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PRODUCTIVITY AND WAGES:
COMMON FACTORS AND IDIOSYNCRASIES ACROSS COUNTRIES AND INDUSTRIES

Edward P. Lazear

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ABSTRACT

Average wage growth is closely related to aggregate productivity growth across countries and within countries over time. The commonality of patterns across OECD countries suggests that common factors are at work. Are productivity-based explanations of wage changes consistent with increasing variance in wages as well as increases in mean wages as suggested by skill-biased technological change or other factors? To answer this, it is necessary to observe education-specific productivity growth. Cross-industry comparisons reveal that industries dominated by highly educated workers experienced higher-than-average productivity growth that is more than sufficient to account for increasing skill differentials.

Edward P. Lazear
Graduate School of Business
Stanford University
Stanford, CA 94305
and Hoover Institution
and also NBER
lazear@stanford.edu

I. Introduction

What causes wages to grow? Either the demand for labor must increase or the supply of labor must decrease. The amount of labor supplied can be affected by institutional factors, such as the availability of payments when unemployed, by immigration, by population growth over the longer run or by changes in household technology altering the value of time outside work.[1] But much, perhaps most of the wage growth that is of primary interest is associated with demand increases that result from improving productivity of labor.

There is a direct and unequivocal empirical link between wages and productivity. The positive relation of one to the other is strong in cross-country comparisons, within a given country over time, and among workers in a given country at a point in time. The relation, while positive and strong, is neither perfect nor necessarily unitary. In some situations, productivity differences outstrip wage variation, while in others the reverse is true.

More important is that the shifts in productivity have not been neutral. Cross-industry data provide evidence that rather than merely displacing upward, the entire distribution has changed shape. The upper tail of the distribution has moved away from the lower tail. The rise in productivity of the high skilled, typically highly educated workers, relative to the low skilled typically less educated workers, has generated an increase in skill disparity, which is consistent with observed increases in inequality over time.

The analysis here does three things. First, it briefly reviews the theory that links productivity to wages. Second, OECD data are examined to check, elaborate and replicate findings that exist in the literature on the relation of average wages to average productivity. Third, and the heart of this research, is to show that aggregate productivity masks a key part of the story. The productivity distribution has not merely shifted. It has stretched out. Productivity among more educated workers has grown more rapidly than productivity of less educated workers. This is consistent with growing wage dispersion, where the wages of highly educated, high wage workers have pulled away from wages of less educated, low wage workers.

There are a number of potential causes of the spreading out of the productivity

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[1] The mechanization of much of household work freed up time and was almost certainly a major factor in the increased labor force participation of women over the 20th century.

distribution. One is the frequently referenced skill-biased technological change[2] that postulates that changes in technology have affected the productivity of highly educated workers more than less educated ones.

Another is that trade has increased in a way that enhances the productivity and wages of the most skilled workers. For example, trade may allow the developed countries to couple their labor with that of the developing countries. The low skilled in developing countries, who are complements to skilled workers, enhance the productivity of developed nations skilled workers. Those same workers reduce the productivity of developed nations' low skilled workers for whom the developing countries' labor is a substitute.

A third possibility is that schools in the United States may have become more proficient over time in educating the better students relative to the weaker ones. This may be an explicit or implicit strategy. For example, if tertiary education in the US has improved while K-12 has remained stagnant or even fallen back, those who go on to college in 2017 will possess more skill than college graduates in 1987. At the same time, those who complete high school or less in 2017 may be no more skilled than their counterparts who completed their education in 1987.

II. The State of the Literature

The literature on productivity and growth began with growth models going back at least to the 1930s.[3] All growth models have as byproducts implications for factor shares and wages. A direct feature of the models is to 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 (discussed below) links wage growth to productivity growth in a one-to-one manner, but this is a

[2]Early well-known papers on this issue include Berman, Bound and Machin (1998), Card and DiNardo (2002), Autor, Levy and Murnane (2003).

[3]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.

consequence of both supply assumptions and assumptions about technological change.

There is also a literature that examines explicitly, both empirically and theoretically, the link between wages and productivity. There are a number of historic and recent examples. More recent ones include Karabarbounis and Neiman (2013), which examines the decline in labor's share across 59 countries. The commonality of the decline across many countries at different income levels and with varying institutions is noteworthy. They attribute about half of the decline 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 relation of wage growth to average productivity growth. Stansbury and Summers look at various parts of the income distribution, but relate it primarily to changes in average productivity to determine whether different parts of the wage distribution have grown at different rates and whether those differences in wage growth rates relate to changes in average productivity. Their primary conclusion is that productivity increases translate into pay growth and in general, the authors cannot reject the hypothesis that the increase for the median worker is one-for-one. The relation of various deciles of the wage distribution to changes in aggregrate productivity is non-monotonic. The highest coefficient is obtained for the 20th percentile and the lowest for the 30th percentile, although the latter is imprecisely estimated.

A few prior studies speak to the primary issue of this 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. Haskel and Slaughter (2002) examine sector-biased technical change using data from 10 OECD countries in the 1970s and 1980s. They find that sector-biased technical change is important in accounting for rising skill premiums. Skill-premiums tend to be rising in skill-intensive sectors.

Dunne et al. (2004) use plant level data to determine variations in productivity and wages at the level of the establishment. 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 and conclude similarly that productivity inequality across firms has increased over time using a company-level panel dataset.

Complete equilibrium models of the labor market are described in Lee and Wolpin (2006, 2010). In the first paper, the goal is to address the fact that employment in the service sector has grown dramatically relative to the goods sector while wages have not. With complete labor mobility across sectors, this would not be a surprising outcome because workers would move to equilibrate wages, but Lee and Wolpin estimate that the costs of mobility are large. They also estimate that there is a large output loss as a result of the lack of mobility. Wages are equilibrated by new entrants to the labor market.

Lee and Wolpin (2010) is more directly related to the subject of this analysis. This is a comprehensive study that addresses a large number of issues in an integrated framework that allows for different forms of technological change (skill biased and neutral), capital-labor complementarities and supply-side considerations like changes in household production that caused increased labor supply of women. Most germane to the issue here is their finding that skill-biased technological change accounts for the bulk of the increased college wage premium and the general increase in wage inequality.

Hornbeck and Moretti (2018) examine the recipients of benefits from productivity growth by analyzing geographical differences and find that local effects are more pronounced for high-school than for college graduates in part because of more mobility among the latter. Van Biesebroeck (2011) uses data from three African nations and finds, among other things, that education has larger effects on productivity as the level of development rises.

The analysis below differs from prior studies either in that of the focus on changes over time, in the use of industry data for large segments of the population, or in the emphasis on international comparisons to determine which of the patterns are common across countries.[4] Some of the 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

[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.

matching it with the spreading out of the productivity distribution as it relates to education. Fundamentally, the question 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?

There are many papers that have studied changes in 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 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.

III. Theory

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) $\text{Productivity} \equiv \text{Average Product of Labor} = Q / L$

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 from (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,

(4) $[\partial \text{Productivity} / \partial A] / Q =$

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

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

(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 (4) and both equal 1/A. This generates the intuition that a 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 for the empirical purposes below, by examining technology, 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, for example, an extreme alternative case where the supply of labor is perfectly elastic. Then 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.

At the microeconomic level, it is usually assumed that in the short run, labor is variable and that capital is fixed. But at the country level, the reverse is likely to be true. In the short run, the elasticity of labor supply to the entire country is likely to be low. Higher wages may increase the amount of labor supplied by the typical worker either through increased employment or increased hours worked per worker, but not likely by much. Neither population nor labor force participation rates are too 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. As a result of the inelasticity of labor supply at the country level, it might be appropriate to expect that most of country-wide productivity increases take the form of wage increases, rather than employment increases but those increases could also reflect additional capital, which raises the average product of labor and wages.

The nature of technological change is also a determining factor. Consider an alternative to the neutral shift assumed above that characterizes digitization and may be what many worry about when thinking about future changes associated with artificial intelligence. An example is the grocery business as it existed 70 years ago. In the mid-1950s, adding machines were primitive, mechanical and expensive. Early cash registers, which relied on similar technology, performed few tasks and were also costly. In many stores, especially small mom and pop ones, 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

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

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 errors might be reported asymmetrically by customers, more likely when the customer was overcharged than when undercharged. In those days, retail clerks, many of whom were unionized, were skilled workers. Today, because of digitization, the process is vastly different from that of earlier years. Most items carry a bar code, which is scanned. The register computes the tally, details 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.

Suppose that technological change took the form of the transformation of the grocery industry. Productivity would have increased because the number of items sold per hour of cashier time would be higher than it was earlier, but wages might not follow suit.

Appendix A contains a formalization of that change in technology that characterizes the market equilibrium before and after the change. The features are described here. Before the change, production is smooth (Cobb-Douglas), using two types of labor, skilled clerks and unskilled workers along with standard capital, which is supplied perfectly elastically by the world capital market. Demand for the product is given and in the initial equilibrium, the profit maximizing level of output is produced to support a price of $1 for the product. Profits are zero in equilibrium. There are equal numbers of two types of workers. The skilled workers' wages are three times those of the unskilled. Then the scanner is invented. It 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. Arithmetically astute workers no longer yield any additional value relative to the unskilled. The new technology raises output, which, given demand for the product lowers the price from 1 to .95. At the same time, wages (of all workers) fall to a fraction of their former level, profits are zero again because the cost of the scanner coupled with the fall in price eats up all of the additional profit that would have been generated by the superior technology. Because the number of workers is fixed, output per worker rises. Thus, productivity increases, wages fall and prices fall. Ordinary capital, supplied perfectly elastically on the world market, still receives the same return as it did before, but the scanner's price is bid up to clear the market and eliminate profits in the short run. 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.

