New technologies and earnings variation within U.S. occupations since 1960

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Preliminary and incomplete. Feedback to pbmeyer@econterms.net is welcome

Abstract. Using Census and CPS data on incomes and a new standardized occupational category system that extends from the 1960s to the present, this paper shows measures of inequality of earnings within narrowly defined occupations. Inequality within most occupations is stable over the decades. As theorized by Rosen (1981), the “superstars” occupations such as athletes where performances can be replicated and transmitted have increasing inequality within them. Rosen also theorized that other professionals such as doctors would experience this effect but the evidence does not show it. The categories of computer hardware and software engineers and technicians have rising inequality within them, whereas other engineers and technical occupations do not. This paper argues that the high tech effect comes about because there is so much creation and destruction in the semiconductor-related areas – both great opportunities and rapid obsolescence. The high tech population creates new technology, and is also buffeted by it. The high tech and superstars effects would naturally occur to some extent in many occupations. Therefore we examine also occupations in which these effects are likely to be the weakest – those that call for personally interacting with other individuals. On average inequality within occupations at this other extreme has not risen.

Introduction

New information technology is one cause of the rise in income inequality in the U.S. since 1970. Autor, Katz, and Krueger (1998) showed that wage inequality tended to rise more in those industries which had more computers, invested proportionately more into computers, and whose

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employees used computers more. By their accounting, 30 to 50 percent of the increase in income inequality since 1970 could be attributed to the use of computer technology.

Particular capabilities of computer technology produced some of this rise in inequality.\(^2\) Semiconductor technology helped enable the expansion of media markets through quicker and cheaper communication, e.g. on CDs and through cable television systems. This increased the scale of distribution of the most-preferred performers and therefore their competitive advantage in revenue. This *superstars effect*, discussed by Rosen (1981), will be measured here.

Influential new technologies arrive along with *technological uncertainty* which can cause economic turbulence and a temporary increase in earnings inequality. It is difficult to predict the future of an immature technology with great potential. Organizations change their products and processes to reduce costs, raise quality, and to avoid obsolescence. The new technology can therefore produce a wave of experimentation, new engineering standards, and entrant firms. Characteristically many of the entrants fail and a few become big successes. This turbulence can widen the distribution of individual earnings in affected occupations by (1) temporarily opening up valuable opportunities (such as starting a firm, or receiving incentive stock options); (2) rapidly obsolescing existing technologies, methods, and opportunities; and (3) expanding the range of activities in the affected occupation. These effects do not come from using a computer, but from being connected to the creative ferment which defines what computers will be.

A human-capital model is sometimes used to characterize the increase in earnings inequality. New technologies are found to raise the payoffs to various preexisting skills. These skills are sometimes proxy-measured by the duration of formal education and work experience. One problem with this is that the meaning and value of skill, formal education, and work experience vary with time and evolve with the technology. Another is that the person’s fields of substantive knowledge and actual role in economic production are left out. A third is that education has a signaling role or a credentialing role in a tournament game for high incomes, apart from its role in creating skills. This paper uses a different paradigm. It depends on occupational categories to locate the economic roles of the respondents, and measures how these occupations have slowly evolved to see effects of technological change.

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\(^2\) For example, much of the computer-related rise in inequality could be explained by reorganizations of tasks to use computers to do routine work, as illustrated by Autor, Levy, and Murnane (2003).
The data includes the occupations and earnings measures of respondents to large U.S. surveys. Occupations that experienced amplification through the media, or participated in the high-tech developments directly, will be shown below to have had rising inequality of earnings within them. At the other extreme, “care work” occupations in which a face-to-face role with other people is central, had earnings distributions which became narrower over time.

**Data sources and definitions of variables and measures**

The data come from repeated cross section samples of the U.S. population. From 1968 to 2003 we use the survey results from the annual March CPS (Current Population Survey) with about 30,000 employed people, and every ten years since 1960 there is a large population Census sample. The 1960, 1970, 1980, and 1990 Census samples cover 1% of the U.S. population, and the 2000 sample covers 5% of the population. The data samples come from the IPUMS.org project site (King, Ruggles, and Sobek, 2003).

The data set includes respondents aged 16 to 75 years old with an occupation and a positive income. Occupations were assigned by Census specialists, and mapped into one of several hundred codes. The category systems for these occupation codes changed each decade. The standardized occupation category system defined by Meyer and Osborne (2005) is used here. A close variant of this definition was adopted by IPUMS.org as their occ1990 variable.

The graphs regressions which follow leave out respondents with zero or negative earnings, by the definition of earnings relevant to each regression. Earnings were usually measured by wages and salaries, and in some regression also include self-employment (or “business”) income. Data on capital gains income was not consistently available, and is not used here.

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3 The 1960 Census definitions were used in the 1968-1970 CPS, the 1970 Census definitions were used in the 1971-1982 CPS, the 1980 definitions were used in the 1983-1990 CPS, the 1990 Census definitions were used for the 1991-2002 CPS, and the 2000 Census has been used in the CPS starting in 2003. Apart from this remapping, occupations are reported with error for a variety of reasons. For example, the respondent may have had several jobs during the year, and only one will be recorded. There has also been no adjustment for workers who worked only part of the year; their incomes and occupations are taken literally as describing their experience in the year.

