TECHNOLOGICAL INNOVATIONS AND THE LABOR FORCE: DOES JOB POLARIZATION LEAD TO WAGE POLARIZATION?

An Undergraduate Research Scholars Thesis

by

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ABSTRACT

Technological Innovations and the Labor Force: Does Job Polarization Lead to Wage Polarization?

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Technological innovations have drastically increased labor productivity, but low labor force participation continues to exist, with labor force participation at its lowest rate since 1977. Our analysis draws from the job polarization phenomenon, which explains how automation has been a contributing factor in the drastic decrease of middle-skill jobs, while it has assisted in the increase of employment shares for high-skill and low-skill occupations. The purpose of this research is to investigate the relationship between job polarization and wage polarization. We test whether changes in employment shares affect occupational income trends. We analyze real annual median income using a time series approach, focusing separately on low, middle, and high-skill occupational categories. We further analyze these broad occupational categories at a micro level by examining changes in the real median annual income of individual occupations that comprise them. Results from our time series analysis are compared to the trends in employment shares of each occupational category. We find minimal evidence that changes in employment shares affect income trends. Job polarization, in fact, does not lead to wage polarization. Finally, we speculate on the future of the labor force as technological innovations continue to alter tasks performed and change the configuration of occupations.

ACKNOWLEDGMENTS

I would like to thank the Texas A&M University Department of Economics for their support and guidance through my undergraduate studies. I am particularly grateful to my research advisor, Professor Dennis Jansen, for the technical advice he offered throughout the entirety of this project. Without the numerous hours Dr. Jansen and several professors devoted in providing quantitative help, this undergraduate research thesis would not have been possible. I would also like to thank Dr. Jonathan Meer for directing the Undergraduate Economics Research Opportunities Program and for providing additional scholarly resources that aided in the completion of my thesis. A final thanks to the person for whom I brought about this research — my mother, Margarita Sanchez.

SECTION I

INTRODUCTION

Technological innovations have altered the share of employment across different skill levels. In a recent article, "Why Are There Still So Many Jobs? The History and Future of Workplace Automation", David Autor (2015) focuses on evaluating the job polarization phenomenon, which explains how automation has been a contributing factor in the drastic decrease of middle-skill jobs. As noted in figure 1, Autor shows that employment in high-skill and low-skill occupations have increased while jobs in the middle-skill sector have decreased. Our analysis draws from the job polarization phenomenon. We attribute changes in the share of employment to shifts in labor demand. As noted by Autor, technological innovations are a primary driver of shifts in labor demand. We test whether changes in employment shares, *ceteris paribus*, affect occupational income trends. Using a time series approach, real annual median income will be analyzed for the top ten occupational categories that comprise the low, middle, and high-skill levels.

Given the labor demand/ technological change interpretation suggested by Autor, movements in employment should be accompanied by movements in income or wages. Given Autor's employments results, we expect real annual median income for the personal care, the food/cleaning service, the protective service (low-skill), technicians, professionals, and the managers occupational categories (high-skill) to rise over time according to changes in their employment shares. On the other hand, we expect real annual median income for the operators/laborers, the production, the office/admin, and the sales occupational categories (middle-skill) to decline according to the shifts in their labor demand. We primarily expect the

production category to experience a drastic decline in real annual income due to the fact that labor demand has drastically decreased since 2007. We attribute this drastic decrease to a higher amount of technological innovations introduced to the production category. Subsequently, we expect real median annual income to steeply rise for occupational categories whose share of employment exhibit large increases and vice versa, for occupational categories who experience declines in labor demand.

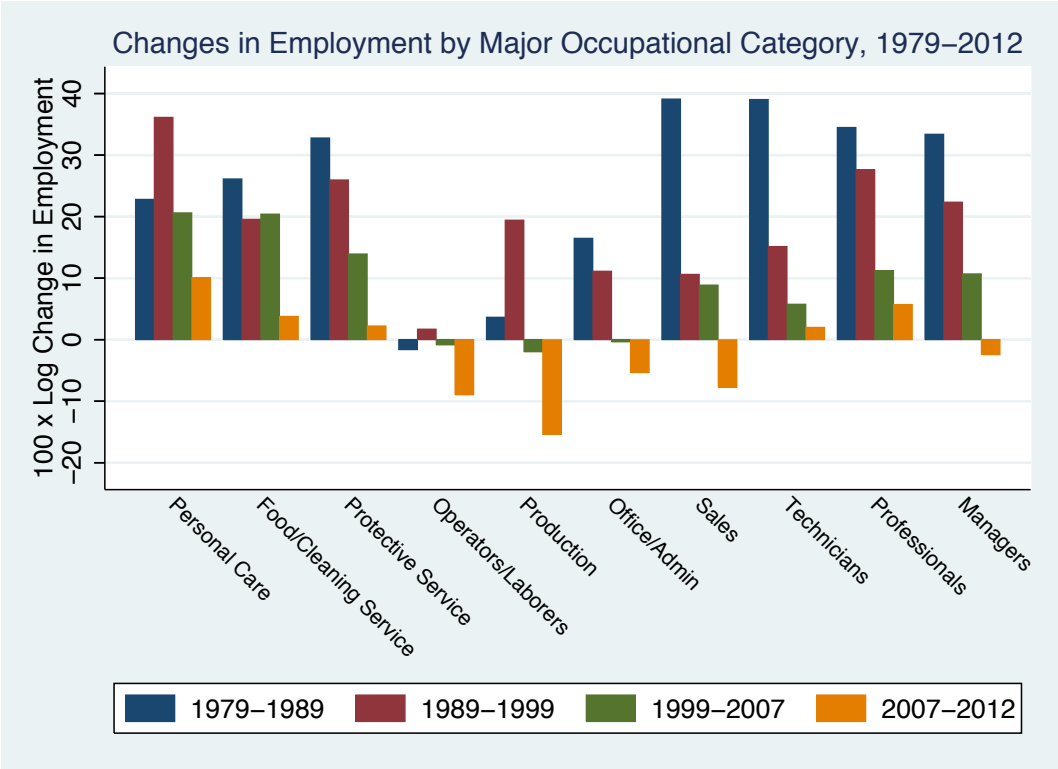

Figure 1. Change in employment shares for major occupational categories. From left to right, the personal care, food/cleaning services, and protective service occupations comprise the low-skill level. Operators, the production, the office/admin, and the sales occupational categories comprise the middle-skill level. Technicians, the professional, and the managers occupational category comprise the high-skill level.

SECTION II

DATA AND METHODOLOGY

Data and Methodology

Large sample sizes are necessary in analyzing changes of annual income over time within Autor's (2015) top ten occupational categories. Toward that end we use the Census samples from the Integrated Public Use Micro Series (IPUMS USA) for the years 1980, 1990, and 2000 and the American Community Survey (ACS) for the years 2001-2014. According to the Census samples, for the years 1980, 1990, and 2000, five percent of the US population is represented. The ACS samples indicate that for year 2001 0.43 percent of the population is represented, for 2002 0.38 percent, for 2003 and 2004 0.42 percent, and for years 2005-2014 the ACS samples represent one percent of the US population. Additionally, we further analyze Autor's (2015) top ten occupational categories at a micro level by observing individual occupations that comprise each category. Sampling densities of the micro samples follow the same population percentiles as the Census and ACS samples.

We follow Autor's (2015) sample restrictions; thus, the individual workers are between the ages of 16 and 64, which allows us to focus on representative samples of the working-age population. Following these restrictions is necessary in order to replicate our analysis using Autor's data set for comparability. Individuals belonging to institutional groups such as mental institutions, nursing homes, prisons, or correctional institutions are removed from the data set, along with

those who were employed five years ago[1]. Individuals not employed and unpaid family workers are excluded as well. We drop individuals whose occupations do not comprise the personal care service, food/cleaning service, protective service, operators/laborers, production, office/ administration, sales, technicians, professionals, and managerial broad categories.[2] For our primary analysis, further restrictions are added; we observe employees who work in the 50 states and the District of Colombia, dropping employees whose workplace is in Puerto Rico and foreign countries. This does not change our results significantly; therefore, comparison to Autor's data sets are acceptable.