This form of automation, where formerly skilled workers are no longer superior to others, is at the heart of the discussion on artificial intelligence. Machines will replace middle-skilled workers and capital while a few very skilled workers will reap the rewards. The economic phenomenon of automation is not a new one, but the concern is that it will be more widespread and deeper in its effects. This is, of course, an issue of distribution only. The society is richer after the new technology comes in because more output is produced with a given amount of labor. In the retail clerk example, the beneficiary was neither labor nor traditional capital. The surplus and more went to the inventor of the technology. Indeed, the inventor captures more than the entire additional output in this example because wages are driven down, bringing about not only the gain from new technology, but also the transfer that goes from labor to the innovator.[6]

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.

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[6]This is the "genius effect" that some have discussed. See, for example, Benzell and Brynjolfsson (2019). Using a somewhat different framework, but related to the model in the appendix, they derive a number of implications. The declining wages (or lack of growth) comes about in a different manner here than there. The mechanism here is the homogenization of labor as well as replacement by machines that are substitutes for skilled labor.

Unlike Autor and Dorn (2013), machines in the retail example are a substitute for skilled labor and render skilled and unskilled labor identical. Skilled labor now floods the unskilled labor market and it is this supply effect that drives down the wages of unskilled labor. Skilled labor's wage declines because the skills are no longer needed. The implication is that the ranks of the unskilled would be larger and the skilled fewer, but it is conceivable that those few could earn very high wages.

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 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, 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.

IV. The Empirical Question

The central empirical issue here is whether shifts in average 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.[7] The second extreme alternative is that all labor markets are completely competitive and wages move directly with productivity. If productivity of the highly skilled increases more when the economy's average productivity rises, then 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 analysis.

Figure 1 illustrates 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 different shape. In particular, the productivity of high productivity workers has grown by more than the productivity of low productivity workers. The 90th productivity percentile worker before the change had productivity P90 and the 10th productivity percentile worker before the change had productivity P10. After the increase in productivity, the 90th percentile worker has productivity P90' an the 10th percentile worker has productivity P10'. In this example, the 90th percentile worker's productivity has risen by more than P'-P while the productivity of the 10th 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.[8] For example, suppose it were found that the wage of the 20th percentile grew less rapidly with aggregate productivity than did the wage of the 90th percentile. This could be explained by the fact that 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 worker-type. To

[7]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.

[8]This is what is done in Stansbury and Summers (2017).

disentangle these two explanations, measures of productivity changes by worker skill level are required.

V. Data

A number of data sources are used from the OECD and from the Bureau of Labor Statistics. 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.[9] 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 10^{th} and 90^{th} percentile as well as median wage is available for most of the OECD countries.[10] The consistency of OECD data across countries and time periods make 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). This is verified by downloading the BLS data and comparing

[9]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).

[10]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.

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 90s 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.[11] 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 the productivity analysis. By merging the BLS ASEC data with the BLS productivity data described below, 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.[12] These data

[11]The CPS is a monthly U.S. household survey conducted jointly by the U.S. 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

[12]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

provide detailed information on hourly wages, demographics, and education. They are used primarily to document trends in skill differentials.

C. US Bureau of Labor Statistics Data on Productivity

An important aspect of the analysis involves comparing the productivity and changes in the productivity of various educational groups with wages and 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 demographic characteristics is generally unavailable.[13] Consequently, it is useful 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 Measures". Three-digit industries based on the NAICS classification are used here. Both value added per hour in absolute terms and a productivity index are contained in the dataset. [14]

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.

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[13]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).

[14]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.

VI. Wages and Aggregate Productivity

A. Across Countries

The most obvious illustration of the correlation between wages and productivity at the aggregate level comes from cross country comparisons. OECD data on wages and productivity across countries make immediately apparent that the two are linked. Figure 2, which plots the 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 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 wage equals to marginal product, rearranging terms and taking logs yields

(7) $$ln\ (Wage_i) = ln\ \lambda + ln(\ Average\ Product\ of\ Labor_{\ i}\ )$$

for any country i. This forms the basic specification for table 1. The implied coefficient on the labor productivity in the regression in (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) 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 3 provides a different kind of evidence than that shown in figure 2. Figure 2 relates the level of wages to the level of productivity across countries. Figure 3 looks very much like figure 2, but the evidence is different. Figure 3 examines how the growth in productivity affects the growth in wages. The countries that have highest productivity levels in figure 2 are different from the countries that have highest productivity and wage changes in figure 3. In figure 2, the highest wage countries are Denmark, Iceland, Luxembourg, Norway and Switzerland. They are also, without exception, high productivity countries. The highest wage, highest productivity countries in Figure 2 were not typically the countries that experienced the most rapid increases in productivity between 1997 and 2017. The countries with the most rapid gains in both productivity and wages tended to be those like Poland and Lithuania that moved from command structures to market economies over the period. When the period began in 1997, countries like Switzerland already had high productivity and high wages, which reflected past increases in productivity that propelled prior high wage growth in these already rich countries. Countries that are high productivity and high wage today are high because they experienced favorable wage growth in the past, but not necessarily in the recent past.

Columns (2) and (3) 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 2017. 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 with clustering at the country level. The coefficient on productivity is .81 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 20 year period rather than a 5 year period. The coefficient is approximately the same as in the five year difference version, equaling .77. Once again, the constant term is zero, consistent with (7) where ln λ is differenced out.

Columns (4) and (5) repeat the analysis of column 1 in levels, but do so on an annual basis rather than merely for 2017, clustering standard errors at the level of the country. Column (4) includes country fixed effects while column (5) excludes them. The levels regression with fixed effects estimates the productivity effects by examining effect of the (average) within-country variation over time. This is akin to columns (2) and (3). Column (5), which excludes fixed effects, uses cross-country variation as well, more comparable in logic to column (1) and the estimates from the two columns are close in magnitude. In column (5), the coefficient is close to that in column (1). In column (4), which exploits within-country variation because of the fixed effects, the coefficient is close to those in columns (2) and (3). Taken together, there is little doubt of the close positive connection between wages and productivity in the OECD countries, but more ambiguity about whether a 1% increase in productivity generates a 1% increase in wages.

Figures 2 and 3 and table 1 speak only to the average (mean) wage in a country and to output per worker averaged over all workers in the economy. They do not address how wages are distributed within the country, which will be discussed later. Although not all share equally in productivity growth, it will be shown that a general proposition is that most, even the poor, tend to be better off in countries that have high levels of aggregate productivity and that most, even the poor, tend to enjoy the best wage gains during periods when productivity is growing most rapidly. More important, it will be shown that the productivity distribution has spread out and that the increasing variation in productivity across worker types is consistent with increases differences in wages between top and bottom wage earners.

B. The United States Over Time

Data from the Bureau of Labor Statistics databases[15] are used to create Figure 4, which

[15]U.S. Bureau of Labor Statistics, 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 U.S. 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.

shows the relation of average hourly wages to productivity over time in the United States only. 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 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. Column 1 simply regresses the BLS compensation index on the BLS output index for the period shown in figure 4, namely 1951-2017. Column 2 fits the relationship shown in figure 2 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 .77, almost identical to that in the levels specification of column (1). During the period since 1990, which stands out in figure 3, a 1% change in productivity was associated with only a .64% increase in compensation growth. This is shown in column (3) of table 2, which reports the regression of column (2) but restricts the sample to the period from 1990 on. The coefficient is lower in column (3) than in column (2), but the difference is not significant.

C. Within-Country Variation in OECD Countries

Table 3 based on the OECD data addresses the issue of within-country productivity and wages variation over time and parallels the analysis of the last section for the United States. Log wage is regressed on log of productivity for each of the 34 countries taken separately, which parallels the specification in column (1) of table 2. Table 3 estimates eq. (7), but does so over time within a country.

In all cases, but one (Portugal) the relation between average wage and productivity over time is positive and significant at conventional levels. This evidence, comparable to that for the United States using the BLS data, suggests a strong positive connection between productivity and average wages over time.[16] As labor productivity rises within a country, so too does the average wage.

Table 3 is a fully-interacted version of column (4) of table 1. In table 1, countries are allowed to have different intercepts, but are constrained to have the same relation of wages to productivity over time. In table 3, each country has not only its own intercept, but also a country-specific relation of wages to productivity. Unsurprisingly, the typical coefficient on log wages in table 3 does not seem out of line with that estimated in the constrained form in column (4) of table 1.

It is important to acknowledge that the magnitudes of the coefficients in table 3 vary widely, in many cases being below one and in some cases being above one. Nor does there appear to be any obvious pattern that would easily explain the size of the coefficients. 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.