4 A note on unmeasured income: Wage and salary measures do not include all income coming from high technology employers. In regressions above when self-employment income is included the substantive results are similar to the wage-and-salary results. Employees of startups in the new microcomputer-related industries often received stock options, whose returns vary widely. In one survey of high
Income variables are said to be top-coded if the reporting agency does not report the value of incomes above some level, only that they reach that level. The Census and CPS report only top-coded incomes to protect the privacy of respondents with distinctive levels of income. Similarly, negative values for self-employment income are bottom-coded. The average of top-coded incomes each year is known, and that value was used in place of the top-coded value.

The measure of earnings dispersion (or inequality) in an occupation used in this paper is the standard deviation of the natural logs of the incomes. This measure of earnings inequality is unaffected by a general inflation changing all wages by the same percentage and incomes are only compared to other incomes in the same year. This makes it possible for inequality measures to sidestep the complicated issues about comparing prices over time. Using this measure, the earnings distributions within occupations are overall slightly compressing over time. The dispersion or inequality within these occupations is declining.

**Media amplification and the superstars effect**

Rosen (1981) modeled an effect that would occur in certain occupations, like musicians, if their labor market were to grow in size. The services of sellers vary in desirability (“quality”), and the sellers can deliver services to many buyers simultaneously. In this environment, an expansion of the market (quantities demanded and supplied) for the service leads to more revenue for the top-quality sellers, but less revenue for the least-preferred sellers (who now have more competition) and therefore there is a rise in revenue inequality among the sellers. If the market expands, revenue inequality would therefore increase.

Several standard examples illustrate the theory. An athlete or musician before the age of mass media performed only for those who were present. Small differences in quality would not affect how many customers a performer would get, since it was hard to rank them and the

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*technology employees, 10% of executives, 85% of managers, and 42% of other employees participated in stock option plans in 1997 (Southwick, 1999, p. 165). 24.1% of electrical engineers in one survey were offered employee stock option plans (IEEE, 1995, p. 5-2). The CPS has a measure of capital gains income (some of which comes from earlier stock options) but it is not incorporated into the dependent variables in this paper. The Census does not have a measure of capital gains.*
opportunity to see either one was rare. With the appearance of recording technologies, consumers could more easily buy and hear the work of any of them, and the best or most famous one may get most of the sales and unknown ones are driven down to no sales. Now, many listeners can hear a recorded musician without imposing significant costs on one another’s experience. Similarly, before broadcasts, if there were only one basketball game available in town, it would not face direct competition for basketball fans, but when there are several games on television the most appealing one may get most of the viewers.

It follows that earnings inequality in the performance occupations would increase as recorded or transmitted performances became more widely available. Availability increases with the invention and standardization of compact disks, computer networks, and cable television, and also with expanded trade and globalization. The work of famous and distinctive musicians and authors is available around the world, and successful performers can now become international celebrities with a larger audience than was ever possible before. These are superstars, in Rosen’s memorable language. Labor markets with superstars have two distinctive characteristics: (a) the outputs of different sellers are not perfect substitutes for one another in the minds of buyers, and (b) there are economies of distribution, meaning that the costs of production rise more slowly than the number of buyers. Top earners in these professions thus benefit disproportionately from improvements in information and communication technology, and the expanded, “globalized” market for their output. Here these are called media-amplified occupations.

The superstars effect could occur to some degree in many occupations. For clarity of discussion let us select out some in which the effect is strong, or expected to be strong, based on several sources: occupations which Rosen (1981) used as examples; occupations which the related book by Frank and Cook (1995) used as examples; the occupations which are available in the Census data for extended periods of time; and at the margin, the occupations available in the data in which the effect seems to be visible. The ten most media-amplified occupation groups are taken to be: actors, directors, or producers; artists (artistic painters, sculptors, craft-artists, and print-makers); other art and entertainment performers; athletes and sports instructors; related

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5 The coefficient of variation of incomes (the standard deviation of the distribution divided by the mean) also has this property of being robust to any measure of inflation, and the substantive claims here also hold for that measure of inequality.
occupations; authors; dancers, dance teachers, and choreographers; designers; editors and reporters; musician and composers; and photographers. Empirically, the average earnings in these jobs have not risen much more than earnings in other jobs, perhaps because there is a kind of Malthusian constraint on performers.

The superstars hypothesis found to work in the data is that in professions whose output performance can be reproduced or amplified by electronic communications, earnings inequality rose over the recent decades. This is not because the technologies are new per se, but because they have been used increasingly to transmit work content and performances. In the media amplified occupations, the dispersion measure rose on average about .2% per year, whereas it was declining on average in the other occupations.