For our samples we consider workers with positive annual incomes, eliminating employees that responded net losses or $0.00 in annual income. We further restrict our income variable by dropping workers whose annual employment earnings are less than $5,356.00 in 1999 dollars or $10,240.67 in 2015 dollars (equal to one-half of the 1999 real minimum wage based on a 40-hour week).[3] Annual income reports include the respondent's total pre-tax wage and salary income. Census samples for the years 1980, 1990, and 2000 report income received for the previous calendar year. Therefore, we will refer to the Census samples as years 1979,1989, and 1999. The reference period for the ACS samples report a respondent's annual income for the past

[1] Respondents who report active participation in an occupation in the last five years are individuals who served in military specific occupations. As classified by IPUMS these individuals are "unemployed, with no work experience in the last 5 years or earlier or never worked." These individuals perhaps are not included in the unemployment occupation code because they receive unemployment benefits through the Unemployment Compensation for Ex-servicemembers program. Individuals receiving these benefits are not subject to the maximum duration of unemployment benefits set by the federal government.

[2] Visit http://dx.doi.org/10.1257/jep.29.3.3 to access all the occupations that comprise Autor's top 10 broad occupational categories.

[3] This calculation draws from Juhn et al. (1993) income restriction methods.

12 months from the month the respondent was surveyed[4]. Sources of income include employee's wages, salaries, commissions, cash bonuses, tips, and additional money received from an employer. We exclude income earned from a respondent's own business, professional practice, farm income, Food Stamps, Social Security pensions, housing subsidies, disability pension (other than Social Security), Supplementary Security Income (SSI), welfare benefits, money from an estate or trust, interest, dividends, royalties, and rents received.

Furthermore, person sampling weights (PERWT) are used to provide the population represented by each individual within the Census and ACS samples. The 1979 Census sample is the only exception since it is a flat sample where each individual accurately represents the population of the sample.

Multiple studies use the Census and ACS samples, but none analyze Autor's occupational categories year by year (2001-2014) for annual income trends. Autor uses Census samples for years 1979, 1989, 1999, a combined three year ACS sample for 2006-2008, and an ACS sample for year 2012 to analyze mean wages by occupational skill percentile. This study proves to be more informative because we observe Autor's top ten occupational categories at a granular level, year by year since 2001, which allows us to provide more accurate results that might be hidden or not able to be observed in Autor's analysis. Outliers can dramatically affect the mean leading to unreliable measures of annual income. Studies conducted by the PEW Research Center have shown that real wages have increased by 9.7% for workers near the top of the earnings distribution, almost 7% more than workers in the lowest tenth of the earnings distribution.

[4] See limitations for further details.

Focusing on median annual income results in a better income representation because outliers, such as workers at the top of the income distribution within each occupational group will not affect earnings analyzed. Additionally, this study analyzes recent observations for years 2013 and 2014, which previous studies did not have access to. These additional years may uncover new findings which other studies were not able to observe due to the lack of data.

This study further analyzes the top ten occupational categories at a micro level. We dissect the top ten broad categories by composition of individual occupations. The top two occupations in 1979 with the largest percentage of composition for each broad category is individually analyzed for median annual income trends. We analyze these occupations at a micro level to see if they follow the same income trends as that of its broad category. If these occupations do not follow the same trends, this will show us that the broad occupational categories are not an accurate representation of the individual occupations that comprise them, suggesting that occupations should be analyzed individually rather than relying on broad occupational statistics as an indicator of its median income trends.

For each broad occupational category and its two major occupations, we analyze median and mean hours worked per week. This helps us determine if trend changes in annual median income result from changes in employees' hours worked per week or if such trends result from shifts in labor demand.

Limitations

We do our best to restrict and omit certain observations to analyze reliable representative samples of the labor force. However, certain limitations can affect our results. For example, the Census samples are top-coded at nominal income values of $75,000 for the year 1979, $140,000 for the year 1989, and $175,000 for the year 1999. The ACS samples are top-coded at nominal income values of $200,000 for years 2001 and 2002, and for year 2003-onward top codes are coded at the 99.5th percentile in states reported annual income.[5] We do not adjust annual incomes for top-coding, which may affect our reported median incomes, especially for high-skill occupations. Furthermore, IPUMS annual incomes represent midpoints of intervals instead of exact dollar amounts. Year 1979 represents midpoints of ten-dollar intervals, and year 1989 expresses annual income in exact dollar amounts instead of intervals. The 1999 Census sample and the ACS samples report annual income as follows:

No income	$0
$1 - $7	$4
$8 - $999	rounded to nearest $10
$1,000 - $49,999	rounded to nearest $100
$50,000 or more	rounded to nearest $1000

This table displays how annual income is rounded for individuals surveyed. Respondents who report no income are assigned annual income of $0.00. Income is rounded to the nearest hundred dollars for those reporting annual income between $1,000 to $49,999. Therefore, we report

[5] For the year 1989, higher amounts are expressed as the state medians of values above the top code. For year 1999 and all ACS samples, higher amounts are coded as the state means of values above the listed top code value for each sample year.

estimates of median annual incomes instead of accurate dollar values, potentially losing credibility for accurate annual incomes. This could have been avoided by utilizing individuals' social security data to retrieve exact annual income reported.[6] However, access to this data is limited, causing us to rely on IPUMS annual income reports.

Furthermore, income reported for the ACS samples is not an accurate representation of an individual's income for the year surveyed. Respondents are surveyed throughout the year. Therefore, the reference period for annual income earned by a respondent surveyed in February of year 2011 will be February 2010 – February 2011. The ACS income reports are therefore underestimated for January respondents and overestimated for December respondents.[7]

[6] Kopczuk et al. (2010) use Social Security Administration micro data to analyze the evolution of annual earnings. Annual earnings are top-coded prior to 1978, but after 1978 earnings are no longer top-coded.
[7] Adjusting income dollar amounts to calendar-year dollars still produces over and underestimates. We therefore do no adjust nominal values. For adjustment factors visit https://usa.ipums.org/usa/acsincadj.shtml.

SECTION III

RESULTS

Macro Occupational Categories

Autor examines broad (macro) occupational categories such as protective services. These broad categories might hide what is happening in more specific (micro) categories, such as private investigators and detectives, a subset of protective services. After conducting a time series analysis, we find little evidence that changes in employment shares affect income trends. Job polarization, in fact, does not lead to wage polarization. We observe that real median incomes within Autor's top ten occupational categories have experienced scant growth over the last two decades. Figures 9, 10, and 11 demonstrate this by depicting median annual income trends from the years 1979 to 2014. Figures 2a, 2b, and 2c demonstrate the cumulative percentage growth for annual income using 1979 as the base year. Median incomes for the top ten occupational categories do not follow the same trends as their employment shares. With the exception of the protective service occupational group, real income for low-skill occupations began to fall in 1999 and has remained stagnant since. In fact, in 2014, real annual income for these occupations was roughly $2,500 lower than their earnings in 1999. Therefore, instead of experiencing increases in annual incomes, as expected, these occupations had a reverse outcome. Given the fact that low-skill workers have not been completely replaced by technological advances, these income trends show that technological changes resulting in shifts in labor demand are not a major catalyst for stagnation of median annual incomes within occupations.