What then do the different coefficients across the various countries reflect? Consider the theory laid out at the outset. There are two obvious candidates. First is that the nature of technological change that generates productivity increases differs by country. For example, country 1 might have enjoyed technological change of the neutral variety (in the A term in eq. (2)) while country 2 might have experienced the retail-grocer style of technological change. In country 1, the coefficient on wages might be expected to be 1, whereas that in country 2 would be less than 1, and conceivably even negative if average wages were to fall as in the numerical example provided in appendix A. 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.

The question is whether one story is more likely than another or whether either is plausible. Supply elasticities could differ because countries might have different labor force

[16]The coefficient for the United States in table 3 using the OECD data is not substantially different from that obtained directly from the BLS data, the latter using a much longer time period to obtain the estimates (see column (1) of table 2).

participation levels. Bringing in marginal workers or additional hours might be tougher when most are employed. This suggests an interaction effect. Using the specification in column (4) of table 1, one can add an interaction between the log of productivity and the employment ratio. The expectation is that the higher is the employment ratio, the more inelastic is labor supply, which would imply that more of the productivity increase would go into increased wage than into additional employment.

When an interaction term,

[employment ratio in year t in country i] x [log of annual productivity in year t in country i] ,

is introduced into column (4) specification of table 1, which is based on the OECD data, the coefficient on that term in a column is indeed positive and significant.[17] Although this evidence is hardly compelling, it does suggest that supply elasticities vary by country in accordance with current employment rates. In countries with high employment rates, the marginal supply elasticity may be lower, which would imply a greater wage gain for a given change in productivity.

VII. Wages and Productivity Variations by Wage Percentile

The OECD data contain information on the wage levels of the 90th and 10th percentile as well as the country's level of output-per-worker for some countries dating back to 1973 and as recent as 2017. Additionally, the median wage can be computed for many countries dating as far back as 1960. These data can be used to determine how various parts of the wage distribution respond to increases in aggregate productivity.

Before proceeding, it is important to point out that although interesting for a number of purposes, the data that match wage increases at various parts of the wage distribution to

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[17] An alternative specification, that allows the effect of productivity to depend on GDP-per-capita was also tested. The interaction term ([GDP-per-capital in year t in country i] x [log of annual productivity in year t in country i]) does not enter significantly.

aggregate productivity do not speak to the fundamental question, which is "do wages move with productivity and can the increased skill differential be a reflection of increased disparity in productivity among the skill classes?" To address this issue, it is necessary to have information on the productivity of various parts of the skill distribution, not merely information on aggregate productivity across countries or over time. That is done in a later section. This section simply relates the change in wages at various parts of the skill distribution to aggregate productivity measures.

It is well known that the spread between the wages of the 10th percentile and that of the 90th percentile has grown over time. In the United States, the OECD data reveal that the ratio of the 90th percentile annual wage to the median annual wage has risen from about 2.05 in 1985 to over 2.42 in 2017. At the same time, the ratio of the median worker's wage to that of the 10th percentile worker's wage has risen also from 2.01 to 2.09. This is shown in figure 5.

The pattern observed in the US is common across OECD countries. Complete 10th, median and 90th percentile wage data are available for 17 countries from 1997 to 2015.[18] Figure 6 displays the results for the 16 OECD countries that excludes the United States, averaged together. Figure 7 shows the same ratios for the United States, but over a similar period as used for figure 6. (Figure 5 shows the longer period for the US, which begins 1980.) Both the 90th/50th ratio and 50th/10th ratios have risen over the 1997 to 2015 period for these 16 countries taken together. Table 4 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.[19]

The fact that the wage gap between top and bottom earners has widened over time is consistent with productivity having an effect on wages for many or all income groups. Increasing wage or skills gaps can occur despite a positive effect of productivity on wages. This can happen

[18]The countries are Australia, Canada, Czech Republic, Finland, Germany, Hungary, Ireland, Italy, Japan, Korea, New Zealand, Norway, Poland, Sweden, Switzerland, United Kingdom, and the United States.

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

in two ways. First, the increase in productivity may not benefit the poor as much as it does the upper middle class. That will be shown below to be untrue. Second, the increase in *average* productivity may be insufficient to offset whatever is happening to within-distribution differences in productivity.

Table 5 reports the results of examining the relation of wages at the 10th and 90th percentiles to average productivity using the OECD data. Column 1 estimates the relationship between the 10th percentile wage and average productivity for the United States only over a 45 year period from 1973 through 2017. It appears that the effect of average productivity on 10th percentile wage is negative, but this merely captures that fact that the 10th percentile wage has fallen over time (in real terms) and that average productivity has risen over time. Column 2 provides a more accurate picture. The year effect on the 10th percentile wage is negative, but is mitigated by the average productivity effect. If the scenario in figure 1 is accurate, then the wage distribution is spreading out over time, which leads to a decline in wages of the 10th percentile worker. It remains true, however, that a 1% increase, even in average productivity, is associated with about a 1% increase in the wage of the 10th percentile worker. As average productivity has grown over time, wages at the 10th percentile have grown with it approximately one for one. Between 1973 and 2017, the net effect is negative by about .1 log points. Wages for the 10th percentile are approximately 10% lower in 2017 than in 1973 in real terms.

Columns 3 and 4 repeat the analysis for countries in the OECD data set other than the US, with country fixed effects included and standard errors clustered at the country level. As was the case for the US, the coefficient that relates average productivity to 10th percentile wages is large and significant, but smaller than that for the US. A 1% change in average productivity is associated with about a 2/3% increase in 10th percentile wages. Column 4 suggests that unlike the US, the year effect is zero. In non-US OECD countries, wages at the lower end have not grown one-for-one with aggregate productivity although the difference between the US coefficient and OECD coefficient (columns (2) versus (4)) is not statistically significant.

Columns 4-8 are identical to columns 1-4, except that the dependent variable is the 90th percentile wage, rather than the 10th percentile wage. As was the case for 10th percentile wages, 90th percentile wages move with average productivity approximately one-for-one in the US when year effects are included. The net effect over the 1973-2017 period is that wages at the 90th percentile rise by .22 log points or by about 24%. Columns 7 and 8, which report results for countries in the OECD data set other than the US also show a positive relation of 90th percentile wages with average productivity, but once again, the relationship is weaker than it is for the United States, albeit not statistically so.

Table 6 repeats the analysis, but relates changes in wages to 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 results are qualitatively similar to those in table 5. The coefficients are somewhat different from those in table 5, but none of the differences is statistically significant. The changes in wages, both for at the 10th and 90th percentile, move with the change in average productivity, although not necessarily one-for-one. The non-US countries have coefficients that are significantly below 1.

Summarizing, as is well-known, wage gaps between high earners and low earners have increased over time in the US and in other countries. Perhaps more important and less well-known is that increases in aggregate productivity have mitigated the fall in wages for low wage workers. 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. Furthermore, if anything, the association between wages and aggregate productivity at both extremes of the wage distribution is stronger in the United States than in the typical other country in the OECD dataset.

It is encouraging that changes in aggregate productivity result in higher wages not just for the median worker, but for those at the low and high ends of the wage distribution. It is important to note however that the distribution of productivity has not merely displaced over time. As may be captured in the year effect of table 5 for the US, the trend has been for wages to spread out. Below results are provided that are consistent with the productivity distribution having spread out over recent decades.

VIII. Has the Middle Class Vanished?

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 explain.

A. Relative Wages Over Time

Figure 5 speaks to this most directly. 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. The median worker earns 2.1 times that of the 10th percentile. In the early 80s, that ratio was below 2.

A closer look reveals that there was a fall in the 50/10 ratio during the late 90s, that reversed before 2000, with wages of the median rising relative to those of the bottom 10% while those at the top rose, for the most part, relative to the median. By 2007, before the recession began, the ratio of the median wage to that of the 10th percentile wage was about back to its earlier peak and has remained there since, albeit with the standard oscillations that are found in all time series.

B. Ratios of Wages Actual Changes

The clearest description of what has occurred with respect to wages is that the top half of the distribution has moved away from the bottom and the further from the median, the larger the movement. The bottom has moved almost together and not much at all. That is most easily seen in figure 8, which is also based on CPS outgoing rotation group data and plots the ratio of the real wage in 2017 to the real wage in 1990 for full time workers, by percentile.

For example, the 70th percentile worker earned 16% more in 2017 than the 70th percentile worker did in 1990. The 90th percentile worker earned 28% more in 2017 than the 90th percentile worker did in 1990. The curve that connects the points is convex and relatively flat for the lower half of the distribution, but steeper for the part above the 60th percentile. The lower part of the income distribution has moved almost in unison at the same time that the top part of the wage distribution has moved away from the bottom part. This pattern corresponds quite closely to that shown in figure 1, which illustrates a hypothetical shift in the productivity distribution. Both variance and skew have increased as the top of the wage distribution has stretched out while the bottom has not. The question, addressed next, is whether the productivity distribution has moved in the same way.

IX. Productivity and Wages By Worker Type

The analysis up to this point and most that has come in earlier papers examines the effect of average productivity on average wages or on some parts of the income distribution. The fundamental question, though, is not whether changes in average productivity affect a high wage worker's wages more than changes in average productivity affect the wages of a low wage worker. It is whether changes in a high wage worker's productivity affects a high wage worker's wages and whether changes in a low wage worker's productivity affect the wages of a low wage worker. Thus, the key issue is what has happened to the productivity of different groups by skill and what is the link between changes in productivity and the wages of those groups. If skill is proxied by education, then have wages of the least educated workers lagged behind those of the most educated because some market imperfection, monoposy or some other non-competitive force is causing the discrepancy or simply because those with less education have experienced less of an increase in productivity than those with more education?

