Labour Market Statistics database. The productivity data are from the OECD Compendium of Productivity Indicators.

Figure 6
Compensation and Productivity in the United States Over Time



Source: The output index is from the U.S. Bureau of Labor Statistics, "Nonfarm Business Sector: Real Output Per Hour of All Persons," and retrieved from FRED (https://fred.stlouisfed.org/series/OPHNFB). The compensation index is from the U.S. Bureau of Labor Statistics, "Nonfarm Business Sector: Real Compensation Per Hour," and retrieved from FRED (https://fred.stlouisfed.org/series/COMPRNFB).

Figure 7

Wage Rates for the 10th and 90th Percentile, United States

Source: The data are from the OECD Employment and Labour Market Statistics database.

Figure 8

Wage Rates for the 10th and 90th Percentile, All OECD Countries

All OECD countries (16 countries included; excludes US)

Source: The data are from the OECD Employment and Labour Market Statistics database.

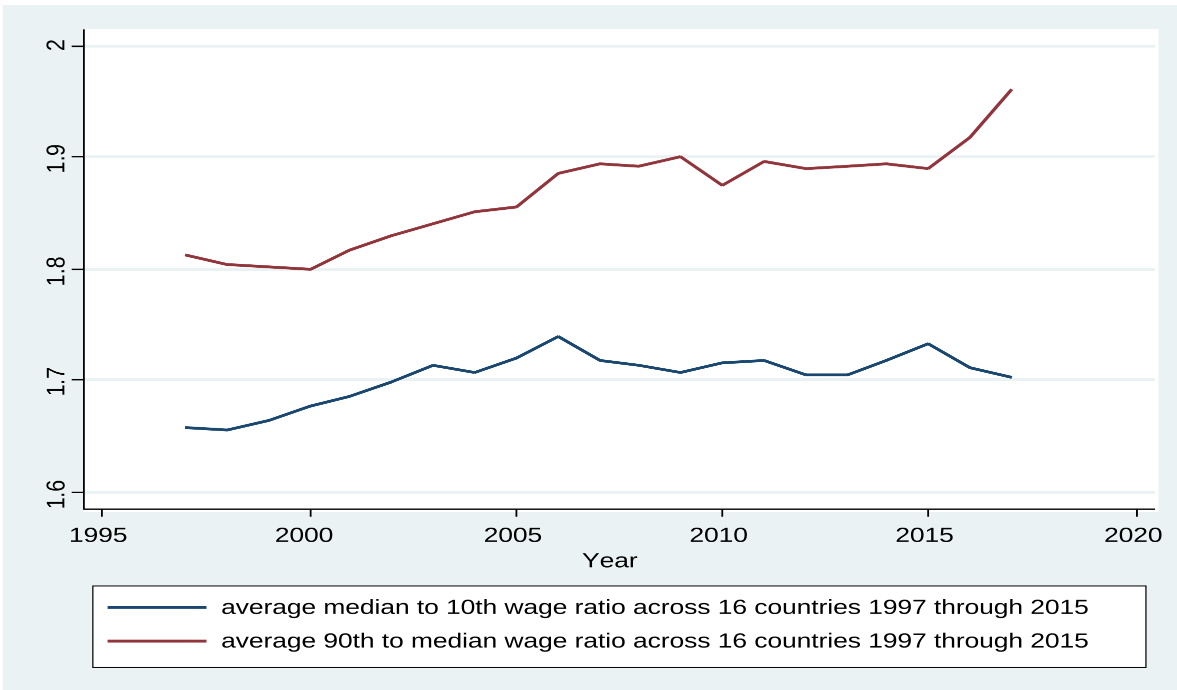
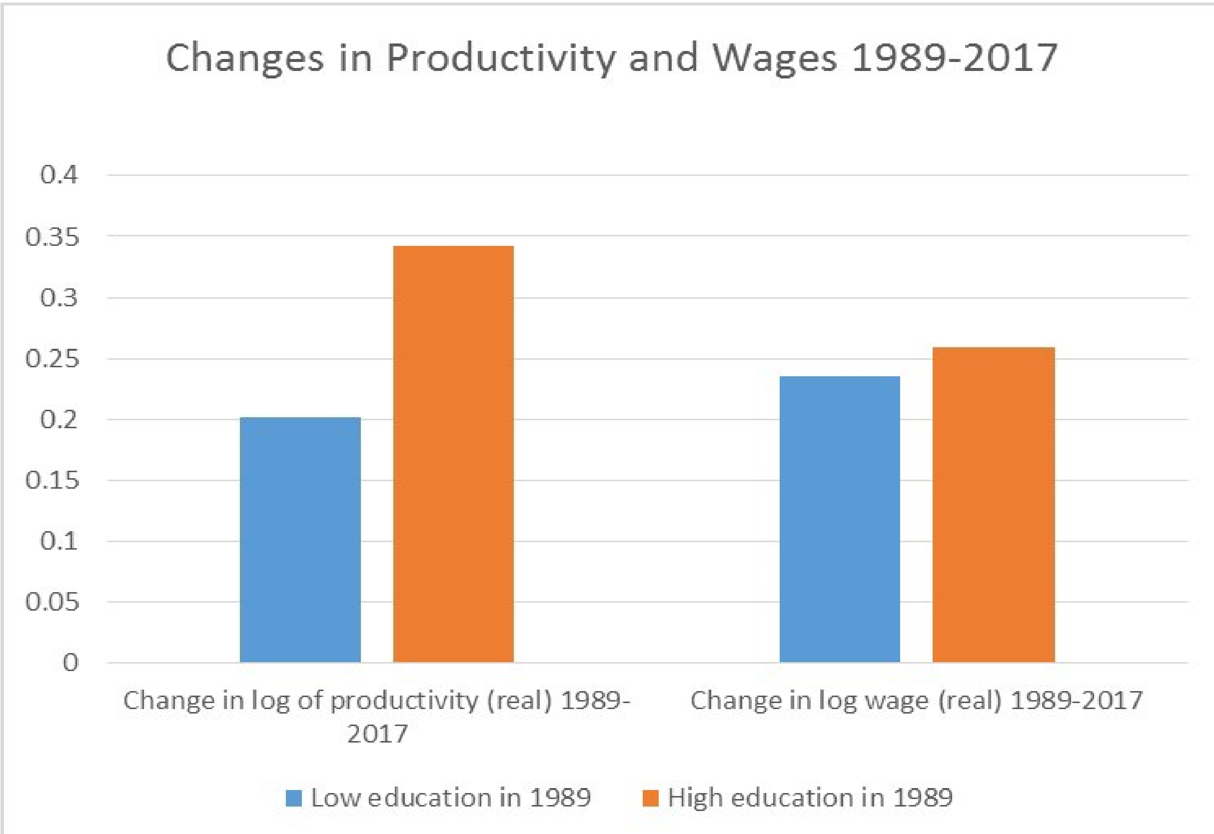