On the contrary, the protective service group has experienced higher median income trends than middle-skill occupations; following Autor's occupational coding methods, we observe that criminal investigators and detectives, which are highly paid, are included in the protective

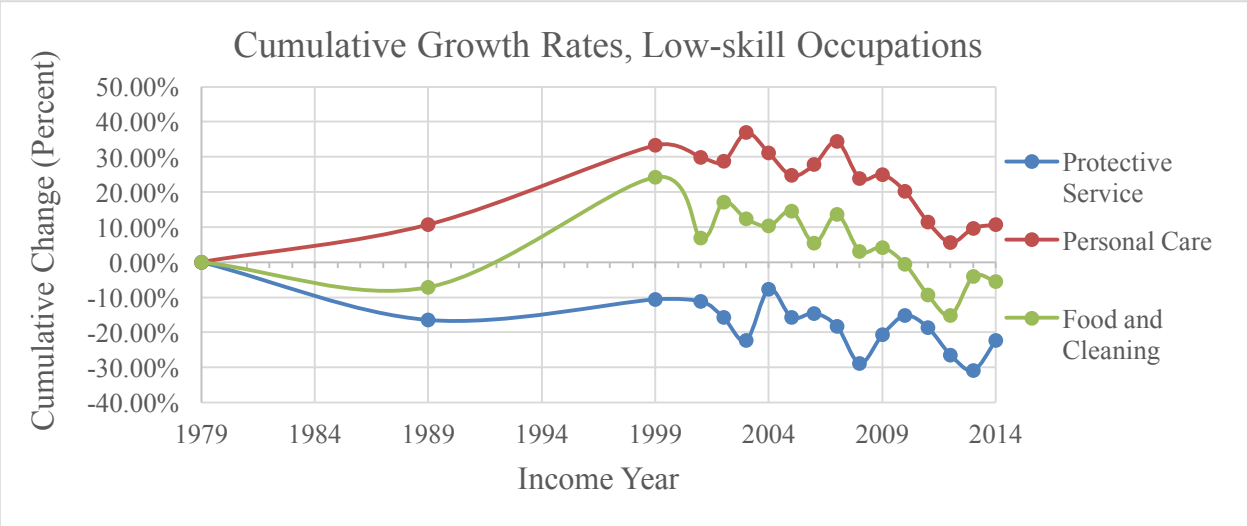

Figure 2a Cumulative growth rates for low-skill occupations.

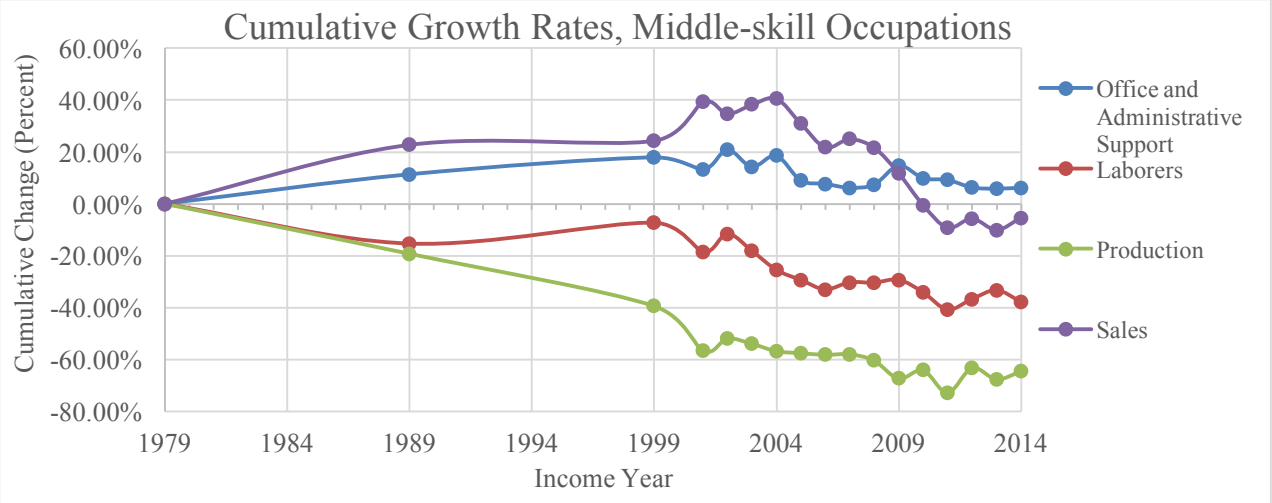

Figure 2b. Cumulative growth rates for middle-skill occupations.

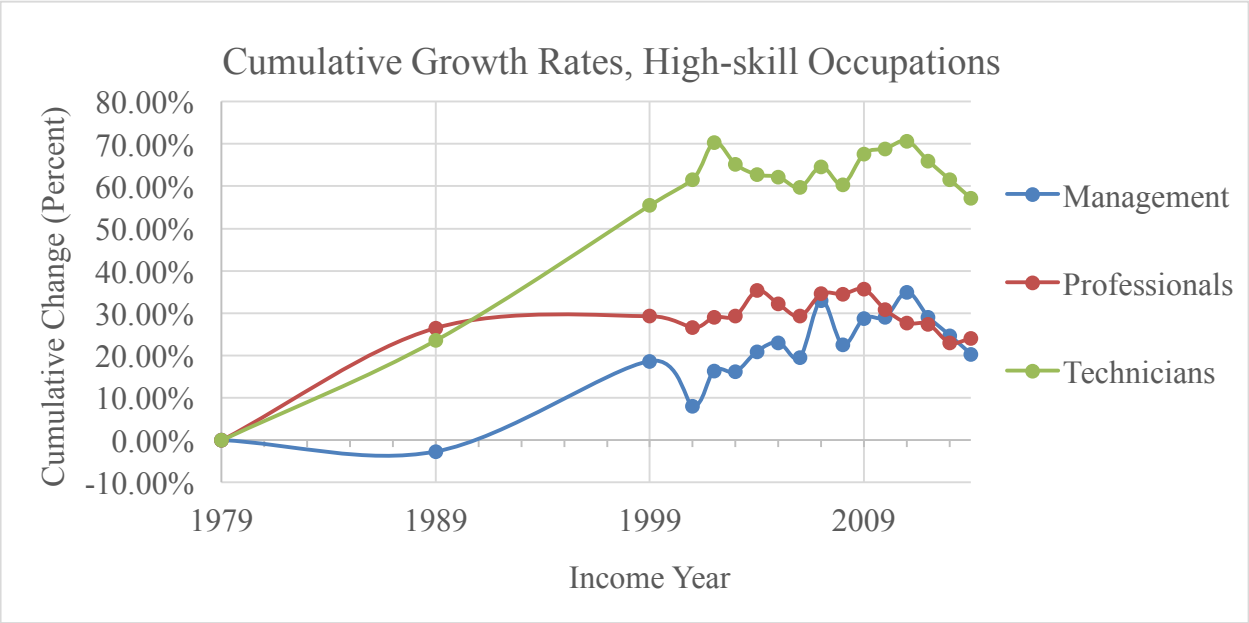

Figure 2c. Cumulative growth rates for high-skill occupations.

service category[8]. According to the Bureau of Labor Statistics (BLS), the median annual wage for detectives and criminal investigators is $79,870, while the median annual wage for guards is $24,410. Although criminal investigators and detectives are highly paid, these jobs may not require high skill levels. Private detectives and investigators, for the most part, need a high school diploma and several years of work experience in the military or law enforcement occupations (bls.gov). Due to these somewhat minimal educational requirements, they are still included in the low-skill protective service category. The inclusion of these high paying occupations (detectives and criminal investigators) is the major driver for the protective service group experiencing higher annual median incomes than middle-skill occupations. Although the

[8] The protective service occupation is comprised of protective service occupations, not elsewhere classified (n.e.c.), sheriffs, bailiffs, and other law enforcement officers, correctional institution officers, guards and police, except public service, guards supervisors, crossing guards, protective service administrators, police and detectives supervisors, public service police and detectives, firefighting and fire prevention occupation supervisors, firefighting occupations, fire inspection and fire prevention occupations, detectives and criminal investigators, private detectives and investigators, security guards and gaming surveillance officers, and transportation security screeners.

annual median income for the protective service occupational category is higher, their income patterns are similar to the personal care service and food and cleaning service occupations (low-skill), where real median income has declined about $2,500.00 since 1999.

As the labor demand for employees in middle-skill occupations declines, we expect these occupations to experience a decrease in real annual income. This is primarily evident in the sales and production occupational categories. The production group has experienced a 20% decrease in real median annual income since 1979. This occupation category has experienced a fall in income similar to that of low-skill occupations, with an 8% real median income decline for production and 10% decline for the sales category since 1999. The decline in real median income can be explained by a large decrease in the share of employment. Based on Autor's job polarization graph[9], we observe that the production industry has experienced the largest decline in share of employment among the top ten occupational categories. Additionally, the BLS affirms that the production industry is projected to experience the largest and fastest job contraction by 2022. This large decrease in labor demand for production occupations, resulting from technological innovations, helps explain the 20% decrease in real annual median income. The BLS credits productivity gains in the manufacturing sector, which is a primary employer of production occupation workers, as a driver for decreases in labor demand for production occupations. To maintain productivity gains, more investments have been allocated to capital factors of production. These investments have resulted in the decline of the share of employment for the production category, consequently, decreasing its real median income. As technology advances and improves capital factors of production, robots (capital) will begin to substitute

[9] See Figure 1

human workers at faster rates, negatively affecting the share of employment for production occupations in the long run.