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 Bureau of Labor Statistics compiles detailed wage data by industry and demographic characteristics. Additionally, the Bureau of Labor Statistics 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. Industry-Based Estimates of Productivity Determinants

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. Education is used as the primary measure of skill. Note that there is a positive correlation between changes in industry productivity and changes in average wage in the industry (.13 and significant for the log values of the two variables), but this says little. Recall that as long as workers can move across industries, there is no reason to expect that productivity changes within an industry will be reflected in wages within that industry. 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.[20] For that reason, it is reasonable to assume that different education groups cannot substitute perfectly for one another meaning 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.

The most important finding is summarized in figure 9. Forty 3-digit industries for which complete productivity, wage and education data are available over the period 1989-2017 are split into two groups. The top and bottom groups are comprised of industries that rank in the highest and lowest 50% based on average education level in the industry in 1989. The left two bars

[20]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. "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

compare productivity growth in logs for high and low education industries. Productivity in the top education industries grew by over .34 log points between 1989 and 2017. Productivity in the bottom education industries grew only .20 log points during that same 30 year period. The right two bars compare wage growth in those same industries. The same pattern holds, but not with the same force. Wages in highly educated industries grew by .26 log points while those in the low education half grew by .24 log points during the 1989-2017 period. The difference in productivity between the groups is more pronounced than the difference in wages. This simple comparison suggests that productivity growth differences between groups is more than sufficient to explain the better wage growth that more educated workers enjoyed as compared with less educated workers.

Table 7 examines this in a more detailed manner. As above, a variable that measures average education in each industry is calculated by matching the CPS-ASEC data with the BLS productivity data by industry. This variable is continuous as opposed to the discrete version shown in figure 9. Column (1) 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 educational, as is shown by the positive and significant coefficient (.14 in logs). Column (4) performs the same analysis, but uses the industry's level of education at the end of the period, rather than the beginning. The conclusion is unchanged. Higher education industries experienced higher productivity growth during the period.

Columns (2) and (5) examine an industry's wage change as it relates to education. The same pattern holds, with higher education industry experience higher wage growth, but the change in wage is significantly correlated only with industry average education when measured at the end of the period. Data from the CPS outgoing rotation group, used below, provide more reliable information on wage changes by educational category.

Columns (3) and (6) show positive coefficients relating changes in an industry's employment to education level. In this case, it is only education in the first year that has a statistically significantly relation with employment growth.[21] Some of the declining employment

[21] 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.

industries, like apparel and rubber manufacture are unsurprising, but the most rapidly growing industries include building material and garden equipment, miscellaneous retailers, and food and drinking places, while computer and electronic product manufacturing saw rapidly declining employment. Because this is manufacturing, the changes in employment may reflect the off-shoring of some of these production activities.

The CPS-ASEC data provide demographic detail on gender, race and age in addition to education and industry information. It is useful to examine how productivity and changes in productivity over time relate to demographic characteristics. As with education, the demographic data are merged with the BLS industry productivity data at the industry level. Table 8 reports the results from that analysis.

Including additional demographic variables does not alter the conclusions with respect to education. As in table 7, industries with high levels of education have both high levels of productivity and productivity that grew more rapidly over the 1989 through 2017 period. The more inclusive specification suggests that workers in industries with more educated workers also have higher wage levels, but not higher wage growth through the period. Industries with higher proportions of male workers have higher productivity and higher wages, but lower wage growth during the period.

B. Productivity-Based 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 wage change variation across educational groups is compared with actual wage change. The goal is to determine if non-neutral changes in productivity across educational groups are sufficient to explain the observed spreading out of the wage distribution over time. Figure 9 already suggests that at least by a rough cut, differential productivity growth is more than sufficient to account the increased skill differential. Here, that same issue is examined with greater granularity.

Estimates from column (4) of table 7 are used to forecast changes in productivity by educational group. The estimate of the educational effect in column (4) does not differ markedly from that in column (1) and the education used in column (4) is closest to current day levels. Furthermore, the r-squared of the column (4) specification exceeds that of column (1), but the choice is little consequence to the conclusions drawn below.

Table 9 reports the results. Wages are based on the 153,815 individual level observations from the CPS outgoing rotation groups for 1989 and 2017. Consider an 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 or the average log wage was 6.40 (columns 4 and 5). In 2017, similarly schooled individuals earned on average $757 or an average log wage of 6.42. The difference in log wages for that education group was .02 over the 28 year period (column 6). The average level of education for that group of individuals was 11.79 years in 2017 (column 3). Then the regression in column (4) of table 7 predicts that individuals with that 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 that 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 change in log wages for this group of individuals, again taken directly from the outgoing rotation of the CPS in 1989 and 2017, was .01. Productivity for this group, based on the regression of change in productivity on education in column (4) of table 7, is predicted to have risen by .46 log points during that period. Thus, the 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. Furthermore, the differential growth in productivity exceeds the differential growth in wages. This is most easily seen in the columns 8 and 9 of table 9. 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 9 are all greater than those in the second to last column of table 9 implies that the education-predicted productivity distribution has spread out more than the education-based wage distribution between 1989 and 2017. This also implies that productivity changes more than account for widening of skill wage premiums over time.

The main conclusion of this analysis is that productivity has grown more for the highly educated and has done so by more than enough to account for growing wage inequality. Wages of more educated workers have grown relative to wages of less educated workers. But productivity of more educated workers has grown relative to productivity of less educated workers by even more. Productivity changes more than account for the increased skill differential that is actually observed. Also, the correlation between the values in column 6 and those in column 7 is almost perfect, equal to .94, and statistically significant despite having only four observations. Productivity changes line up with wage changes by educational category.[22] The coefficient from regressing the change in log real wage (column 6) on the change in log real productivity (column 7) yields a coefficient of .05 with a standard error of .01. A 1% increase in productivity is associated with a .05% increase in wages across education groups.

[22] This result is consistent with that found in table 6 of Lee and Wolpin (2010), which suggests that skill-biased technological change can account for more than 100% of the differential changes in wages.

C. 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.

D. Wage Analysis Using Individual Worker Data

Although the purpose here is not to provide an in-depth analysis of wage changes over time, the wage results above are derived from industry averages. The logic was to make them comparable to the productivity estimates, which necessarily are based on industry averages. Of course, there are extensive studies of wages and trends over time that use data better suited to studying wages than the aggregated industry averages. Those data are based on individuals, where the worker is the unit of analysis. As a check on the results above, the CPS outgoing rotation data are examined in this section.

Table 10 shows that the return to education has increased over the period between 1989 and 2017. Compare the coefficient in column (1) to column (3). The estimated effect on the log of real wage (in 2019 dollars) is .102 in 1989 and .121 in column (3). The increase over time in the effect of about 20% is statistically significant. Columns (2) and (4) estimate the effects for full time workers only, defined as those who usually work more than 34 hours per week. The education effects are smaller, but again, the increase over time is substantial (22%) and statistically significant.[23] Over the same period, the effects of age and gender have declined significantly.

Individual level data are useful for the wage analysis, but because there is no comparable data on individual productivity, the industry level comparisons are most informative for the purposes of determining whether productivity differences are sufficient to explain wage differences. The conclusion in the last section was that productivity more than explains the rise in wages for highly educated workers relative to less educated ones. The individual level data on wages do not contradict that finding. For example, table 9, column 9 reports that productivity for those with some college or college graduates' productivity rose by .45 log points more than the productivity gains of those with some high school or high school graduates. The difference in

[23]The 1989-2017 period was one that might have experienced inordinate technological change benefitting those most educated workers. There is no evidence for this in the individual level data. The difference in education coefficients across years is about the same even when the sample is restricted to those with college degrees or more.

average education level of those two groups is 14.68-11.65 or 3.03 years in 1989 and 14.6-11.79 or 2.8 years in 2017. The estimate of the education effect in column (1) of table 10 implies that wages of the more educated group would have been .102 (3.03) = .31 log points higher than those of the less educated group in 1989. Analogously, using the estimated effect in column (3) implies that the wages of the more educated group would have been .121 (2.8) = .34 log points higher than those of the less educated group in 2017. The difference in log wages of the two groups are predicted to have increased by .03 log points over the period, based on the individual level wage regressions in table 10. This is much less than the .45 log point difference in estimated productivity growth that is shown in table 9, column 9. Again, productivity growth differences more than explain wage differences even when wage differences are estimated using individual level data. It is important to note that this particular example is the most relevant one because in 2017, 83% of the population was in one of the two educational groups (some high school or high school graduate and some college or college graduate) considered in this example.

E. Capital

Capital has been ignored throughout this investigation. There are a number of reasons, among them and most important is that the statistics at the country and industry level are generally for labor productivity rather than total factor productivity. Second, in the context here, capital is an endogenous choice variable. Third, there is no attempt to estimate a production function, but rather merely to describe what has happened to labor productivity over time and to relate it to the wages of labor.