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6 Rosen (1981) illustrated the superstars discussion with these examples of occupations providing services which were imperfectly substitutable for one another. Only some of these also meet Rosen’s other criterion that their services can be consumed by many customers jointly without rivalry between those customers, although this will be empirically important: artists; authors (mentioned 3 times); authors of textbooks; comedians; doctors (3 times); economic theorists and methodologists; lawyers (2 times); musical soloists; network news broadcasters; news reporters; performer on television; performers (theater, TV, and movies); performers (2 times); pro athletes (3 times); scholars (as writers); singers; surgeons; writers. Rosen’s article quoted Marshall (1947), who described this phenomenon too, with these examples: business men; barristers; jockeys; painters; and musicians. Frank and Cook (1995) use a wider spectrum of examples what they call “winner-take-all” markets in which competition for big payoffs would be increasingly intense: fashion models; screenwriters; actors; directors; composers; business consultants; financiers; journalists; accountants; chiropractors; dentists; salespeople; painters; writers; musicians; athletes; business managers; authors; lawyers; academic faculty; scientists; researchers; news reporters; and performers on television.
Rosen (1981) and Frank and Cook (1995) discussed a related effect, of more intense competition among other professionals that can occur in an environment where communication and transportation are easier. It has become easier over time to compare surgeons or attorneys through phone recommendations or online information, and also easier to travel to these specialists. Therefore the value of a one percent increase in expected performance to a customer could be increasingly valuable in these professions, and competition could have increased at the top of the professions. There could be a tendency for superstars with international audiences to appear, and their wages to be bid up higher and higher.

Though this second argument is plausible, the evidence on earnings does not support it. The occupations available that best matched the professional occupations mentioned by the authors were: physicians; dentists, veterinarians, optometrists, podiatrists, and lawyers. In the CPS data these earnings distributions are compressing over time on average. It seems that the joint-consumption effect is visible but the bidding-up effect is not.
A key difference between the groups where the superstars effect is visible and this second group of professionals is that non-rivalrous consumption of the performances is possible for the first group. For the doctors and lawyers, this property, which Rosen called “joint consumption” is not present, and apparently because of this, any superstars effect is overwhelmed by other forces. One such effect could be that most of them satisfy the property of being “face-to-face care work” in a sense to be defined later. Another could be that with better information available, these occupations face increasingly perfect competition as forecast by Stigler (1960).

High tech ferment -- uncertainty, opportunity, and turbulence

Since 1968 semiconductor chips have improved dramatically and fallen in price while the quantities produced have skyrocketed. The resulting products and changes in work process have redefined white collar work around the world.\(^7\) Semiconductor performance improvements have followed an exponential pace since 1959 known as Moore’s Law. They result from the efforts of a variety of specialists including a class of electrical engineers and other specialists, and these improvements then reverberate to buffet the population of electrical engineers and computer specialists. Electronic design and software design changed dramatically. Electrical engineering became less about continuous flows of electricity and more about digital encoding. The dramatic technological changes put them in a state of technological turbulence that is more intense than that felt in other occupational categories.

Here technological uncertainty means a lack of common knowledge and agreement about what production technology will be relevant in the future. “It involves not only lack of knowledge of the precise cost and outcomes of the different alternatives, but often also lack of

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\(^7\) Examples of new semiconductor-dependent technologies and industries: Disk drives (1960s); semiconductor memory (1971); microprocessors (1971); pocket calculators about 1973; bit-mapped video output, in the late 1970s; word processors, at least since in 1976; general purpose microcomputers in the late 1970s; the Internet, since 1970; electronic spreadsheets (circa 1978), graphical user interfaces with mice, icons, and drop-down menus, client / server distinctions, the Web (since 1990), object-oriented computer languages, mobile phones, streamed transmission of content, handheld music and game devices, and e-commerce.
knowledge of what the alternatives are.” Uncertainty in markets associated with a new technology takes several forms such as uncertainty over prices, tools and materials, products and customers, financing, and the work force. Rosenberg (1996) lists issues of technological uncertainty. For one, the impact of an innovation depends on later complementary inventions; one does not at the beginning see the whole technological system built around the original invention. And, second, the original invention is targeted at some particular problem to begin with, and its useful scope may expand and evolve in a way that is hard to predict. In this paper, as in Rosenberg’s, uncertainty about making a product is conflated with the market uncertainty about selling it, under the general heading of technological uncertainty.

The hypothesis to be taken to the data is that earnings dispersion rose within occupations which involved designing semiconductor products or using novel, incomplete or malfunctioning computer systems. The next graphs shows the level of earnings dispersion for electrical engineers, electrical engineering technicians, computer programmers, systems analysts, and data processing repair persons. Many of these persons are direct participants in creating or fixing novel semiconductor-related systems. They created and experienced Moore’s Law most directly, through declining semiconductor prices, quality improvements, and continuing novelty in products, processes, and markets.

The graphs show earnings inequality within these occupations for each year from 1968 to 2003, where earnings (‘‘occupational income’’) includes wage, salary, and self-employment income. Observations of inequality were dropped from the graphs if they were estimated from fewer than 10

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8 Dosi (1988) p.1134. The subject is also well discussed in Rosenberg (1996). No source seems to give a direct definition but this one seems to be approximately what they mean. Tushman and Anderson (1986) measured uncertainty by the magnitudes of the errors in forecasts of demand growth made by financial analysts. This was much higher in semiconductors than in other industries.
The Moore’s Law occupations above experienced something distinctive. There is indeed a trend toward rising inequality in these occupations. Other engineering and technical jobs, more distant from semiconductor improvements, do not show this trend. Comparable graphs for other engineering fields are shown below. They are relatively flat.
One might think that all the Moore’s Law occupations were growing rapidly, or their salaries were rising rapidly, and this caused the inequality measure to change as a side effect. This does not seem to be the case. Average salaries for the occupations rose at roughly the same pace as earnings in other occupations. The software categories first appeared in the data in the 1970 Census and the 1971 CPS for the first time, and grew quickly, but the electrical engineers were a stable proportion of the workforce over the period, as shown:

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<tr>
<td>Electrical and electronic engineering technicians</td>
<td>0.09%</td>
<td>0.13%</td>
<td>0.18%</td>
<td>0.25%</td>
<td>NA</td>
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<tr>
<td>Computer software developers</td>
<td>NA</td>
<td>0.13%</td>
<td>0.21%</td>
<td>0.40%</td>
<td>0.76%</td>
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<tr>
<td>Computer systems analysts and computer scientists</td>
<td>NA</td>
<td>0.07%</td>
<td>0.13%</td>
<td>0.28%</td>
<td>0.38%</td>
</tr>
<tr>
<td>Electrical engineers</td>
<td>0.16%</td>
<td>0.23%</td>
<td>0.21%</td>
<td>0.29%</td>
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The population within each of these occupations evolved slowly and did not change much in terms of years of education or age distribution.
Why did the high tech “Moore’s Law” occupations experience this effect? I believe it can be summarized by three kinds of changes affecting people in these occupations especially: (1) new opportunities to do something unique and valuable; (2) rapid obsolescence of previous opportunities and capabilities; (3) expanding kinds of activities within the occupations as they evolve. These forces can affect the payoffs to various pre-existing attributes of persons, like education, skills, experience, and ability. But also there appears to be a historical phase in which there is a high level of noisy surprises in the payoffs from the environment.

Consider first the pre-existing, ex ante measurable capacities of persons. In the theory of Greenwood and Yorukoglu (1997) and Greenwood (1997), workers have the opportunity to improve the technology of the firm at times of radically new technology. Workers differ in their ability to make such improvements, therefore there is an increase in the dispersion of worker productivities and in the dispersion in the distribution of earnings when innovations are most desired by the employers. In that model there is also a productivity slowdown at that time, as employers invest in trying to usefully adapt the new invention to practical use. The model was meant to match the phenomenon of computer technology appearing in practice, along with earnings dispersion, but contemporaneous with a productivity growth slowdown despite the new technology. This hypothesis, that workers differ greatly in the ability to adapt (the adaptability hypothesis) has been made in other models of technological change such as those of Caselli (1997), Rubinstein and Tsiddon (1999) and Galor and Moav (2000). Offering evidence for this interpretation, Bartel and Sicherman (1999) found wages and the wage premium to education were higher in industries which had more technological change by several measures, including research and development as a fraction of sales. Using a specification with fixed effects on individuals they controlled for unmeasured abilities of workers who switched industries over time. They found that technologically changing industries tended to employ workers who had more of this unmeasured ability, and more years of formal education.

But there is also evidence that the Moore’s Law environment of rapid technological change is distinctive. It has uncertainty and surprises, apart from attributes of human capital or ability. Throughout the history of the semiconductor industry there has been evidence of high uncertainty such as asset price fluctuations, retreats by firms from product markets they had just entered, and poor understanding of production processes. These also characterized the software
and e-commerce markets as they developed. Uncertainty about the future means today’s choices are gambles, with noisy payoffs, and this could induce noise into the semiconductor-related occupation wages. Indeed the persons in the occupations are both experiencing technological change, and creating it. Here are measures and stories from the environment:

- Tushman and Anderson (1986, p. 448-9 and 455-6) measured uncertainty in an industry by the errors in forecasts by financial analysts of 1967-1976 industry sales. Forecast errors were twice as high in the minicomputer business as in the other industries measured.
- Hunter, Kobelsky, and Richardson (2003) and Chun, Kim, Lee, and Morck (2004) have found that greater investment by firms in information technology was correlated with more volatile earnings, sales growth, and stock returns subsequently. Indeed information technology projects have for decades had high rates of finishing later than planned or with unexpected outcomes. Brooks (1975) attributes this to complexity and the interrelationships of those on the project. This evidence shows uncertainty on the employer’s side of the relationship.
- Venture capitalists expect that most of the high tech firms they finance will fail financially.
- There has been extraordinary change and volatility in the prices of semiconductor and computer components. One read-only memory chip declined in retail price from $110 in 1983 to $10 in 1984, and to $3 in 1985. (Morris, 1990, p. 78).
- In a predictable market, the top firms are unlikely to be overturned. But in the semiconductor-descended industries, it occurs with some frequency. Digital Equipment Corporation (DEC) surprised IBM in the late 1960s and early 1970s by delivering minicomputers that competed with IBM’s mainframes. IBM then introduced its own minicomputers. DEC’s founder and president did not foresee uses for home computers in 1977 (Norman, p. 234). When, DEC experienced competition from microcomputers, it never successfully released its own.
- Semiconductor work in the 1960s was characterized by failures that were not well understood. It is now thought that the failures were results of uncontrolled impurities in the silicon. “Sometimes the problems would disappear for no apparent reason, only suddenly to reappear. Solutions that worked one time might not work the next. Semiconductor manufacturing was so poorly understood that some problems were given colorful names,
such as ‘Purple Plague’ and ‘Red Death.’ Scientists routinely referred to ‘black magic’ and ‘witches’ brew’ in describing their process techniques.” (Berlin, 2001, p. 83) Rising productivity in this area depended on empirical experimentation and imitation.

- Handwriting-input computer maker GO found that standard manufactured chips did not behave according to their specifications outside the bounds of what regular PCs would put them through. GO also had trouble writing on flat displays for which the existing technology had not been used in a production environment (Kaplan, pp. 56 and 108). GO had not planned on such difficulty with those devices -- the gamble was a surprise.