Figure 9
Productivity and Wage Changes for Two Education Group, HS or less, College



Sources: (1) The wage data are from the CPS-ASEC (Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [dataset]. Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D030.V6.0) (2) The productivity data are from the Bureau of Labor Statistics, Major Sector Productivity and Costs data file (https://www.bls.gov/lpc/data.htm).

Low and high education in 1989 is defined as follows. Each industry reports an average (mean) level of education for that industry. Low education in 1989 is then all industries that have average levels of education below the industry median and conversely for high education in 1989. The bars are the unweighted averages taken across the relevant industries for wages and productivities.

Appendix A

There is a before-and-after the scanner technology that is characterized by two different production functions. Refer to one type of labor as skilled, S, and the other as unskilled, U. Initially, output is produced according to

$$Q_0 = L_U^{1/6} L_S^{1/2} K^{1/3}$$

with revenue equal to the price of the product, $P_0 Q_0$. The demand for the product is given by

$$Q = 3183 - 3000 P .$$

There are 100 of each type of labor supplied perfectly inelastically. Capital is purchased in the world capital market supplied perfectly elastically at a fixed price, set equal to .1. Each factor is paid its marginal product, which in equilibrium, exhausts total output so that profits are zero. Because of the inelasticity of labor supply, wages are determined completely by marginal product and are set such that the wage of each type of worker equals the value of the marginal product or

$$W_S = P_0 \left(½ L_U^{1/6} L_S^{-1/2} K^{1/3}\right)$$

and

$$W_u = P_0 \left(1/6\right) L_U^{-5/6} L_S^{1/2} K^{1/3}$$

Because capital's price is fixed, the quantity of capital used is determined by setting the value of the marginal product equal to its price, .1 or

$$.1 = P_0 (1/3) L_U^{1/6} L_S^{1/2} K^{-2/3}$$

The equilibrium given constant returns technology is characterized as follows:

$Q_0 = 234.6$
$W_S = .913$
$W_U = .300$
$K = 608.6$
$P_0 = 1$
Productivity = $Q_0 / (L_U + L_S) = .913$
Profit = 0

The number of firms is both indeterminate and irrelevant since profits are exhausted and returns are constant.

The scanner is invented. Now, there is no distinction between skilled and unskilled labor. All workers can operate the scanner equally effectively so total labor is simply equal to 200. The technology takes the following form

$Q_1 = \lambda[L^{1/3} \quad + K^{2/3}]$ with scanner
$= Q_0$ without scanner

As before, workers are paid the value of their marginal products, which in this case is

$$\text{Wage} = 1/3 \quad \lambda \quad L^{-2/3}$$

Also as before, the amount of capital used is determined by

$$.1 = 2/3 \quad \lambda \quad K^{-1/3}$$

Equilibrium now has firms with u-shaped cost curves because returns are diminishing in K and L, but there is the fixed cost of the scanner. Let λ=2. The solution is

$Q_1 = 332.6$
W = .019
L=200
K=2032.2
$P_1 = .95$
Productivity = Q_1 / L = 1.65
Profit = 0
Price of Scanner = 109

The producer of the scanner can charge up to 109, which results in zero profit. Over time, if 109 exceeds the cost of producing a scanner, others will enter driving the price down.

The fact that 332.6 > 234.6 means that output has increased and price of the product falls. All labor is of now the same type and labor productivity has also increased because the number of workers remains unchanged. Specifically, productivity increases to 1.65 from .913, but note also that the wage falls substantially, not only because the skilled category is lost but because the change in technology, coupled with the fact that skilled and unskilled are alike, reduces the wage of both types of workers.

Appendix B

Data Sources

Variable or analysis	Source	Dataset title	Description	Citation
Average hours worked across countries	The Conference Board	Total Economy Database	The Total Economy Database, (TED) is a comprehensive database with annual data covering GDP, population, employment, hours, labor quality, capital services, labor productivity, and total factor productivity for 123 countries. Average hours worked represent the aggregate number of hours actually worked by an employee or a self-employed person during the accounting period and when their output is within the production boundary. Data are mostly sourced from national accounts and are available for 68 countries.	The Conference Board. (2019). *Total Economy Database*. Retrieved from https://www.conference-board.org/data/economydatabase/ total-economy-database-productivity-growthaccounting
Adjusted net national income per capita	The World Bank	DataBank	Adjusted net national income is gross national income minus consumption of fixed capital and natural resources depletion. The measure is in constant 2010 U.S. dollars.	World Bank. (2020, May 19). *Adjusted net national income per capita (constant 2010 US$).* Retrieved from https://data.worldbank.org/ indicator/NY.ADJ.NNTY.PC.KD
Average wage in US dollars	OECD	Average annual wages	This dataset contains data on average annual wages per full-time and full-year equivalent employee in the total economy. Average annual wages per full-time equivalent dependent employee are obtained by dividing the national-accounts-based total wage bill by the average number of employees in the total economy, which is then multiplied by the ratio of average usual weekly hours per full-time employee to average usually weekly hours for all employees.	OECD (2019), "Average annual wages", *OECD Employment and Labour Market Statistics* (database),https://doi.org/10.1787/data-00571-en (accessed on 04 February 2019).
Hours worked per year	OECD	Average annual hours actually worked	The concept used is the total number of hours worked over the year divided by the average number of people in employment. The data are intended for comparisons of trends over time; they are unsuitable for comparisons of the level of average annual hours of work for a given year, because of differences in their sources. Part-time workers are covered as well as full-time workers.	OECD (2019), "Hours Worked: Average annual hours actually worked", *OECD Employment and Labour Market Statistics* (database), https://doi.org/10.1787/data-00303-en (accessed on 04 February 2019).