Still, there is information on capital expenditures by industry in the BLS dataset. When the regressions of changes in productivity on education in table (7) are augmented with either a capital expenditure variable at a point in time or with the change in capital expenditures for that industry over the 1989 to 2017 period, neither enters significantly. The education coefficient is essentially unaltered and retains its same level of statistical significance. Capital expenditures are associated with the level of labor productivity (positively and significantly), but they do not speak to the issue that is at the heart of this analysis, namely whether productivity changes over time are consistent with the wage changes over time by skill category.

X. Co-Movement of Employment and Wages

The theory and evidence presented is consistent with a causal link that runs from productivity to wages. When productivity rises as a result of technological change, the demand for labor increases and for any supply curve other than one that is perfectly elastic, some of that increase in demand is reflected in higher wages. The patterns observed in figures 2 - 4 are certainly consistent with the view that technological improvements generate increased labor demand and higher wages, but neither the cross country comparisons nor time series evidence provides clean evidence of causation running from productivity to wages. To determine causation, one strategy is to try to find changes in the hypothesized driving variable (in this case, productivity) that are clearly exogenous. That is not easy in this context, given the aggregate nature of the data.

An alternative approach is to consider confounding explanations and rule them out on the basis of other observable implications of those mechanisms that are refuted by data. That is the approach taken here. In this case, the alternatives is that an exogenous increases in wages causes an increase in productivity as well. At first blush, it seems implausible that increasing wages exogenously would force an increase in productivity, but it is a possibility. Suppose that unions, legislation or some other factor exogenously raised wages. Firms would respond by moving up the labor demand curve, using less labor. Additionally, they would opt for a higher average quality of labor as workers whose productivity fell short of the higher wage were terminated or not hired. Both responses would result in higher average productivity because the reduction in labor usage would occur to the point where the marginal product of labor equaled the new, higher wage. Inframarginal workers would have higher average productivity because the lowest productivity workers and hours would be cut.

This implication is testable. With the typical upward sloping supply curve, an increase in demand for labor causes wage and quantity of labor used to move together. When wages are raised exogenously or when there is a decrease in the supply of labor, wages and the quantity of labor move in opposite directions. Evidence on this can be provided both across countries and over time within countries.

Figure 10 uses the OECD country observations in 2017 and plots the employment-to-population ratio (defined as the number of people working divided by the number of people in the working age population expressed as a percentage) against the log of the country's average wage. The relation is positive, as is evidenced in column (1) - column (4) of table 11. The first two columns replicate statistically what is shown in figure 9. Column (1) uses a specification of wages in levels while column (2) uses the log of wages as the independent variable. Column (2) corresponds directly to figure 4 because it is the log of country average wage in 2017 that appears on the horizontal axis. Column (3) uses the entire panel, including all years of data across all countries, which yields 642 observations. Standard errors are clustered at the country level. The estimated coefficient in column (3) based on the full panel is quite close to that obtained in column (2) where only 2017 data are used. Column (4) includes country fixed effects. Perhaps somewhat surprisingly, the coefficient on log of wages doubles, suggesting that the within-country relation of employment rate to wages is stronger over time within the typical country than it is across countries. For the majority of countries, the time period covered is from the late 1990s to 2017. During this period, the typical country for which data are reported experienced a rise in both the employment rate (from 64% to 69%) and in the average wage (from about $33,000 to about $40,000). The fact that employment rates and wages are positively correlated within a country over time implies that those periods with the most rapid growth in wages also experienced the most rapid growth in employment. [24] Both the cross-country and within-country time series patterns imply that wages and employment move together. There is no obvious argument to be made for wages driving productivity. It does not appear that higher wages induce movements up the demand curve. If anything, the data support the opposite conclusion. When wages rise, employment rises, which is consistent with productivity-induced demand increases rather than a movement up the demand curve in response to decreased supply or institutionally mandated wage increases.

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[24]Note that the employment rate as calculated by the OECD is higher than that from the BLS method because the definitions of working age population and employment are not identical. Most important, the OECD does not include the elderly (65+) in the definition of working age population and the BLS does. Going in the other direction, the BLS defines workers as being 16 and older, while the OECD defines workers as 15 and older.

XI. Conclusion

There is compelling evidence that productivity and wages are linked. The pattern is clear in cross-country comparisons and for virtually all individual countries over time. Furthermore, all parts of the income distribution seem to benefit from increases in aggregate productivity. The mean wage rises as does the wage of the lowest wage earners and highest wage earners when productivity increases.

It is also true that wages have spread out over time in most OECD countries where data are available. The ratio of wages of the 90th percentile worker to the median worker has risen in 15 out of 17 countries between 1997 and 2015. In the United States, this is apparent not only in percentiles, but in returns to education. The education coefficient in log wage regressions is significantly higher in 2017 than it is in 1989.

The commonality of the pattern across countries suggests that global rather than institutional factors are at work. The most obvious candidate is the often discussed biased nature of technological change that has benefitted disproportionately highly skilled workers.

It is difficult to observe productivity at the individual level, but industry data on productivity can be linked with demographic and data on education. This permits an examination of changes in productivity industries that are dominated by highly educated workers versus those dominated by less educated ones. By doing this, it is possible to determine whether the productivity distribution has spread out over time consistent with the changing wage distribution.

The main conclusion is that changes in productivity at different educational levels are more than sufficient to account for changes in the wage distribution. The college-high school premium in wages has increased by much less than the college-high school premium in productivity has increased over the past almost-three decades. These changes are consistent with a number of possible causes, which include skill-biased technological change, trade patterns that have altered prices in a non-neutral fashion, and changes in human capital production technologies that favor tertiary over primary and secondary education. The analysis cannot address the specific cause, nor does the fact that non-neutral productivity growth can account for growing skill differences lessen the problem.

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Table 1
Regression Results Wages and Productivity
OECD Data

	(1) Log of Annual Wage in 2017 (expressed in 2017 USD)	(2) Change in Log of Annual Wage between t-5 and t	(3) Change in Log of Annual Wage between t-20 and t	(4) Log of Annual Wage in year t (expressed in 2017 USD)	(5) Log of Annual Wage in year t (expressed in 2017 USD)
Log Annual Productivity in 2017 (Output-per-hour times 1500)	1.517*** (.169)				
Change in Log of Annual Productivity between t-5 and t		.806*** (.139)			
Change in Log of Annual Productivity between t-20 and t			.765*** (.183)		
Log Annual Productivity in year t (Output-per-hour times 1500)				0.819*** (0.0768)	1.475*** (0.121)
Constant	-6.654*** (1.909)	0.000 (.010)	.016 (.053)	1.234 (0.855)	-6.065*** (1.365)
R-squared	.715	.377	.534	.991	.728
N	34	699	196	869	869
Sample	2017	1990-2017	1990-2017	1990-2017	1990-2017
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

*** 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.

Table 2

Regression Results Real Compensation and Productivity in the US 1951-2017

Bureau Of Labor Statistics Data

VARIABLES	(1) Compensation Index BLS	(2) Change in Four Year Moving Average of Non-Farm Compensation Index BLS	(3) Change in Four Year Moving Average Non-Farm of Compensation Index BLS
Non-Farm Output Index BLS	0.760***		
	(0.0213)		
Change in Four Year Moving Average of Non-Farm Output Index BLS		0.767***	0.637***
		(0.116)	(0.141)
Constant	30.00***	-0.00124	-0.00304
	(1.374)	(0.00269)	(0.00307)
Years	1951-2017	1951-2017	1990-2017
Observations	67	67	28
R-squared	0.952	0.400	0.441

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

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).

Table 3
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	.525*** (.067)	28	.705
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.

Table 4

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	0.13	1.68	1.62	0.06
Canada	1.9	1.76	0.14	1.94	2	-0.05
Czech Republic	1.84	1.71	0.13	1.93	1.79	0.13
Finland	1.77	1.69	0.08	1.44	1.4	0.03
Germany	1.9	1.75	0.15	1.84	1.66	0.18
Hungary	2.26	2.16	0.09	1.63	1.92	-0.28
Ireland	1.95	2.56	-0.6	2.03	1.53	0.5
Italy	1.47	1.57	-0.1	1.5	1.5	0
Japan	1.85	1.84	0	1.58	1.62	-0.03
Korea	2.38	1.92	0.46	1.92	1.93	-0.01
New Zealand	1.88	1.7	0.18	1.57	1.58	-0.01
Norway	1.51	1.4	0.11	1.68	1.38	0.29
Poland	2.07	1.92	0.15	1.88	1.79	0.09
Sweden	1.67	1.6	0.06	1.75	1.37	0.37
Switzerland	1.78	1.67	0.11	1.5	1.52	-0.01
United Kingdom	1.96	1.89	0.07	1.78	1.85	-0.07
United States	2.4	2.2	0.19	2.1	2.09	0