- After Intel’s first microprocessors in 1971, its marketing department did not want to sell them to the public because the applications were not clear and the customer support problems would be difficult (Freiberger and Swaine, p. 14). Later, Intel became principally a huge microprocessor manufacturer.

- Even after the microprocessor was an established product, Intel did not venture into the business of selling applications for it, although in retrospect many of these would have been valuable businesses. In the early 1970s at Intel “talk had come up about getting into end products, designing machines around the microprocessors, even about using a microprocessor as the main component in a small computer. Microprocessor-controlled computers, however, seemed to have a marginal sales potential at best. Noyce felt that microprocessors would find their chief market in watches.”

- Demand has sometimes wildly exceeded predictions. In 1975, the maker of the first extensible microprocessor-based computer kit for sale worried that no one would buy it. Then, within the first two months, electronic hobbyists placed hundreds of thousands of dollars in orders (Freiberger and Swaine, p. 37). Later, IBM under-predicted sales for the first year of its IBM PC by a factor of six (Langlois 1992, p. 23).

- High tech customer requests are not a reliable guide to future demand. Christensen (1999) and Utterback (1996) documented cases of established firms that were ruined because they repeatedly followed the advice of customers and made only minor updates to their product technology, when fundamental technological changes were called for instead. Customers did

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9 Freiberger and Swaine, pp. 15-16. Integrated circuit co-inventor and Intel co-founder Robert Noyce was a legend beforehand and long afterward. He was not just ill-informed.
not know this or could not evaluate it, or had fundamentally different interests from the vendor. The usual approaches to figuring out what customers want are inappropriate, according to Don Norman, who was a psychology professor then became a vice president of Apple: “[F]ocus groups can be very misleading. They tend to reveal what is relevant at the moment, not about what might happen in the future. Users have great trouble imagining how they might use new products, and when it comes to entirely new product categories – forget it.” (Norman, 1998, p. 192).

- There were substantial flows of entrant firms and exits from semiconductor manufacture, associated with the arrival and departure of specific technologies and niches. (Wilson, Ashton, and Egan, 1980; Levin, 1982, p. 44; Berlin, 2001, p. 61), There was also turnover at the top. Of the top ten U.S. manufacturers of vacuum tubes in 1955, only RCA was a significant independent producer of integrated circuits in 1978. (Morris, 1990, p. 80)

- Intel, Hewlett-Packard, Xerox, and DEC all declined to mass-manufacture personal computers, in the early stages when one of them could have led that industry.\footnote{Xerox’s Alto office computer had a user interface something like a Macintosh in 1974, and could be networked, but was expensive. Xerox executives were ambivalent about the attempt and did not rush to try again. If Xerox had revised the product quickly and seriously they might then have led the industry.} (The founders of Apple meant to make their computers for HP but HP turned them down so they started their own company.) When later the experienced computer makers did try to make personal computers, most of them failed financially at it, except for IBM. Similarly, few minicomputer software makers made software for microcomputers; new firms took the field almost entirely. This illustrates the degree of surprise.

- The first industry sales leader in microcomputers was MITS (the maker of the Altair) in 1975, then IMSAI in 1975-78 (Langlois, 1992, p.12), then Apple (1978-81), then IBM, then Compaq. IBM’s attempted to regain control from the clone-makers with its proprietary standards for the PS/2 hardware design and OS/2 operating system, but these were overturned in 1987 by revised industry standards.

- A surprise leader emerged in personal computer operating systems. Before making its PC, IBM expected DRI, the established leader in personal computer operating systems, to supply the new computer’s operating system. DRI unexpectedly declined to discuss a contract with
IBM. IBM offered the contract instead to Microsoft which seized the opportunity and agreed to provide an operating system. Microsoft quickly acquired one, adapted it to look like the DRI product, and came up with PC-DOS. This turned out to be an astonishingly important product, changing the whole industry in a path-dependent way as Microsoft could define standards, exercise leadership, and undermine alternatives. Microsoft had not been in the operating systems business in 1979, but by 1987 had locked down a kind of dominant position.

- Applications software categories were turbulent too. Industry-leading word processors repeatedly lost their position: Electric Pencil (1976), WordStar (1978), WordPerfect, and finally Microsoft’s Word. In the 1980s the leading database program was Ashton-Tate’s dBase II, which ran aground on technical complexity and was replaced as the leader by Borland’s Paradox, until Borland self-destructed. The inventors of electronic spreadsheets made millions in the 1970s selling their VisiCalc program, but it was then beaten by the focused effort of startup Lotus to make its 1-2-3 program on the then-new IBM PC. This program made billions in revenue but then lost out to Microsoft’s Excel.

- By the definition of a new technology, engineers with experience with it are not widely available, and their experiences are idiosyncratic. In labor market terms, the supply of workers is thin and heterogeneous. So the right person for a job may not exist, or may not be available. A key engineer designing a new technology product may be irreplaceable since the market may disappear before a substitute could be competent (Perez, 1986, p. 104-5).

- Turnover in the semiconductor and software industries tends to be high,\(^\text{11}\) so there is uncertainty about who will be in next year’s workforce. Almeida and Kogut (1999) show that Silicon Valley has a distinctive pattern of job mobility and that high mobility regions generate more-cited patents.