Although technological innovations seem to affect median incomes for production and sales occupations, we cannot credit technological innovations as the sole stimulant in declines of real median income for middle-skill occupations because not every occupational category comprising the middle-skill sector has experienced a high percentage decline in real wages. Based on the changes of the share of employment, each occupational category in the middle-skill sector has not experienced the same level of technological innovations. For example, median annual income for laborers and the office and administrative support category is expected to fall roughly 20% (similar to production occupations) in 2014 in comparison to its 1979 income values. In fact, the laborers and the office and administrative support categories have similar income trend patterns as low-skill occupations. Laborers and the office and administrative support categories have both experienced scant growth in real median annual income. As seen in figure 10, the laborers and office and administrative support occupational categories have followed similar income trends since 1989. Real median annual income for these occupational categories has fallen by 4% in the last ten years. Income has fallen by 10% for laborers since 1999, while it has remained stagnant for the office and administrative support group, which have experienced a 4% decline in real median annual income. These minimal declines do not reflect the same income declines as seen since 1989 in the production and sales categories, that also belong to the middle-skill sector. Therefore, we do not conclude that technological innovations decrease real median annual incomes for middle-skill occupations.

Through the years, high-skill occupations have experienced more variability in their real median income trends, but overall, real median income for these occupational categories have barely changed in comparison to their 1999 median annual income. The management occupational category experienced steady growth in real income until 2007. In 2007 real median income had grown by 5% since 1999. After 2007 real income fell, most likely due to the great recession, which began in December of 2007. It should be noted that Autor's job polarization graph (Figure 1) also demonstrates that the managerial category experienced a decline in the share of employment beginning in 2007. Due to declines in the share of employment and the fact that the great recession began in late 2007, we do not credit technological innovations as the only stimulant for the decrease in real median income. Income then grew at a moderate pace only to decline back in 2011, almost returning to its 1999 median annual income in 2014. In fact, real median annual income was only 1% higher in 2014 than income in 1999. Income for the managerial occupational category has not drastically risen as we had expected.

The professional occupational category experienced moderate increases in median annual income until 2009. After 2009 real median income fell by 2% in 2010, followed by a 1% decline in 2011, remained stagnant in 2012, then fell by 2% in 2013. Income increased by less than 1% in 2014 but has declined by 2% in comparison to its 1999 real median annual income. We expected annual median incomes to rise but instead observed minimal decreases since 2009. Comparing these income trends to the trends in the share of employment for the professional category leads us to conclude that technological innovations do not affect changes in real median income. We conclude the same results for the technician occupational category. Real median

income fell moderately year by year since 2002 and increased slightly in 2007. By 2014 income grew a mere 1% in comparison to the median annual income of the year 1999.

Our time series analysis primarily indicated that real median annual income for workers in all occupational categories have slightly declined in comparison to the 1999 corresponding income, and have experienced scant growth through the years. We analyzed usual hours worked per week for each broad occupational category to determine if the hours worked are the culprit behind the observed stagnant wages. Analyzing the median number of weeks worked for each occupational category can further clarify the observed income trends. This data is not available so analysis of usual hours worked is sufficient. We expected hours worked to slightly decline for occupational categories whose real median annual income has fallen. Our results showed that 40 hours are the median usual hours worked per week for every occupational category year by year. Since hours worked have not changed, we do not attribute changes in hours worked to cause income declines and stagnations for the broad occupational categories.

We replicated our analysis using Autor's data set for comparison. As seen in figure 12 high-skill occupations presented growth in real wages since 1989, as expected. Median annual income trends for middle-skill occupations displayed decreases in real income since 1989. While low-skill occupations depicted stagnant and minimal decreases in real median annual income. Figures 3a, 3b, and 3c displayed cumulative growth rates for annual incomes using 1979 as the base year. Autor's data set depicted the expected income trends for middle and high-skill occupations. With the exception of the combined 2006-2008 data files, our analysis generated identical median annual income values as Autor's 1979, 1989, 2000, and 2012 data files. Although figure 12

proves to display the expected median annual income trends for high and middle-skill occupations, adding two more years of data changes these outcomes. The additional data available generated income trends as those seen in figures 9, 10, and 11. Our analysis for income trends in occupational categories is more informative with the inclusion of annual income data for the years 2013 and 2014.

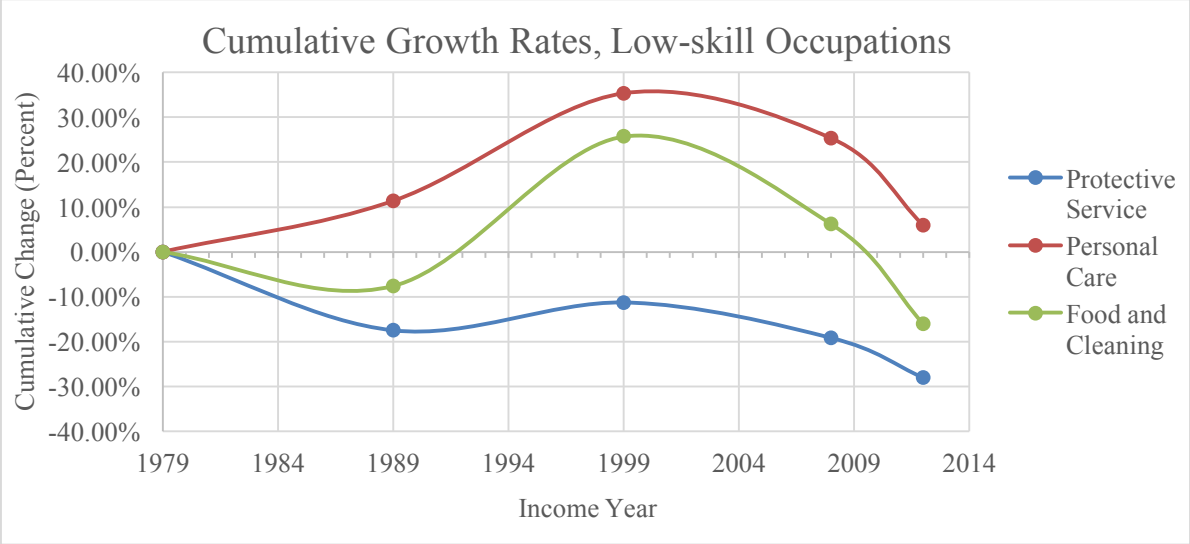

Figure 3a Cumulative growth rates for low-skill occupations using Autor's data set.

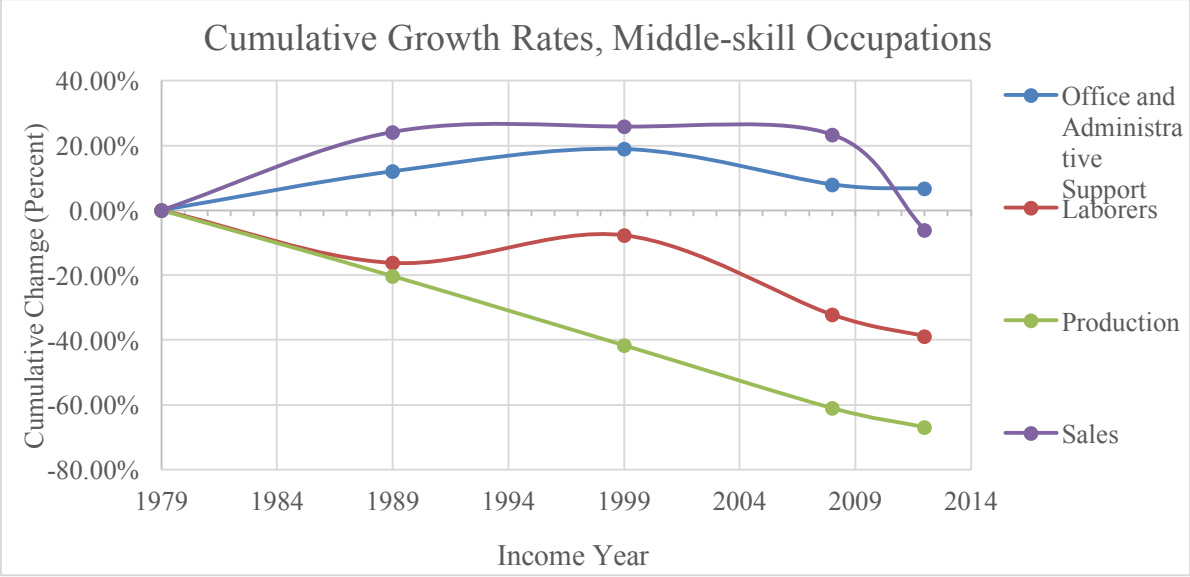

Figure 3b Cumulative growth rates for middle-skill occupations using Autor's data set.