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

Table 5

Relation of Wages to Productivity: 10^{th} and 90^{th} percentiles

VARIABLES	(1) log 10^{th} percentile wage	(2) log 10^{th} percentile wage	(3) log 10^{th} percentile wage	(4) log 10^{th} percentile wage	(5) log 90^{th} percentile wage	(6) log 90^{th} percentile wage	(7) log 90^{th} percentile wage	(8) log 90^{th} percentile wage
Log Annual Productivity in 2017 USD ≡ Log (Output-per-hour times 1500)	-0.0983*** (0.0353)	1.154*** (0.248)	0.691*** (0.0977)	0.753*** (0.120)	0.390*** (0.0220)	1.023*** (0.170)	0.796*** (0.160)	0.778*** (0.220)
year		-0.0208*** (0.00409)		-0.00157 (0.00245)		-0.0105*** (0.00280)		-4.45e-06 (0.00507)
Constant	11.04*** (0.398)	38.36*** (5.338)	1.788 (1.070)	4.251 (4.232)	7.035*** (0.248)	20.86*** (3.689)	1.884 (1.756)	1.184 (8.622)
Observations	45	45	349	349	45	45	349	349
R-squared	0.153	0.475	0.991	0.991	0.879	0.910	0.989	0.989
Notes	United States 1973-2017	United States 1973-2017	All non-US countries – country fixed effects included, clustered at country level Unbalanced panel	All non-US countries – country fixed effects included, clustered at country level Unbalanced panel	United States 1973-2017	United States 1973-2017	All non-US countries – country fixed effects included, clustered at country level Unbalanced panel	All non-US countries – country fixed effects included, clustered at country level Unbalanced panel

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

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 6

Relation of Wages to Productivity for 10^{th} and 90th Percentiles (Changes)

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

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.
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 7

Productivity, Wages and Employment United States 3-Digit Industry

VARIABLES	(1) Change in Log Productivity (1989-2017)	(2) Change in Log Real Wage (1989-2017)	(3) Change in Log Employment (1989-2017)	(4) Change in Log Productivity (1989-2017)	(5) Change in Log Real Wage (1989-2017)	(6) Change in Log Employment (1989-2017)
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
				(0.0541)	(0.0341)	(0.122)
Constant	-1.461*	0.0574	-4.096**	-1.894**	-0.734	-1.715
	(0.770)	(0.491)	(1.556)	(0.730)	(0.460)	(1.642)
Observations	40	40	40	40	40	40
R-squared	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. 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 8

Productivity, Wages and Demographic Characteristics

VARIABLES	(1) Log Productivity	(2) Change in Log Productivity (1989-2017)	(3) Log Wage	(4) Change in Log Wage (1989-2017)
industry average education	0.289**	0.143**	0.200***	0.0174
	(0.116)	(0.0553)	(0.0277)	(0.0215)
industry average age	0.0228	0.00337	0.0298***	-0.00133
	(0.0297)	(0.0138)	(0.00624)	(0.00665)
industry proportion male	1.125**	0.240	1.092***	-0.333***
	(0.479)	(0.272)	(0.119)	(0.108)
industry proportion white	1.599	-1.282*	-0.410	0.522*
	(1.596)	(0.722)	(0.322)	(0.302)
year	-0.00220		-0.00515***	
	(0.0113)		(0.00148)	
Constant	2.596	-0.916	16.89***	-0.145
	(21.60)	(1.022)	(2.789)	(0.423)
Observations	1,353	40	3,036	70
R-squared	0.266	0.257	0.703	0.168

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. All variables in levels regressions are measured in the current year. 2017 values are used for the independent variables in the change regressions. 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 two following BLS sources. (1) The wage, education, and demographic 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 9

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

Source: Actual change in wages are 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 10

Wage Analysis: Individual Level Observations

VARIABLES	(1) lnw	(2) lnw	(3) lnw	(4) lnw
education (years)	0.102***	0.0888***	0.121***	0.108***
	(0.000954)	(0.000814)	(0.000789)	(0.000676)
age	0.0111***	0.00961***	0.00872***	0.00816***
	(0.000207)	(0.000192)	(0.000149)	(0.000137)
male	0.467***	0.359***	0.347***	0.261***
	(0.00512)	(0.00442)	(0.00408)	(0.00352)
Constant	3.849***	4.275***	4.412***	4.796***
	(0.0155)	(0.0139)	(0.0132)	(0.0118)
Year	1989	1989	2017	2017
Subgroup	All Workers	Full Time	All Workers	Full Time
Observations	53,139	45,013	100,676	86,018
R-squared	0.295	0.311	0.245	0.274

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Full time is defined in accordance with the BLS' definition (https://www.bls.gov/cps/definitions.htm#fullparttime).

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).

Table 11

Employment-to-Population Ratio and Wages

VARIABLES	(1) Percent Employed	(2) Percent Employed	(3) Percent Employed	(4) Percent Employed
wage	0.000165***			
	(4.36e-05)			
log of wage		5.061***	6.666***	13.76***
		(1.579)	(1.155)	(2.408)
Constant	63.34***	17.20	-2.220	-75.70***
	(1.997)	(16.50)	(11.85)	(24.96)
Observations	34	34	642	642
R-squared	0.309	0.243	0.367	0.887
Notes	2017 Sample	2017 Sample	Clustered at country level	Clustered at country level; country fixed effects included

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

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

Figure 1

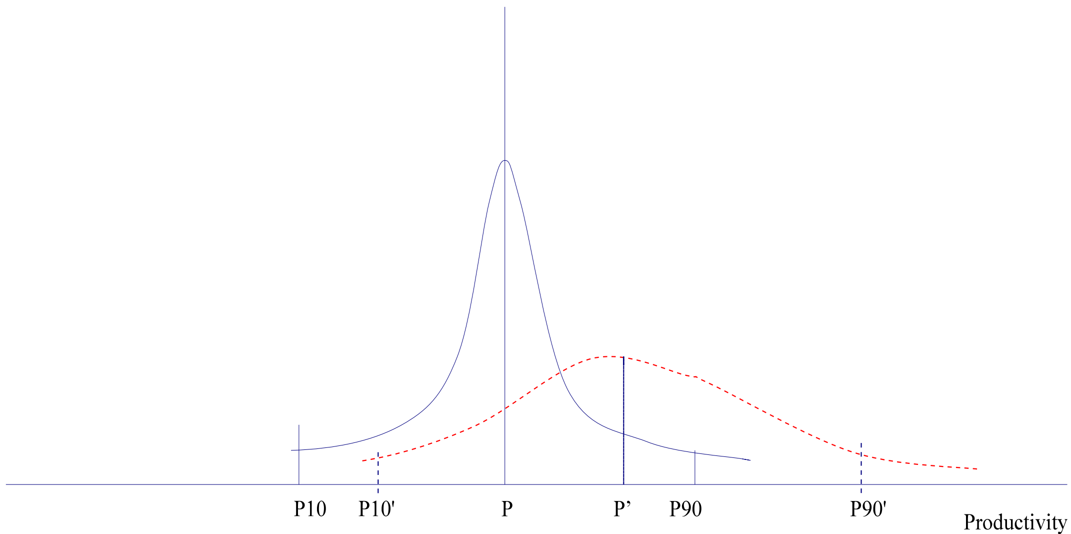
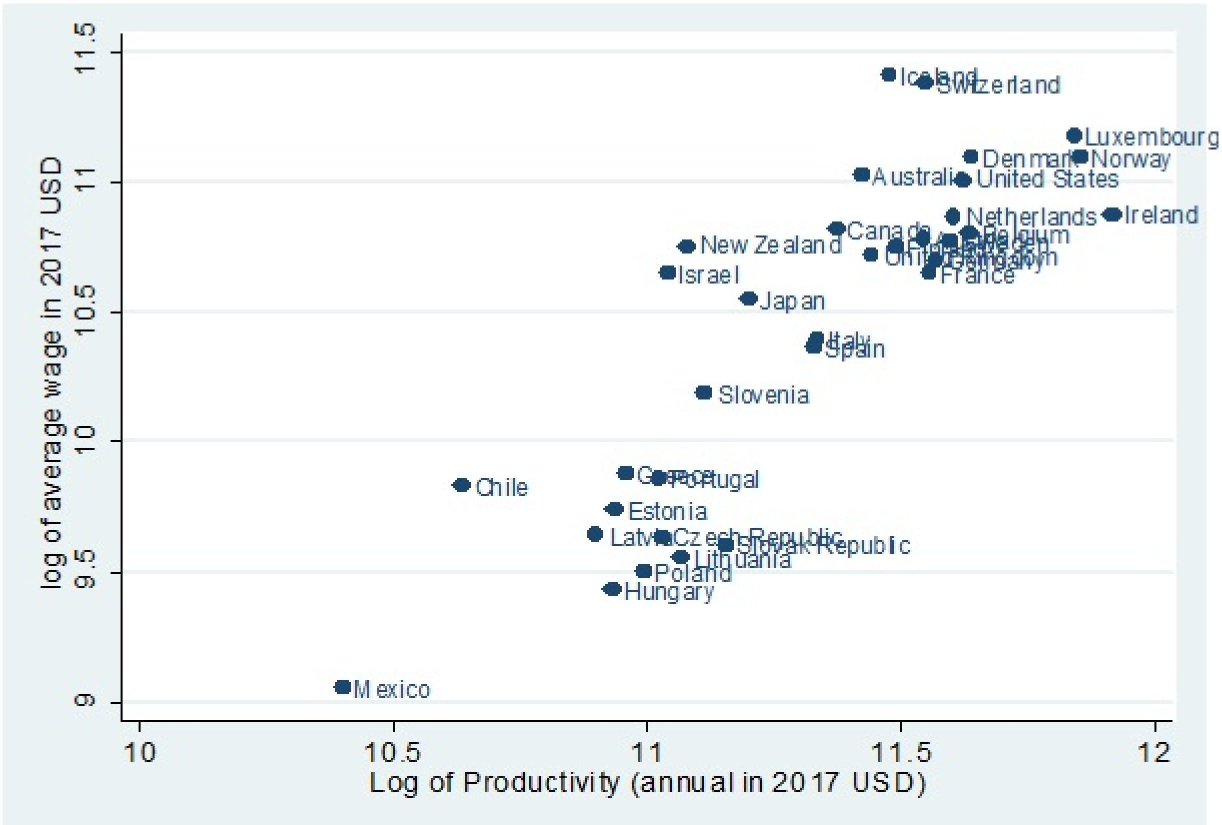