Industry employment	BLS DIPS	Labor Productivity and Costs by Industry and Measure	Employment is a measure that represents the total number of wage and salary workers, self-employed workers, and unpaid family workers working at various occupations within business establishments. An individual who works multiple jobs at separate establishments would have each job included in the employment measure.	LPC Tables and Charts. (n.d.). Retrieved from https://www.bls.gov/lpc/tables.htm
Industry hours worked	BLS DIPS	Labor Productivity and Costs by Industry and Measure	The total number of hours worked by wage and salary workers, unincorporated self-employed workers, and unpaid family workers to produce output.	LPC Tables and Charts. (n.d.). Retrieved from https://www.bls.gov/lpc/tables.htm
Labor productivity	BLS DIPS	Labor Productivity and Costs by Industry and Measure	Labor productivity is a measure that represents the amount of goods and services that can be produced relative to the amount of labor service used. Labor productivity measures the rate at which labor is used to produce output of goods and services, typically expressed as output per hour of labor. Indexed at 100 in 1987.	LPC Tables and Charts. (n.d.). Retrieved from https://www.bls.gov/lpc/tables.htm
Minimum wage in US dollars	OECD	Real minimum wages	Real hourly and annual minimum wages are statutory minimum wages converted into a common hourly and annual pay period for the 28 OECD countries and 4 non-member countries for which they are available. The resulting estimates are deflated by national Consumer Price Indices. The data are then converted into a common currency unit using either US $ current exchange rates or US $ Purchasing Power Parities (PPPs) for private consumption expenditures. Real hourly and annual minimum wages are calculated first by deflating the series using the consumer price index taking 2017 as the base year. The series are then converted into a common currency unit (USD) using Purchasing Power Parities for private consumption expenditures in 2017.	OECD (2019), "Earnings: Real minimum wages", *OECD Employment and Labour Market Statistics*(database), https://doi.org/10.1787/data-00656-en (accessed on 04 February 2019).

Output per hour	The Conference Board	Total Economy Database	Labor productivity per hour worked in 2018 US Dollars. GDP growth and levels are adjusted for rapidly falling ICT prices. More specifically, GDP deflators for 3 countries with significant ICT production and trade, including China, Japan and the United States are adjusted downward using an alternative series of ICT price deflators developed by Byrne and Corrado (2016, updated and revised in 2018).	The Conference Board. (2019). *Total Economy Database*. Retrieved from https://www.conference-board.org/data/economydatabase/total-economy-database-productivity-growthaccounting