Conclusion: Since the 1950s, the Moore’s Law occupations, more than other occupations, face uncertainty about what the products will be; who the potential customers are; what they want; what prices will be; what tools and skills will be relevant in the future; what firms will survive; and how the relevant industry will be organized. Flows of entrants and shakeouts show

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\(^{11}\) This is shown in Fallick, Fleischman, and Rebitzer (2005), and is widely believed in the relevant industries.
that the firms cannot predict this either. Opportunities are available, but they are gambles, and depreciate rapidly. Thus there is noise in the payoff distribution.

**Care work**

Some media-amplification and technological uncertainty occurs in many occupations. For example, most academics and researchers operate in environments where some kind of economies of distribution occur (e.g. through publication or product manufacture), where reknown is possible, and where suppliers are imperfect substitutes for one another.

There exist occupations at the other extreme from the high-tech and media-amplified groups. England, Budig, and Folbre (2002) distinguished a set of occupations in the 1980 Census that do care work, meaning work involving face-to-face service to a recipient which increases the recipient’s capabilities. Most of these occupations were providers of medical services, teachers at any level, and social and religious workers. As they map into the occupational categories used here, the care work jobs are: physicians; dentists; other health and therapy jobs; optometrists; podiatrists; nurses; physical therapists; speech therapists; physicians' assistants; biological science instructors; chemistry instructors; physics instructors; history postsecondary teachers; postsecondary teachers of sociology; postsecondary math teachers; postsecondary teachers of education; teachers of law; postsecondary theology teachers; postsecondary home economics teachers; academic subject instructors, n.e.c. (not elsewhere classified); teachers (secondary, primary, and earlier); librarians; clergy and religious workers; dental hygienists; licensed practical nurses; dental assistants; child care workers.

These occupations tend not to have “joint consumption” or economies of distribution. Furthermore, in some of them different suppliers are near-perfect substitutes for one another. Thus they are at a far extreme from Rosen’s story. These professions do not face the technological uncertainty of the semiconductor, computer, or software industries. The graphs and regressions below show that indeed these occupations have narrowing earnings distributions since 1968. The graphs may be too tiny to read but the key observation is that the dependent variable is not trending up.
Here in a readable size are two of the largest occupations in this category.

Large scale regressions
The hypotheses about high tech occupations, media-amplified occupations, and care work occupations can be combined in a regression framework. The dependent variables in the regressions in the next tables are measures of dispersion of incomes in an occupation-year in one of the two data sets, and the independent variables are attributes of occupations. The hypotheses are about the changes in dispersion measures over time, not their levels. Therefore we include fixed effects on the occupations and measure the coefficients only on the trends. Year fixed effects are included to help screen out effects of business cycles and failures of comparability over time in the data. The year effects remove some effects artificially created by the changes in occupational category systems -- fewer occupation categories mechanically means more variation within them, even if there is no substantive change. The standardized occupation system can only imperfectly compensate for this.

The regressions illuminate tests of these hypotheses: that the high tech category and the media-amplified category will exhibit rising inequality over time in the regressions, and that the care work category will not. Separate regressions were run on the CPS data and Census data. With a fixed effect on occupations and years, we regress the measure of dispersion on a year trend for each of the (a) media-amplified occupations, (b) occupations facing the most semiconductor-related technological uncertainty by the earlier definition, and (c) care work occupations. Observations were weighted in the regression by the size of the sub-samples from which the dependent variable was estimated.
Predictors of earnings dispersion in occupation-years in the decennial U.S. Census 1960-2000

Figures in bold are statistically significant at the 5% level (that is, the p-value<.05). In the regressions, each occupation-year observation has been weighted by its sample size. Robust standard errors underly the p-values.

<table>
<thead>
<tr>
<th>Predictors of std dev of ln(wage) in Census</th>
<th>Regression 1</th>
<th>Regression 2</th>
<th>Regression 3</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>coeff</td>
<td>p-value</td>
<td>coeff</td>
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<tr>
<td>Trend if media-amplified</td>
<td>0.026</td>
<td>0.000</td>
<td>0.025</td>
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<tr>
<td>Trend if high tech</td>
<td>0.025</td>
<td>0.001</td>
<td>0.014</td>
</tr>
<tr>
<td>Trend if care work</td>
<td>-0.005</td>
<td>0.474</td>
<td>-0.005</td>
</tr>
<tr>
<td>Trend if engineer</td>
<td>-0.003</td>
<td>0.940</td>
<td></td>
</tr>
<tr>
<td>Trend if technician</td>
<td>-0.005</td>
<td>0.361</td>
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</tr>
<tr>
<td>Trend if doctor</td>
<td>0.012</td>
<td>0.434</td>
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</tr>
<tr>
<td>Trend if lawyer</td>
<td>0.015</td>
<td>0.278</td>
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<tr>
<td>Trend if scientist</td>
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<td>0.445</td>
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</tr>
<tr>
<td>Trend if college faculty</td>
<td>0.004</td>
<td>0.370</td>
<td></td>
</tr>
<tr>
<td>Trend if manager</td>
<td>0.017</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td>Trend if sales job</td>
<td>0.007</td>
<td>0.240</td>
<td></td>
</tr>
<tr>
<td>Annual trend overall</td>
<td><strong>-0.010</strong></td>
<td>0.005</td>
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</tr>
<tr>
<td>Year (decade) fixed effects</td>
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</tr>
<tr>
<td>387 occupation fixed effects</td>
<td>yes</td>
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<td>Yes</td>
</tr>
<tr>
<td>sample size</td>
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<td></td>
<td>1635</td>
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<tr>
<td>Adjusted R-squared</td>
<td>0.77</td>
<td></td>
<td>0.88</td>
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</table>
Predictors of earnings dispersion in occupation-years in the March CPS, 1968-2003