Figure 2: Cross-Country Comparison of Wages and Productivity in 2017

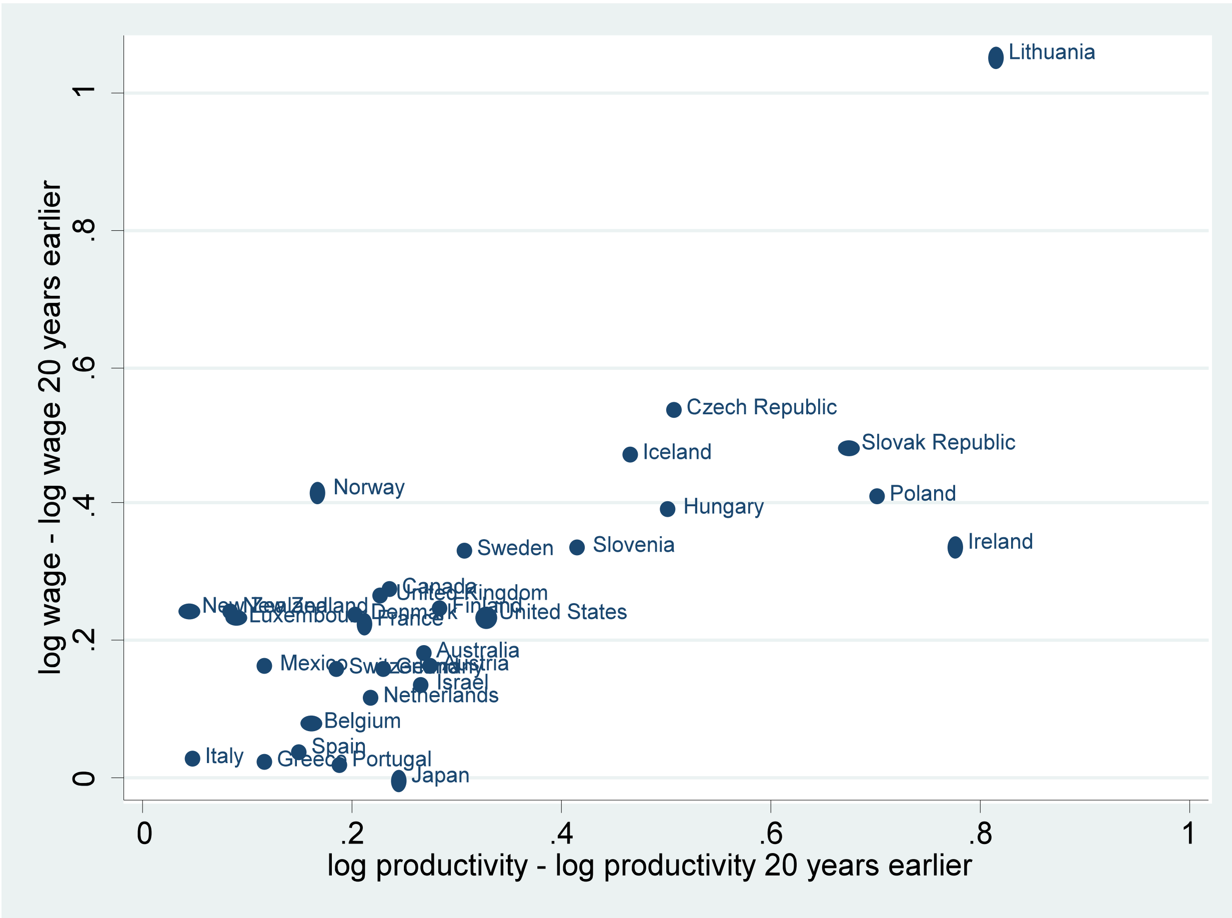
Horizontal axis is the log of productivity in 2017 USD, annualized (which means times 1500). Vertical axis is the log of annual wages in 2017 USD.



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.

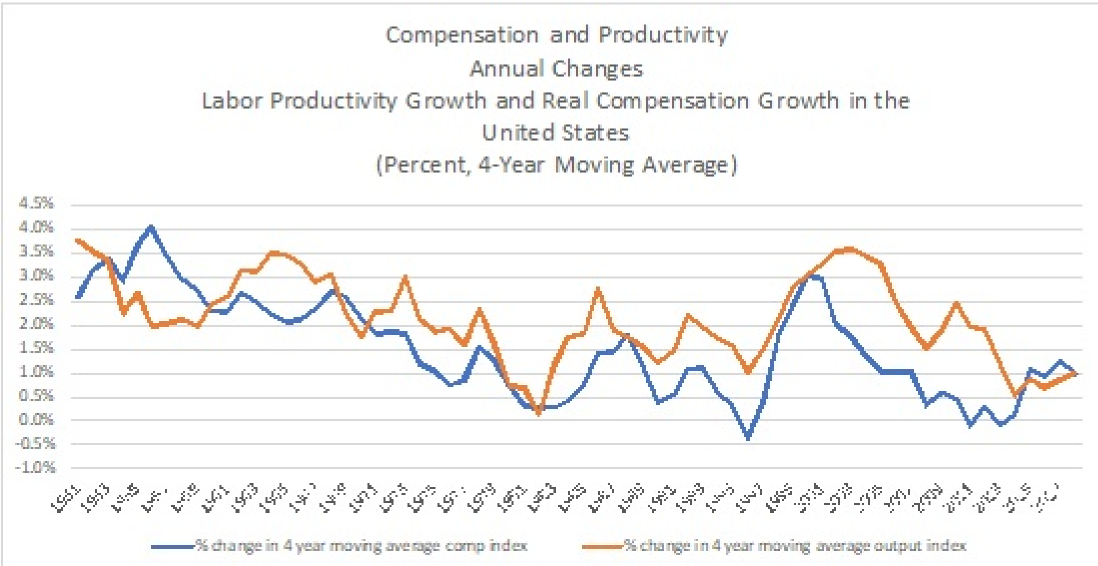
Figure 3: Cross-Country Comparison of Productivity Growth and Wage Growth 1997-2017

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 4: **Compensation and Productity 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 5

United States

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

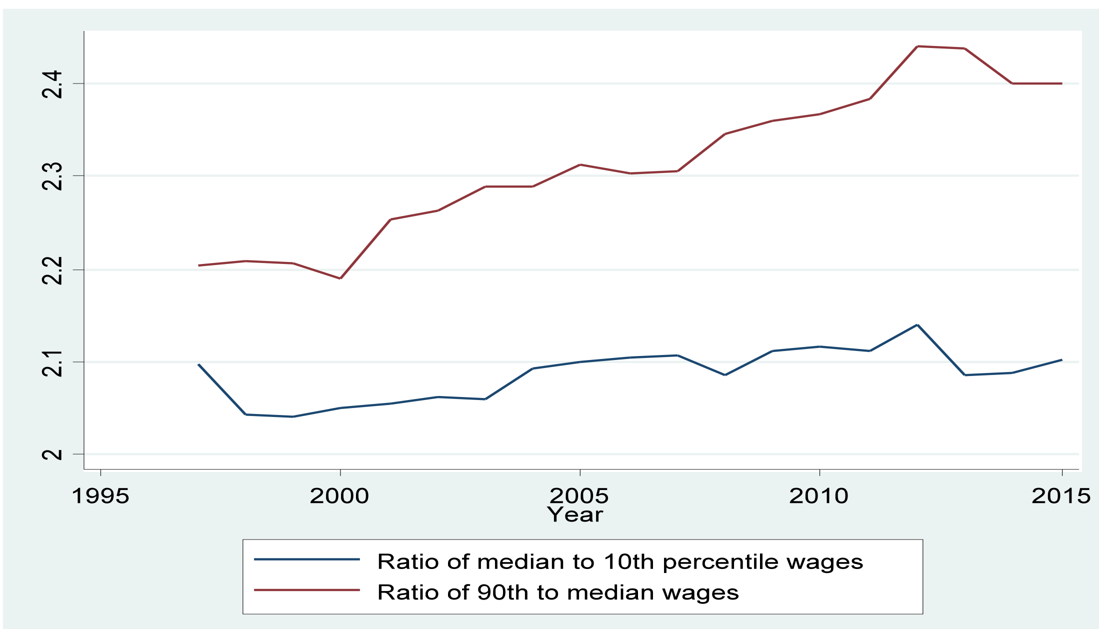
Figure 6

All countries (16 countries included; excludes US)