Percentile-wage charts – occupation	IPUMS USA		OCC1990 is a modified version of the 1990 Census Bureau occupational classification scheme. OCC1990 provides researchers with a consistent classification of occupations using the 1990 coding scheme as its starting point. It spans the period from 1950 forward. Researchers who want consistent occupations prior to 1950 should consult OCC1950. While the 1990 Census occupation classification system is the basis for OCC1990, we combine several categories to improve the variable's comparability over time. Users are encouraged to review the BLS working paper that describes the variable and how available categories map to 1960-2000 Census occupation codes. OCC1990 was created using a series of technical papers published by the Census Bureau shortly after each census was administered. These papers provide detailed analyses of how the occupational coding scheme for each census year differed from the scheme used during the previous census year. These occupational "crosswalks" are based on samples of cases that are "double coded" into the occupational schemes of the current and previous census year. The original Census Bureau crosswalks are available via links in "Occupation and Industry Variables" of the IPUMS documentation. Using the information from the occupational crosswalks, we traced the proportion of each occupation as it broke out into more specific occupations or as it was combined with others into a more general occupation. To take one example from the technical paper produced after the 2000 census: of persons coded as "Gaming managers" in 2000 (2000 code 33), the Census Bureau determined that 35% would have been coded as "Managers, service organizations" in 1990 (1990 code 21), while 65% would have been coded as "Managers, food serving and lodging establishments" (1990 code 17). In OCC1990, we assign original 2000 OCC values of 33 to 17. We generated the same information for every occupational code in every census year from 1950-2000. Researchers at the Bureau of Labor Statistics (BLS) then used the resulting tables to create aggregated occupational categories that were more useful for long-term analyses; these are the categories that are used in the IPUMS variable OCC1990. More specifics on their methods and a detailed comparison of OCC1950 and OCC1990 can be found in the resulting BLS working paper.	Steven Ruggles, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. IPUMS USA: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2019. https://doi.org/10.18128/D010.V8.0

Percentile-wage charts – Wage and salary income	IPUMS USA		INCWAGE reports each respondent's total pre-tax wage and salary income - that is, money received as an employee - for the previous year. The censuses collected information on income received from these sources during the previous calendar year; for the ACS and the PRCS, the reference period was the past 12 months. Sources of income in INCWAGE include wages, salaries, commissions, cash bonuses, tips, and other money income received from an employer. Payments-in-kind or reimbursements for business expenses are not included. See the comparability discussion below for further information. Amounts are expressed in contemporary dollars, and users studying change over time must adjust for inflation (See INCTOT for Consumer Price Index adjustment factors). The exception is the ACS/PRCS multi-year files, where all dollar amounts have been standardized to dollars as valued in the final year of data included in the file (e.g., 2007 dollars for the 2005-2007 3-year file). Additionally, more detail may be available than exists in the original ACS samples.	Steven Ruggles, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. IPUMS USA: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2019. https://doi.org/10.18128/D010.V8.0
Polarization analysis	IPUMS CPS		EARNWEEK reports how much the respondent usually earned per week at their current job, before deductions. Interviewers asked directly about total weekly earnings and also collected information about the usual number of hours worked per week and the hourly rate of pay at the current job. The figure given in EARNWEEK is the higher of the values derived from these two sources: 1) the respondent's answer to the question, "How much do you usually earn per week at this job before deductions?"; or 2) for workers paid by the hour (and coded as "2" in PAIDHOUR), the reported number of hours the respondent usually worked at the job, multiplied by the hourly wage rate given in HOURWAGE. The values in EARNWEEK are in dollars, with no implied decimal places; a value of 500 means that the respondent earned five hundred dollars per week before deductions. Amounts are expressed as they were reported to the interviewer; users must adjust for inflation using Consumer Price Index adjustment factors. Researchers should use the EARNWT weight with this variable. EARNWEEK is one of the Outgoing Rotation/Earner Study questions.	Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [dataset]. Minneapolis, MN: IPUMS, 2019. https://doi.org/10.18128/D030.V6.0

Ratio of minimum wage to median (used	OECD	Minimum relative to average wages	For cross-country comparisons, data on minimum wage levels are further supplemented with another measure of minimum wages relative to average wages, that is, the ratio of minimum wages to median earnings of full-time employees.	OECD (2019), "Earnings: Minimum wages relative to median wages", *OECD*