Dependent variable is standard deviation of log-wage-and-salary within occupation-year

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Regression 1</th>
<th></th>
<th>Regression 2</th>
<th></th>
<th>Regression 3</th>
<th></th>
<th>Regression 4</th>
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<th>Regression 5</th>
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<tr>
<td></td>
<td>coeff</td>
<td>p-value</td>
<td>coeff</td>
<td>p-value</td>
<td>coeff</td>
<td>p-value</td>
<td>coeff</td>
<td>p-value</td>
<td>coeff</td>
<td>p-value</td>
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<tr>
<td>Trend if media-amplified job</td>
<td>0.0023</td>
<td>0.016</td>
<td>0.0022</td>
<td>0.018</td>
<td>0.023</td>
<td>0.000</td>
<td>0.018</td>
<td>0.000</td>
<td>0.018</td>
<td>0.000</td>
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<tr>
<td>Trend if high tech job</td>
<td>0.0069</td>
<td>0.000</td>
<td>0.023</td>
<td>0.000</td>
<td>0.020</td>
<td>0.000</td>
<td>0.016</td>
<td>0.000</td>
<td>0.020</td>
<td>0.000</td>
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<tr>
<td>Trend if care work</td>
<td>-0.0003</td>
<td>0.549</td>
<td>-0.002</td>
<td>0.254</td>
<td>-0.002</td>
<td>0.382</td>
<td>-0.005</td>
<td>0.018</td>
<td>-0.005</td>
<td>0.017</td>
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<td>Trend if engineer</td>
<td>-0.007</td>
<td>0.034</td>
<td>-0.007</td>
<td>0.034</td>
<td>-0.007</td>
<td>0.034</td>
<td>-0.010</td>
<td>0.001</td>
<td>-0.009</td>
<td>0.000</td>
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<tr>
<td>Trend if technician</td>
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<td>0.016</td>
<td>-0.017</td>
<td>0.011</td>
<td>-0.018</td>
<td>0.007</td>
<td>-0.019</td>
<td>0.006</td>
<td>-0.009</td>
<td>0.000</td>
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<tr>
<td>Trend if doctor</td>
<td>-0.007</td>
<td>0.062</td>
<td>-0.011</td>
<td>0.002</td>
<td>-0.011</td>
<td>0.002</td>
<td>-0.011</td>
<td>0.001</td>
<td>-0.011</td>
<td>0.001</td>
</tr>
<tr>
<td>Trend if lawyer</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.007</td>
<td>0.062</td>
<td>-0.011</td>
<td>0.002</td>
<td>-0.011</td>
<td>0.001</td>
</tr>
<tr>
<td>Trend if scientist</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.008</td>
<td>0.159</td>
<td>0.008</td>
<td>0.179</td>
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<tr>
<td>Trend if college faculty</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.001</td>
<td>0.574</td>
<td>-0.002</td>
<td>0.489</td>
<td>-0.001</td>
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<tr>
<td>Trend if manager</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.031</td>
<td>0.000</td>
<td>-0.031</td>
<td>0.000</td>
<td>-0.031</td>
<td>0.000</td>
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<tr>
<td>Trend if sales job</td>
<td>-0.004</td>
<td>0.122</td>
<td>-0.004</td>
<td>0.122</td>
<td>-0.004</td>
<td>0.092</td>
<td>-0.004</td>
<td>0.092</td>
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<tr>
<td>Annual trend overall</td>
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<td></td>
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<tr>
<td>35 year fixed effects</td>
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<td></td>
<td>Yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>386 occupation fixed effects</td>
<td>Yes</td>
<td></td>
<td>Yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
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<tr>
<td>Sample size</td>
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<td>11187</td>
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<td>11138</td>
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<td>Adjusted R-squared</td>
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<td>0.900</td>
<td>0.90</td>
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<td>0.91</td>
<td>0.910</td>
<td>0.91</td>
<td>0.910</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Figures in bold are statistically significant at the 5% level (that is, the p-value<.05). In the regressions, each observation has been weighted by its sample size. Robust standard errors underly the p-values. In the underlying calculations of inequality, observations of income were equal-weighted, that is, did not use the CPS-assigned person-weights which adjust for demographic characteristics. Year fixed effects help compensate for the changing number of occupations -- fewer occupation categories mechanically tends to mean more variation within them, even if there were no substantive change.
By the definitions of the groups and the inequality measure used here, the media-amplified (superstars) professions and the technologically turbulent (high tech) professions experienced growing earnings inequality within them. It is detected at a high level of statistical significance in both data sets. Furthermore the hypothesis that care work jobs do not experience rising inequality based on the forces of technological turbulence or media-amplification is supported. In these occupations the trend in inequality is not statistically significantly different from zero and is more likely to be negative than positive.