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

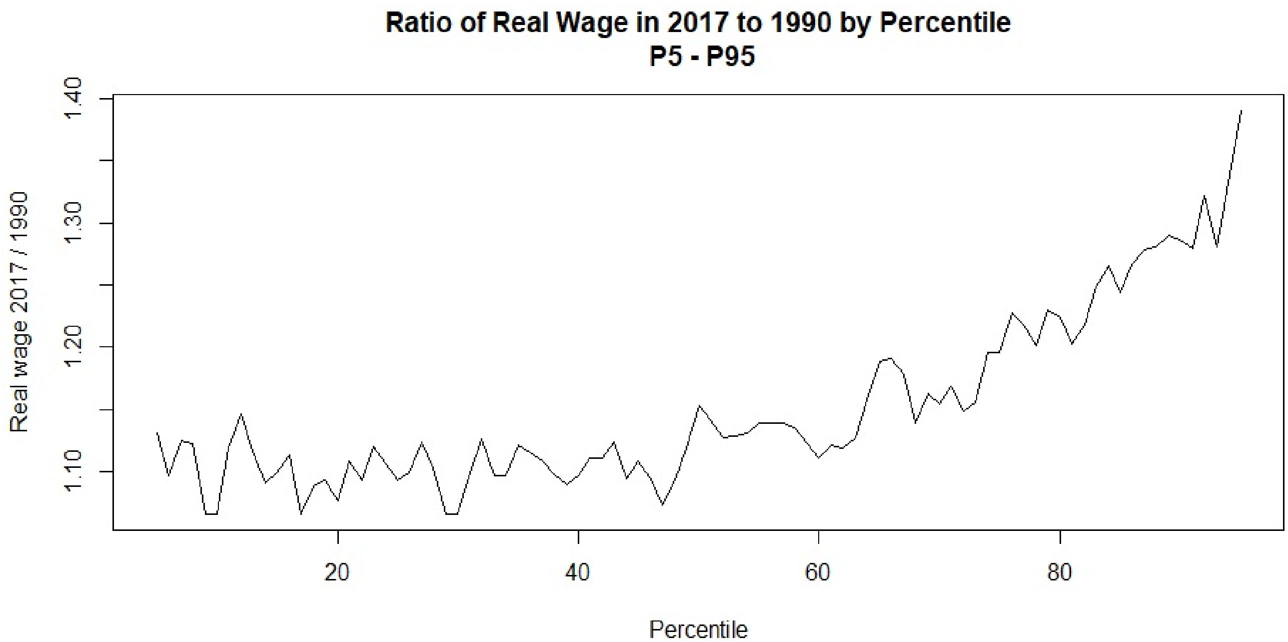
Figure 7

Unites States 1997-2015



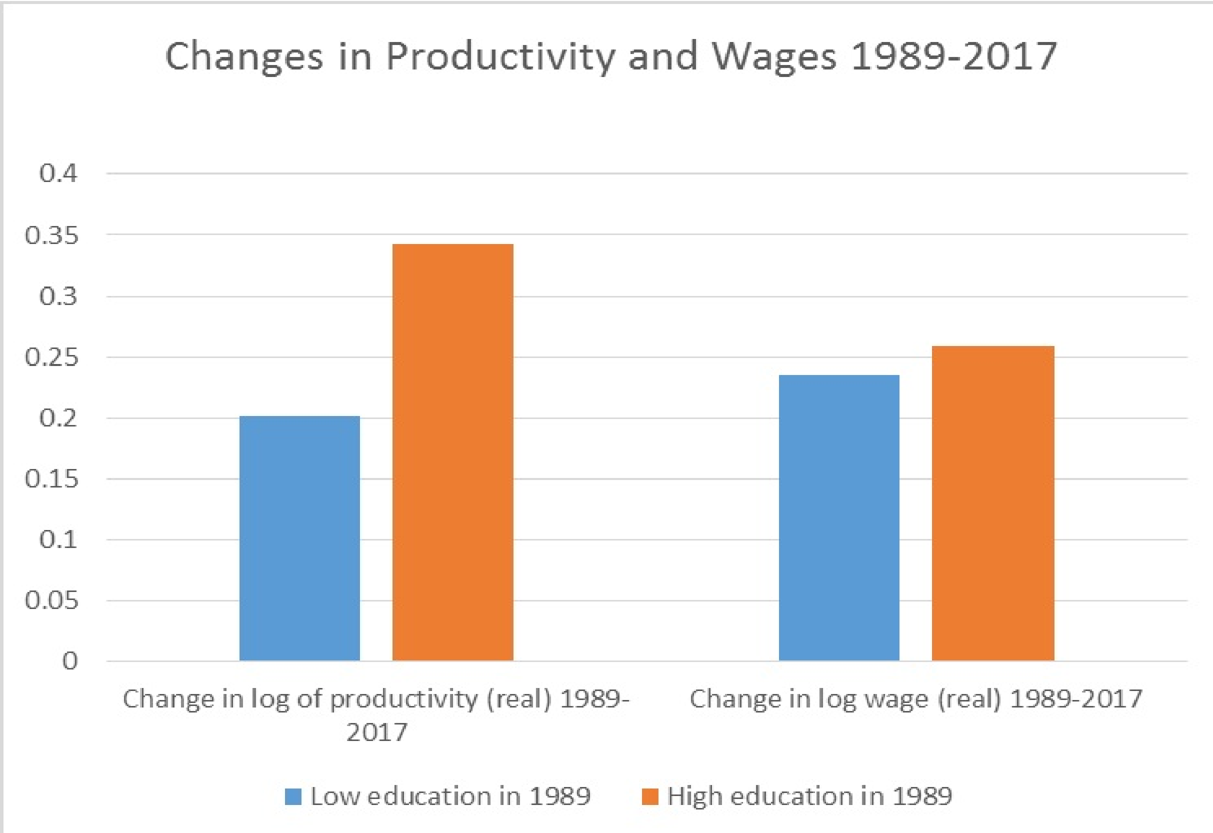
Source: The data are from the OECD Employment and Labour Market Statistics database.

Figure 8



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

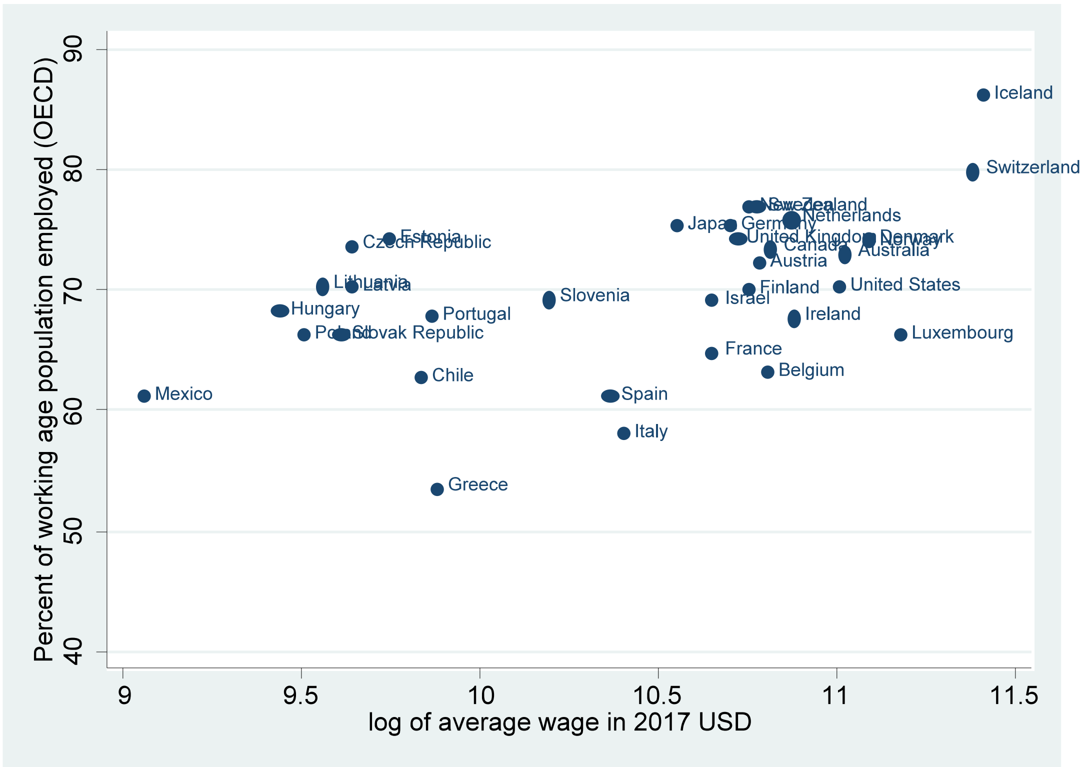
Figure 9



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 relevent industries for wages and productivities.

Figure 10



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

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

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

and

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

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

$Q_1 = \lambda[\, L^{1/3} + K^{2/3}]$ with scanner

$= Q_0$ without scanner

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

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

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

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

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. The solution is

$Q_1 = 332.6$

W = .019

K=2032.2

$P_1 = 1$

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. 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
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).
Ratio of minimum wage to median (used to compute median wage)	OECD	Minimum relative to average wages of full-time workers	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. 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.	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).
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).
Average Wage in	OECD	Average	This dataset contains data on average annual wages per full-time and full-year	OECD (2019), "Average annual

US dollars		annual wages	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.	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).
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
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.	Steven Ruggles, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. IPUMS USA: Version 8.0 [dataset].

			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.	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	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

			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.	.0

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 wage	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).