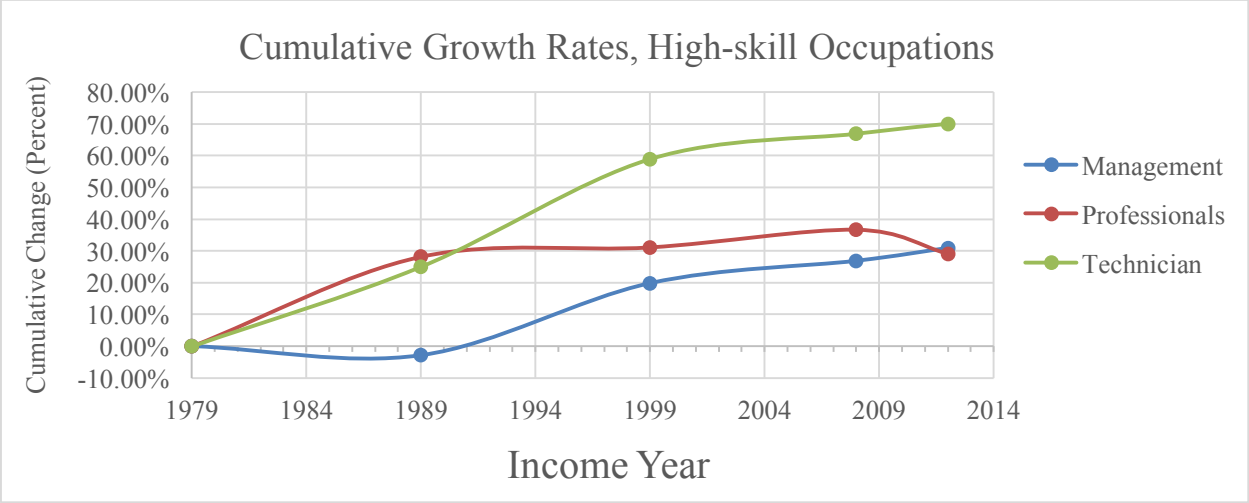

Figure 3c. Cumulative growth rates for high-skill occupations using Autor's data set.

Micro Level Analysis

We now analyze the individual top two occupations in 1979 with the largest percentage of composition for each broad category. We analyze these occupations at a micro level to determine if their annual income trends are similar to that of its broad category. The time series analysis demonstrate that individual occupations do in fact follow the same income trends as their corresponding broad category. We include several graphical examples for comparison. Figure 4 depicts the trends in median annual income for carpenters who belong in the production occupational category (a low-skill occupation). As expected real median income has fallen by 16% since 1979 in comparison to a carpenter's annual income in 2014. This decline reflects the similar decline of 20% for the production category. Figures 5 and 6 display the income trends for occupations belonging to the low-skill sector. Real annual median income for nursing aides and janitors and cleaners are lower than their 1999 income values. Nursing aides have primarily exhibited stagnant to minimal decreases in annual income. On the other hand, janitors and cleaners have experienced drastic income declines since 1979. Instead of experiencing increases

in annual incomes, as expected, these individual occupations had a reverse outcome. Our micro level results were prominent in the macro low-skill occupational categories, which depict similar income patterns to individual occupations. Figure 7 exhibits more variability in annual income for managers and administrators until 2007. After 2007 income decreased and has stagnated ever since. The income trend for managers and administrators behaves according to the income patterns of their corresponding management occupational category. Income for managers and administrators has not drastically risen as we had expected.

The micro level time series results for individual occupations demonstrates that the macro occupational categories provide reliable and accurate representations of annual median income patterns for the individual occupations that comprise them. Furthermore, annual median income trends for individual occupations do not follow the same patterns as trends in employment shares for their corresponding broad occupational categories. Median income trends for individual occupations emphasize that technological innovations are not the only determinant of income patterns.

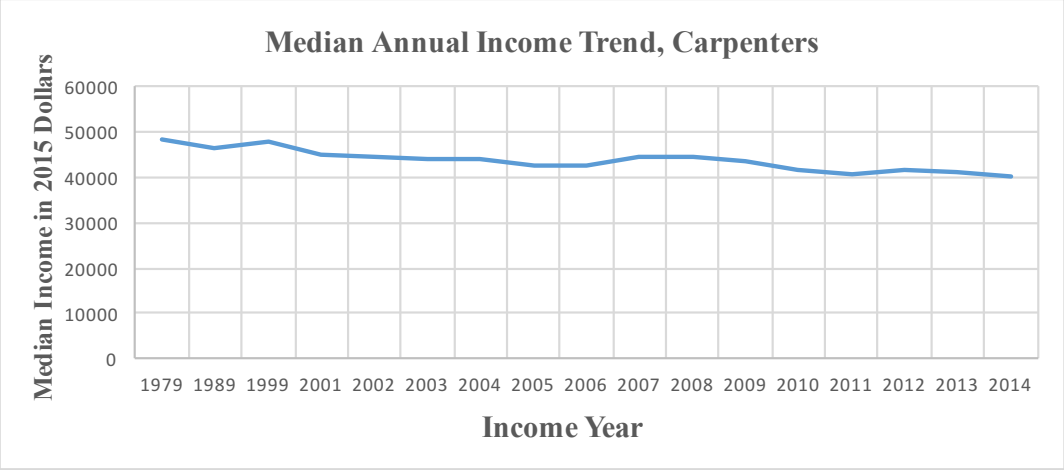

Figure 4. Real median annual income trends in 2015 dollars for carpenters who belong in the production occupational category.

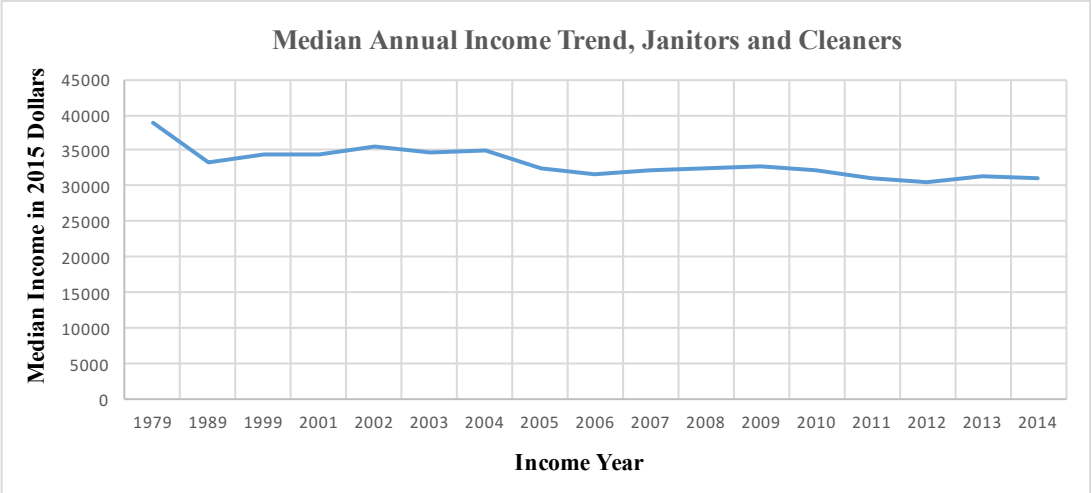

Figure 5. Real median annual income trends in 2015 dollars for janitors and cleaners who belong in the food and cleaning occupational category.