to compute median wage)		of full-time workers	Median rather than mean earnings provide a better basis for international comparisons as it accounts for differences in earnings dispersion across countries. However, while median of basic earnings of full-time workers - i.e. excluding overtime and bonus payments - are, ideally, the preferred measure of average wages for international comparisons of minimum-to-median earnings, they are not available for a large number of countries. Minimum relative to mean earnings of full-time workers are also provided.	*Employment and Labour Market Statistics* (database), https://doi.org/10.1787/data-00313-en (accessed on 04 February 2019).
Total hours worked in the economy	The Conference Board	Total Economy Database	Total annual hours worked (in millions). The measure used in TED is actual hours worked, so it includes paid overtime and excludes paid hours that are not worked due to sickness, vacation and holidays, etc. Series on actual hours worked per person are available for 68 countries.	The Conference Board. (2019). *Total Economy Database.* Retrieved from https://www.conference-board.org/data/economydatabase/total-economy-database-productivity-growthaccounting
Value of production	BLS DIPS	Labor Productivity and Costs by Industry and Measure	Value of production is a measure that represents the difference between the total output of goods and services produced and both the subtotal of goods and services shipped among related establishments (intra-industry shipments, intra-sectoral shipments, and resales) and the net changes in inventory levels.	LPC Tables and Charts. (n.d.). Retrieved from https://www.bls.gov/lpc/tables.htm
Wages at 90th, 50th and 10th percentile	OECD	Gross earnings: decile ratios	This dataset contains three earnings-dispersion measures - ratio of 9th-to-1st, 9th-to-5th and 5th-to-1st- where ninth, fifth (or median) and first deciles are upper-earnings decile limits, unless otherwise indicated, of gross earnings of full-time dependent employees.	OECD (2019), "Earnings: Gross earnings: decile ratios", OECD Employment and Labour Market Statistics (database), https://doi.org/10.1787/data-00302-en (accessed on 04 February 2019).

Appendix C

Summary Statistics

OECD Data

Variable	Obs	Mean	Std.Dev.	Min	Max
Year	13963	1987.43	16.25	1955	2018
1 year change in log 90th percentile wageh	358	.014	.038	-.188	.248
1 year change in log 10th percentile wage	358	.013	.043	-.216	.239
1 year change in log annualized productivity	1600	.022	.027	-.155	.188
20 year change in annualized log productivity	812	.367	.293	-.644	1.315
20 year change in log wage	215	.265	.199	-.052	1.351
5 year change in log wage	737	.072	.095	-.231	.612
5 year change in annualized log productivity	1416	.108	.079	-.094	.43
Average annual wage in 2017 USD	912	36319.14	18807.85	3238.96	90611.52
Log of 90th percentile annual wage	436	10.658	.744	8.63	11.592
Log annual productivity, 2017 USD	1646	10.905	.491	8.479	11.881
Log hourly productivity, 2017 USD	1646	3.591	.491	1.166	4.568
Log of average annual wage in 2017 USD	912	10.321	.661	8.083	11.415
Log 10th percentile annual wage	436	9.367	.819	7.263	10.381
Percent of working age population employed	793	65.97	7.64	45.511	86.525
Ratio of 50th to 10th percentile wage	700	1.715	.221	1.153	2.626
Ratio of 90th to 50th percentile wage	700	1.944	.331	1.397	3.558

Sources: OECD. (2019). "Average annual wages", *OECD Employment and Labour Market Statistics* (database), https://doi.org/10.1787/data-00571-en (accessed on 04 February 2019). OECD. (2019). "Earnings: Gross earnings: decile ratios", OECD Employment and Labour Market Statistics (database), https://doi.org/10.1787/data-00302-en (accessed on 04 February 2019). OECD. (2019). "Earnings: Minimum wages relative to median wages", OECD Employment and Labour Market *Statistics* (database), https://doi.org/10.1787/data-00313-en (accessed on 04 February 2019). OECD. (2019). "Earnings: Real minimum wages", OECD Employment and Labour Market Statistics (database), https://doi.org/10.1787/data-00656-en (accessed on 04 February 2019). OECD. (2019). "Employment rate", OECD Employment and Labour Market Statistics (database), https://doi.org/10.1787/1de68a9b-en (Accessed on 04 February 2019) OECD. (2019). "GDP per hour worked", *OECD Compendium of Productivity Indicators*. https://doi.org/10.1787/1439e590-en (Accessed on 04 February 2019). OECD. (2019). "Hours Worked: Average annual hours actually worked", *OECD Employment and Labour Market Statistics* (database), https://doi.org/10.1787/data-00303-en (accessed on 04 February 2019).