The excluded category, separate from media-amplified occupations, technologically uncertain occupations, and care work occupations, includes most managers, sales workers, researchers, analysts and most clerical workers. The working hypothesis about them is that they can experience some of these high tech or media-amplified effects, more than care workers do.

It does not seem that these results are artifacts of growing or shrinking occupations, or rising or falling wages generally in the occupations. When occupation size is included as a predictor (not shown) its coefficient is near zero.

The remaining regressions test variants of these hypotheses. When an indicator for other (non-Moore’s-Law) engineering and technical occupations were added to the regression, the coefficient on these was opposite in sign to those for the turbulent semiconductor-influenced occupations. Any force of technological turbulence has been overwhelmed by other forces -- perhaps standardization in training, certification, and tools.

The category of superstars occupations which were media-amplified shows rising inequality within the occupations. But when we test the expanded categories of doctors and lawyers who might have experienced a bidding-up effect, it is not there in the CPS data, and is noisy in the decennial Census data. Some of these jobs are also defined as care work occupations, and seem to look more like care professions according to the inequality trends than like superstars professions.

Further work to be done on residuals and occupation categories

A direct test of uncertainty is possible. Predictors of wages ought to lose some traction, that is, predictive power, in a period of uncertainty. Subtracting the wages predicted by a regression from the observed wages generates a series of wage residuals. Regressing the square of these residuals
on various predictors tells us how the magnitudes of the errors in the predictions are a function of time, occupation, or other regressors. The procedure is analogous to an ARCH (autocorrelated) specification of volatility in finance. Based on the residuals from a regression with year, a quartic in age, years of education, and age times education, not shown here, the “unexplained” residuals rise for the media-amplified occupations but not for the high tech professions. There is more to be done in this area.

Generally speaking, the results for the high tech effect were weaker in the regressions from the Census than from the CPS. One possible reason for this comes from the Census 1960 measures of inequality for electrical engineers and electrical engineering technicians, which are higher than in 1970. In 1960, there were almost no semiconductor engineers. Perhaps inequality among electrical engineers (such as experts in telephone systems and power systems) was declining at that time, and the population of semiconductor engineers was too few to make a difference. If so, inequality among electrical engineers would have hit a low some time between 1960 and 1980, and only then would the effect to be estimated have dominated. A second reason that there would be noise in the 1960 data is that the Census had so many fewer classifications of occupations then. With careful work it is possible to impute 1970 occupations to 1960 data on the basis of dual-coded data sets with other variables taken into account besides the 1960 occupation classification (as in Meyer, 2006). This is an avenue for further improvement.

**Conclusion**

There is evidence here of a rise in earnings dispersion within the media-amplified occupations since 1968, supporting Rosen’s superstars hypothesis about joint consumption and trends in economies of distribution. The data here did not support the hypothesis of Rosen (1981) and Frank and Cook (1995) that expanded markets would produce substantially more unequal incomes in the larger class of professions where the output of different workers is not substitutable.

There is evidence also of a long term rise in earnings dispersion within the high tech occupations. Turbulence or uncertainty in information technology seems to have been high throughout the period, presumably because it is closely related to the rapid improvements in the capabilities of semiconductor chips. This would produce in the population several effects:
obsolescence of previous skills; big opportunities; and qualitative differentiation in the tasks of people in these jobs.

Hopefully methods like these can enable observers to detect long-term technological change and turbulence in a statistical way. The U.S. “productivity slowdown” after 1973 may be related to the chaotic economic processes of inventing new devices, competing in disequilibrium markets, and setting new standards. Methods like these can move the analysis of inequality toward a substantive understanding of the effects of particular technological changes on particular occupations. Another long term benefit could be a clarification of the kinds of labor market regulation that restrict adaptations to technological change. To gain the benefits of new technological possibilities, it may be necessary for some workers to operate in disequilibrium environments for long periods.

References


GDP in the United States averaged 7456.57 USD Billion from 1960 until 2019, reaching an all time high of 21427.70 USD Billion in 2019 and a record low of 543.30 USD Billion in 1960. This page provides - United States GDP - actual values, historical data, forecast, chart, statistics, economic calendar and news. The Gross Domestic Product (GDP) in the United States was worth 21427.70 billion US dollars in 2019, according to official data from the World Bank and projections from Trading Economics. The GDP value of the United States represents 17.65 percent of the world economy. Source: World Bank. GDP in the United States averaged 7456.57 USD Billion from 1960 until 2019, reaching an all time high of 21427.70 USD Billion in 2019 and a record low of 543.30 USD Billion in 1960. The Level of Occupational Earnings Inequality We chose the coefficient of variation of earnings, defined as the ratio of the standard deviation of earnings to mean earnings. The occupational coefficient of variation across all occupations was 6.68 in 1960 and 7.70 in 1970, lower than the overall level of inequality in the two years (Table 1). The slight rise in the average level of occupational inequality, despite the finer occupational classification scheme in 1970, suggests that the presence of occupational. The mean coefficient of variation varied considerably between occupational groups. In 1960 it was highest among service occupations, followed by clerical, professional, operative and skilled occupations. Causes of income inequality in the United States describes the reasons for the unequal distribution of income in the US and the factors that cause it to change over time. This topic is subject to extensive ongoing research, media attention, and political interest. Income inequality in the United States grew significantly beginning in the early 1970s, after several decades of stability. The US consistently exhibits higher rates of income inequality than most developed nations, arguably due to the