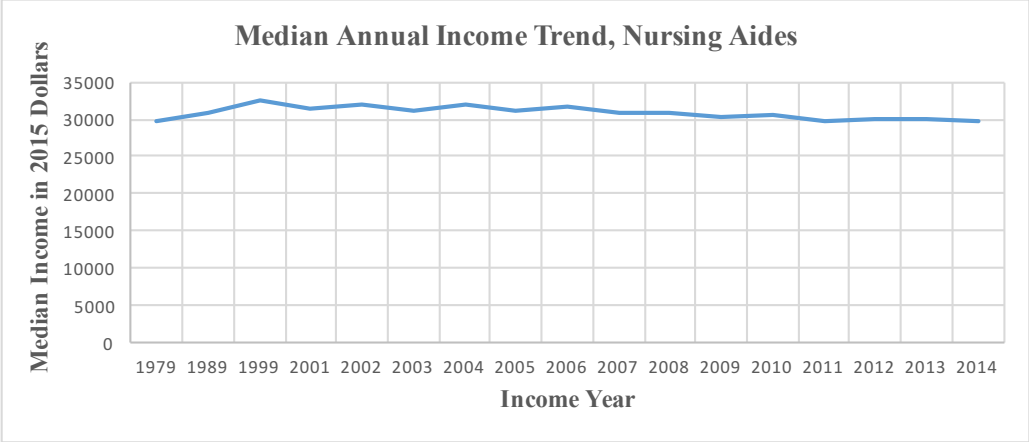

Figure 6. Real median annual income trends in 2015 dollars for nursing aides who belong in the personal care occupational category.

Figure 7. Real median annual income trends in 2015 dollars for managers and administrators who belong in the managers occupational category.

Related Findings

Our results are consistent with those found by Andrew McAfee and Erik Brynjolfsson in *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies.* Brynjolfsson and McAfee find that real (inflation-adjusted) income of the median worker was at a peak in 1999. After reaching this peak, real income for the median American household began to fall and by 2011 income had fallen by 10%. Furthermore, wages for unskilled workers (those belonging to low-skill occupational categories) have trended downward since 1999. Overall, their results show that the median hourly wage for occupations across skill sectors had barely changed between 1973 and 2011. Our analysis of median income trends for low, middle, and high-skill occupations reflect these findings in annual income rather than the hourly wage. The authors further analyze the income distribution and find that over half of the total income in the US has shifted to the top 10 percent of Americans in 2012. The top 1% of earners received over 22% of income, doubling their share of income since the early 1980s. Brynjolfsson and McAfee attribute stagnant and slow income growth to increases in inequality. Those at the top of the

income distribution are capturing an enormous slice of a bigger pie, leaving an even smaller slice to the rest of the distribution. Although the authors attribute productivity gains to technological innovations they conclude that these innovations are not the only drivers behind slow income growth and stagnations.

Furthermore, economist James Bessen finds that median wages have remained stagnant since the introduction of the personal computer. Wages of the top 10% have been growing since the early 1980s in occupations where workers require computer handling. On the other hand, the median workers in these occupations have seen minimal growth in their annual wages. Bessen notes that "even among scientific, engineering, and computer occupations, the median wage has grown slowly, but those with specialized technical skills (those belonging to the top of the income distribution) earn a growing bounty from technology." Technological innovations are not the culprit behind stagnating wages. Bessen attributes the lack of technical skills for the stagnating wages. Bessen highlights the demand high-skill occupations have for workers with technological skills but the lack of supply for workers with these skills results in stagnating wages for median workers in these occupations. Only the few with such skills are able to reap the benefits of increasing real wages. Our analysis and findings from Bessen, McAfee, and Brynjolfsson suggest that shifts in labor demand due to technological innovations do not completely alter median annual income, other factors not accounted for are affecting income trends.

Further Discussions

Our analysis primarily focused on comparing occupational real median income trends to changes in their employment shares, shift in labor demand. The simplicity of our approach does not take into account other factors that affect income patterns. For example, shifts in labor supply may affect how wage rates are allocated. Although jobs in low-skill industries have proven relatively less impacted by automation, employment composition in these industries has changed dramatically. Research by Beaudry, *et al.* (2013) shows that high-skilled workers (workers in middle-skill occupations) have moved down the occupational ladder, consequently taking jobs previously performed by low-skilled workers, pushing these workers further down the occupational ladder and, to some extent, even out of the labor force. Frey and Osborne (2013) show that as computerization erodes wages for labor performing routine jobs, workers will reallocate their labor supply to relatively low-skill service occupations. Our analysis indicated that real median income for low-skill occupations has fallen since 1999. We expected real wages to increase due to increases in labor demand, as seen in Autor's share of employment graph. Taking into account increases in labor supply for low-skill occupations helps explain the decrease in real wages. We suspect that the shift in labor supply is greater than the shift in labor demand for low-skill occupations. Although both demand and supply have increased for the low-skill occupational market, changes in labor supply have impacted the pattern of real median income at greater limits.

Altering our approach in adjusting income for inflation will change our results as well. Senior economist Terry Fitzgerald (2007) proves that deflating incomes using different measures of inflation will have a notable impact on the size of real median income growth. Figure 8 depicts the trend in real median income for the low-skill personal care occupational broad category using the Personal Consumption Expenditure (PCE) and the Consumer Price Index deflators (CPI). Measuring wage growth using the CPI index results in a 10% increase since 1979. On

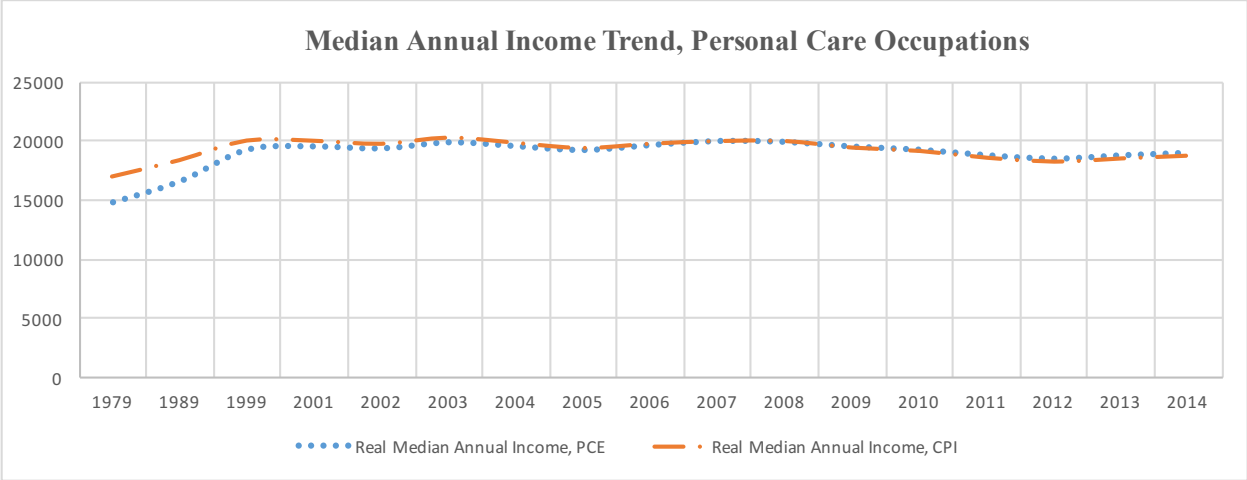

Figure 8. Real median annual income trends in 2015 dollars for the personal care occupations using the CPI and PCE deflators.

the other hand, adjusting for inflation by the PCE deflator results in a 29% increase in real median income. Fitzgerald notes that different measures of inflation such as the PCE, CPI, CPI-W (wage earners and clerical workers), CPI-U (urban consumers), and the CPI-U-RS (urban consumer research series) are used for various micro and macro studies. The PCE index has routinely been used for macro studies, while the CPI for micro related studies. We adjusted for inflation using the CPI deflator for our analysis due to the fact that we analyzed individual's earned annual income. Using the PCE deflator would have resulted in higher observed income growth for the occupational categories.