BLS ASEC Data

Variable	Obs	Mean	Std.Dev.	Min	Max
Average years of education in the industry in 1989	3009	12.589	.924	10.22	14.641
Average level of education in industry	3036	13.026	1.15	9.151	17.417
Average industry wage in 2019 dollars	3036	46322.25	16209.28	5600.227	135000
Average age in industry	3036	39.633	3.663	27.6	50.649
Change in log wage from 1989 to 2017, 2019 USD	1022	.271	.212	-.34	1.283
Change in log employment, 1989-2017	70	-.018	.631	-1.466	1.405
Log wage in 2019 dollars	3036	10.677	.381	8.631	11.81
Proportion of workers who are white	3036	.843	.071	.517	1
Proportion of workers who are male	3036	.578	.214	.009	1

Source: CPS-ASEC (Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [dataset]. Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D030.V6.0)

BLS Three Digit Productivity Data

Variable	Obs	Mean	Std.Dev.	Min	Max
Log of real value of output per hour	2104	4.885	.83	2.594	8.285
One year change in log of real value of output per hour	2023	.007	.068	-.592	.616
Change in the log of value per hour between 1989 and 2017	185	.181	.36	-.696	1.283

Source: Bureau of Labor Statistics, Major Sector Productivity and Costs data file (https://www.bls.gov/lpc/data.htm).

BLS Individual Outgoing Rotation Wage Data

Variable	Obs	Mean	Std.Dev.	Min	Max
Year	2,900,906	2003.947	8.27	1989	2019
Age	2,900,906	42.075	12.755	15	90
Fulltime dummy (= 1 if fulltime worker)	2,900,906	.847	.36	0	1
Log of real wage	2,900,906	6.653	.729	3.689	8.41
Male dummy (=1 if male)	2,900,906	.508	.5	0	1
One year change in log real wage	1,450,453	.029	.526	-4.231	4.262
Real weekly earnings, 2019 USD	2,900,906	985.48	691.598	39.998	4492.923
Years of education completed	2,900,906	13.636	2.586	0	18

Source: CPS outgoing rotation group data (Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [dataset]. Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D030.V6.0).

BLS Compensation and Output Indices

Variable	Obs	Mean	Std.Dev.	Min	Max
Nonfarm Business Sector: Real Compensation Per Hour, Indexed 2012 = 100	72	74.13	20.05	36.2	105.03
Nonfarm Business Sector: Real Output per hour, Indexed 2012 = 100	72	58.97	24.69	23.53	105.37
Percent change in 4 year moving average of Real Compensation Per Hour Index	68	.015	.01	-.004	.04
Percent change in 4 year moving average of Real Output Per Hour Index	68	.021	.008	.001	.037

Source: The output index is from the U.S. Bureau of Labor Statistics, "Nonfarm Business Sector: Real Output Per Hour of All Persons," and retrieved from FRED (https://fred.stlouisfed.org/series/OPHNFB). The compensation index is from the U.S. Bureau of Labor Statistics, "Nonfarm Business Sector: Real Compensation Per Hour," and retrieved from FRED (https://fred.stlouisfed.org/series/COMPRNFB).