Moreover, Fitzgerald notes that supplemental benefits are not included in reported annual income. Including fringe benefits will result in increases of real annual income for median workers. Supplemental benefits take the form of health insurance, pension plans, paid vacations, goods, or services. According to Fitzgerald (2007) such benefits have "become an increasingly important part of employee compensation over the past 30 years." Fringe benefits account for almost 30% of employers costs for employees. Benefit shares are comprising a larger portion of total compensation. Excluding these benefits from our analysis of annual income may lead to misleading statistics. Fitzgerald suggests the inclusion of fringe benefits in measuring labor compensation. The inclusion of these benefits will produce superior income trends for the broad occupational categories our study analyzed.

Additionally, Autor does not take annual income into account[10] when assigning individual occupations to occupational categories. The inclusion of private detectives and criminal investigators in the protective occupational category highlighted this discrepancy in our analysis. Classifying occupations by income level will produce stronger results for income patterns. For example, upon observing the high-skill sector at a micro level, we found that elementary school teachers as well as chemical engineers comprise the professional category. According to the BLS, annual median income for elementary teachers in 2014 was $54,120, while chemical engineers earned $96,940. Ignoring income for occupational classification purposes may not be a suitable statute – especially when analyzing income patterns for Autor's occupational categories. If the majority of year by year median annual incomes observed for the professional category

[10] Individual occupations are categorized by tasks performance. Occupations involving manual tasks are classified as low-skill. Those involving routine tasks are middle-skill, whereas nonroutine tasks represent the high-skill occupational category. Visit http://economics.mit.edu/files/581 for further details.

depict income patterns for elementary school teachers, then our analysis will produce inaccurate statistics. Improving Autor's occupational classification methods by including an income component will add to the clarity of our analysis.

SECTION IV

CONCLUSION

This research contributes to the study of the influence technological innovations have on the US labor market. By utilizing a time series approach, our analysis revealed that changes in labor demand, due to technological innovations, have minimal impacts on occupational median annual income trends. Trends in annual median income for the macro occupational categories, as well as the individual (micro) occupations, did not behave according to the trends of their employment shares. Real annual median income for low-skill occupations have trended downward since the computer revolution. Income for middle-skill occupations have stagnated, while high-skill occupations have seen minimal growth in their annual income. Lack of technical skills have hindered the median worker in computer related occupations (high-skill). Our analysis indicated that the scarce supply of workers with technical skills resulted in the minimal growth of real median annual income for high-skill occupations. Our analysis and related studies suggest that other factors, not accounted for, influence income trends. Taking into account shifts in labor supply, fringe benefits, and utilizing different measures to adjust for inflation will add to the clarity of our results.

Future research could improve this study by adding supplementary variables of labor compensation, which would enable us to determine how technological innovations exactly alter occupational incomes. As technology continues to alter works environments and alter tasks performed wage rates for technical skills will rise steeply. Analyzing wage rate allocations will enable researchers to investigate if the income distribution has a bias for technical skills.

Additionally, analyzing the influx of middle-skill workers to low-skill occupations will allow researchers to explore how these workers affect social support programs, as well as how human capital attainment is affected.

REFERENCES

"25-2021 Elementary School Teachers, Except Special Education." *U.S. Bureau of Labor Statistics*. U.S. Bureau of Labor Statistics, n.d. Web. 11 Jan. 2016.

"33-3021 Detectives and Criminal Investigators." *U.S. Bureau of Labor Statistics*. U.S. Bureau of Labor Statistics, n.d. Web. 18 Feb. 2016.

"33-9032 Security Guards." *U.S. Bureau of Labor Statistics*. U.S. Bureau of Labor Statistics, n.d. Web. 18 Feb. 2016.

"Harmonised Unemployment Rates 2013/12." (2013): n. pag. Web.

"How Technology Has Affected Wages for the Last 200 Years." *Harvard Business Review*. N.p., 29 Apr. 2015. Web. 08 Jan. 2016.

"JEP (29,3) P. 3 - Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *AEAweb:*. N.p., n.d. Web. 11 Jan. 2016.

"Minimum Wage - U.S. Department of Labor - Chart1 | United States Department of Labor." *Minimum Wage - U.S. Department of Labor - Chart1 | United States Department of Labor*. N.p., n.d. Web. 12 Feb. 2016.

Autor, David H. "Why Are There Still So Many Jobs? The History And Future Of Workplace Automation†." *Journal Of Economic Perspectives* 29.3 (2015): 3-30. *America: History and Life with Full Text.* Web. 08 Jan. 2016.

Autor, David H., Frank Levy, and Richard J. Murnane. "The Skill Content Of Recent Technological Change: An Empirical Exploration." *Quarterly Journal Of Economics* 118.4 (2003): 1279-1333. *EconLit with Full Text*. Web. 07 Jan. 2016.

Brynjolfsson, Erik, and Andrew McAfee. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. N.p.: n.p., n.d. Print.

Bureau of Labor Statistics, U.S. Department of Labor, *Occupational Outlook Handbook, 2016-17 Edition*, Chemical Engineers, on the Internet at http://www.bls.gov/ooh/architecture-and-engineering/chemical-engineers.htm (visited January 11, 2016).

Bureau of Labor Statistics, U.S. Department of Labor, *Occupational Outlook Handbook, 2016-17 Edition,* Private Detectives and Investigators, on the Internet at http://www.bls.gov/ooh/protective-service/private-detectives-and-investigators.htm (visited *February 18, 2016*).

DeSilver, Drew. "For Most Workers, Real Wages Have Barely Budged for Decades." *Pew Research Center RSS*. N.p., 09 Oct. 2014. Web. 23 Jan. 2016.

Fitzgerald, Terry J. "Has Middle America Stagnated?." *Region (10453369)* 21.3 (2007): 14. *MasterFILE Complete*. Web. 16 Mar. 2016.

Frey, Carl Benedikt, and Michael A. Osborne. *The Future of Employment: How Susceptible are Jobs to Computerisation? ∗* (n.d.): n. pag. 7 Sept. 2013. Web.

Juhn, Chinhui, Kevin M. Murphy, and Brooks Pierce. "Wage Inequality And The Rise In Returns To Skill." *Journal Of Political Economy* 101.3 (1993): 410-442. *EconLit with Full Text.* Web. 09 Mar. 2016.

Kopczuk, Wojciech, Emmanuel Saez, and Jae Song. "Earnings Inequality And Mobility In The United States: Evidence From Social Security Data Since 1937." *Quarterly Journal Of Economics* 125.1 (2010): 91-128. *Social Sciences Full Text (H.W. Wilson).* Web. 16 Jan. 2016.

Steven Ruggles, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek. *Integrated Public Use Microdata Series: Version 6.0* [Machine-readable database]. Minneapolis: University of Minnesota, 2015.

US. Bureau of Labor Statistics, *Civilian Labor Force Participation Rate*[CIVPART], retrieved from FRED, Federal Reserve Bank of St. Louis https://research.stlouisfed.org/fred2/series/CIVPART, Mar 06, 2016.