Conference Board Productivity Data

Variable	Obs	Mean	Std.Dev.	Min	Max
Year	2,391	1996.6	13.79	1970	2018
Average annual hours worked per worker	2,391	1927.81	280.99	1360.37	2895.1
Productivity per hour in 2018 dollars	2,391	31.61	20.71	1.22	101.04
Productivity per hour in 2018 dollars x 1500	2,391	47409	31064	1832	151561
Total annual hours worked (millions)	2,391	50811	118549	259.45	1111578
Log productivity per year in 2018 dollars	2,391	10.46	0.90	7.51	11.93

Source: The Conference Board, "Total Economy Database". https://www.conference-board.org/data/economydatabase/index.cfm?id=27762

World Bank Per Capita Income Data

Variable	Obs	Mean	Std.Dev.	Min	Max
Year	2,391	1996.6	13.79	1970	2018
Average Annual Per Capita Income 2018 dollars	2,391	17740	15351	208.02	82834
log of Average Annual Per Capita Income 2018 dollars	2,391	9.22	1.27	5.34	11.32

Source: World Bank. (2020, May 19). Adjusted net national income per capita (constant 2010 US$). https://data.worldbank.org/indicator/NY.ADJ.NNTY.PC.KD

Appendix D

Table D1

VARIABLES	(1) Log real wage in 2017	(2) Log real wage in 2017	(3) Log real wage in 2017
log productivity in 2017	0.194***	0.122**	0.00910
	(0.0541)	(0.0495)	(0.0333)
industry average education		0.185***	0.224***
		(0.0451)	(0.0290)
industry average age			0.0295***
			(0.00760)
industry proportion male			0.866***
			(0.145)
Constant	9.869***	7.726***	5.982***
	(0.272)	(0.572)	(0.431)
Observations	45	45	45
R-squared	0.231	0.451	0.803

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses, clustered at industry level in column (1). Unit of analysis is a 3-digit industry. There is one observation per industry that measures the difference during period, 1989-2017, using merged data from the following two BLS sources: (1) The wage, education, and employment data are from the CPS-ASEC (Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [dataset]. Minneapolis, MN: IPUMS, 2018. https://doi.org/10.18128/D030.V6.0) (2) The productivity data are from the Bureau of Labor Statistics, Major Sector Productivity and Costs data file (https://www.bls.gov/lpc/data.htm).

Table D2
Summary of Regression Results of Log Wages on Log Productivity Within Country
OECD Data 1990-2010

Country	**Coefficient on Log Productivity**	**Number of Observations**	**R-squared**
Australia	.788*** (.030)	28	.965
Austria	.544*** (.020)	23	.973
Belgium	.552*** (.032)	28	.919
Canada	1.128*** (.065)	28	.920
Chile	.784*** (.112)	17	.765
Czech Republic	1.039*** (.028)	23	.985
Denmark	.949*** (.062)	28	.900
Estonia	1.243*** (.062)	18	.962
Finland	.693*** (.045)	28	.901
France	.865*** (.044)	28	.937
Germany	.492*** (.038)	27	.868
Greece	1.127*** (.143)	23	.748
Hungary	.701*** (.070)	23	.828
Iceland	.638*** (.085)	28	.686

Country	Coefficient on Log Productivity	Number of Observations	R-squared
Ireland	.580*** (.056)	28	.806
Israel	.273** (.101)	23	.258
Italy	.219*** (.075)	28	.250
Japan	.052** (.019)	28	.224
Latvia	1.229*** (.106)	18	.893
Lithuania	1.310*** (.056)	23	.963
Luxembourg	1.307*** (.125)	28	.807
Mexico	1.735*** (.253)	27	.653
Netherlands	.508*** (.049)	28	.808
New Zealand	1.15*** (.054)	28	.946
Norway	1.412*** (.164)	28	.741
Poland	.522*** (.032)	23	.927
Portugal	.140 (.093)	23	.097
Slovak Republic	.766*** (.026)	23	.976
Slovenia	.815*** (.027)	23	.977

Country	**Coefficient on Log Productivity**	**Number of Observations**	**R-squared**
Spain	.470*** (.063)	28	.685
Sweden	.941*** (.040)	28	.954
Switzerland	.811*** (.032)	28	.961
United Kingdom	.983*** (.040)	28	.959
United States	.709*** (.022)	28	.976

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.
Source: The wage data are from the OECD Employment and Labour Market Statistics database. The productivity data are from the OECD Compendium of Productivity Indicators.