APPENDIX A

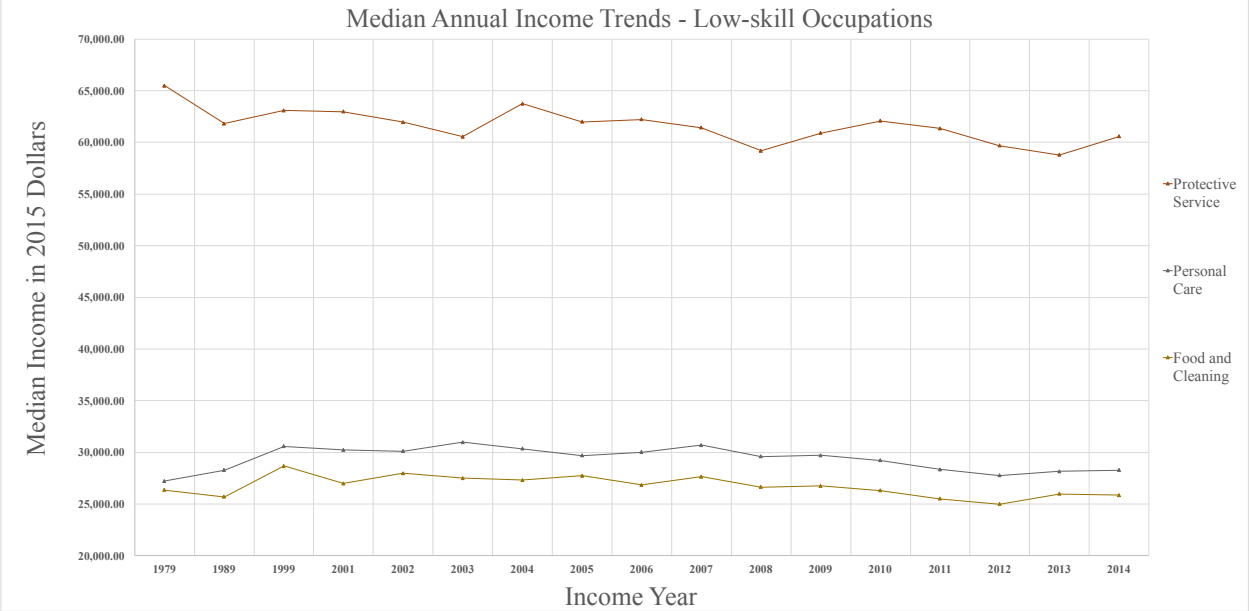

Figure 9. Real median annual income trends in 2015 dollars for the low-skill occupations.

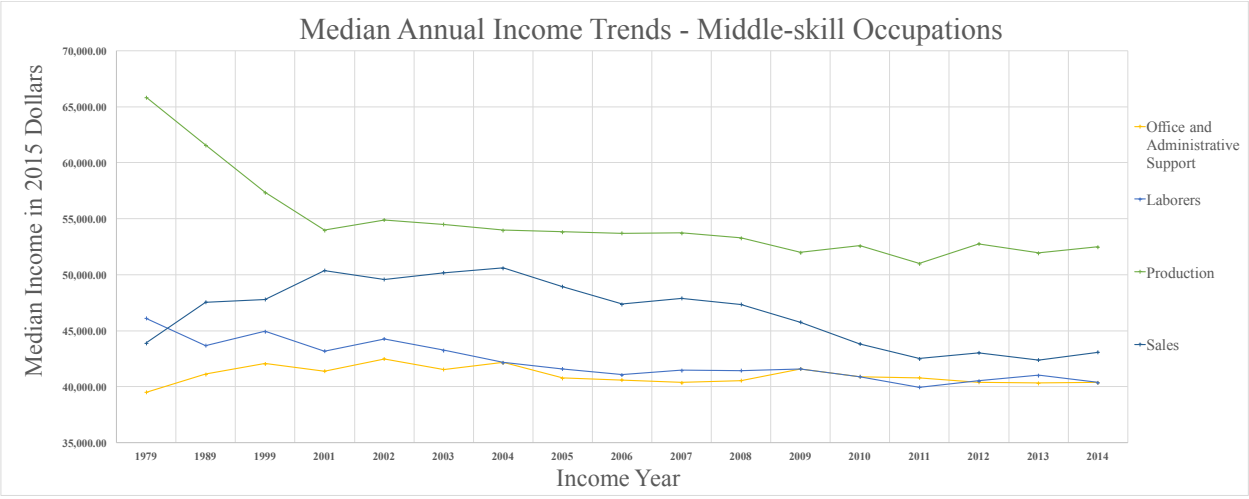

Figure 10. Real median annual income trends in 2015 dollars for the middle-skill occupations.

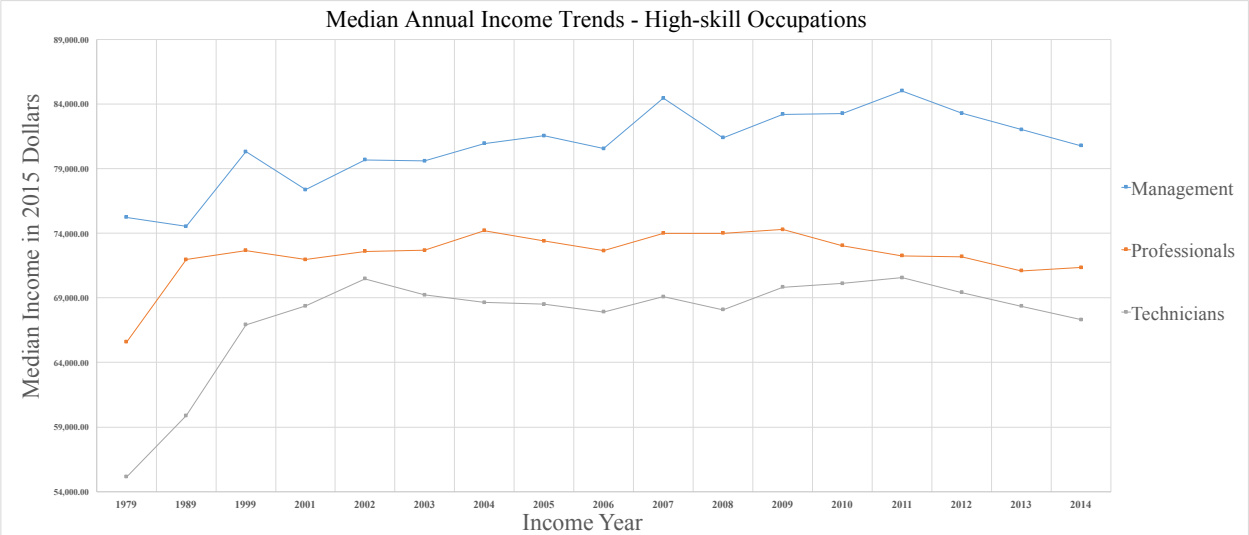

Figure 11. Real median annual income trends in 2015 dollars for the high-skill occupations.

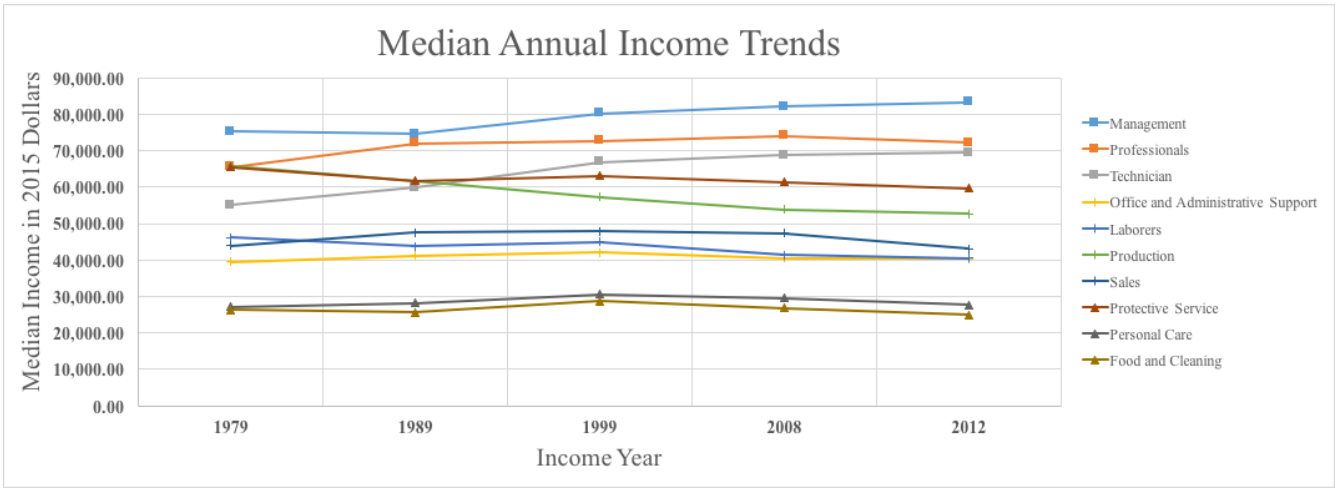

Figure 12. Real median annual income trends in 2015 dollars. *Sources:* We use Autor's data set analyzing data from the 1980, 1990, and 2000 Census IPUMS files, a combined 2006-2008 ACS file, and the 2012 single year ACS file.