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The Changing Nature of Skill Division in the U.S. Economy

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Job polarization has changed the US labor market significantly over the past half century. There has been a significant growth in the share of high-skill jobs, while middle-skill jobs have declined rapidly. Previous research has identified skill-biased technological change (SBTC) and liberalized trade as the driving forces behind job polarization. However, all recent research has been focused around either the overall labor market or a small subset of jobs that represent the overall labor market. This paper instead looks at one sector in particular, manufacturing, to see how polarization has changed it over time. This sector is considered to be solidly "middle-skill," as working in manufacturing typically means that a worker completes routine tasks. Automobile manufacturing is an industry within manufacturing that is frequently brought up in discussions about the decline in the manufacturing sector as a whole and is also subject to analysis in this paper. I use data from the American Community Survey and the Dictionary of Occupational Titles to determine whether job polarization can be observed in these two groups through changes in the shares of different skill-levels between 1980 and a pooled sample of 2013-2017 and whether polarization can be observed in changing wages for different skill levels between 2005 and 2015. I find that although the share of middle-skill workers has decreased in overall manufacturing, the same cannot be said for automobile manufacturing. Additionally, I find that wages had indeed polarized between 2005 and 2015.

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I. Introduction

The composition of jobs and skills in the United States has changed significantly over the past half-century. Where in the 1970s and earlier it was possible to find a well-paying job after graduating high school performing manual "low-skill" labor or routine "middle-skill" labor, there has been a persistent decrease in demand for these skills as more and more work becomes automated or is outsourced to another country. Liberalized trade and advances in technology have caused a structural change in the labor market and driven down both the number of middle-skill jobs and the wages received by those workers still employed in a middle-skill job. Concurrently, wages and relative demand have grown for workers who are able to complete tasks that are not as easily replaced or outsourced. This is due to their cognitive, nonroutine, or place-dependent natures, and which can describe both high-skill and low-skill jobs. Middle-skill jobs, which do not share these qualities, therefore have not benefitted from these changes to the economy.

This phenomenon is known as "job polarization," and has been studied by economists who have attempted to explain this process (Autor, Katz, and Kearney 2006; Autor and Dorn 2013; Barany and Siegel 2019; Lu and Ng 2013; Michaels, Natraj, and Van Reenen 2014). Because of this, the nature, results of, and the processes behind job polarization have thus far been identified, albeit with some discrepancy in results. This research has been primarily concerned with the overall economy, or a subset of industries within the economy, or even workers considered to have similar skill levels. In addition to this body of work, it may also be beneficial to follow a single sector to see how it has been affected by job polarization, and whether the trends found across the given sector and in comparison to other sectors that demand similar skill levels from its workers hold true. In other words, are the macro-level trends found for different industries and skill groups mirrored on a sector or industry scale?

In this paper, I attempted to answer this question by studying the changes in the automobile manufacturing industry to see if it follows the same patterns of changing skill demands and wages that were seen across the whole manufacturing sector and other middle-skill sectors. I analysed data from the American Community Survey on workers within automobile manufacturing and other manufacturing industries, looking at individuals' occupation, educational attainment, and income on either end of a 37-year period accessed through IPUMS (Ruggles, et al. 2019). I used an index of dissimilarity to compare how different the changes in occupational patterns are in automobile manufacturing to all manufacturing. I also run a basic regression to determine how wages have changed for workers within one industry over time. I expected to find that automobile manufacturing had polarized similarly to the overall manufacturing sector, with a large decrease in the relative share of middle-skill workers, a large increase in high-skill workers, and a small increase in low-skill workers. Additionally, in relation to low-skilled workers, the wages of high-skilled workers grew, while the wages of middle-skilled workers decreased.

The rest of the paper is laid out as follows. Section II discusses literature relevant to the concept of job polarization and the effects it has had on the economy. Section III covers the theory of task-based skill demand, which I have based this paper on. Section IV explains the empirical models used to analyse the data and test my hypotheses. Section V will discuss the results of the analysis, while Section VI gives concluding remarks.

II. Literature Review

The process of job polarization has been empirically observed taking place since 1950 (Bárány and Siegel 2019), although most recent studies have focused only on the past 50 years. All of the research exploring the topic has concluded that job polarization is driven by two main factors: the reduction of trade barriers, and advancements and greater access to both mechanical hardware and software. However, despite a large consensus that technology has caused most of the polarization since 1950, there is some conflicting evidence over which of these two factors has had a greater effect in the past and continuing into the future.

David Autor has focused much of his research into exploring the forces behind job polarization and has consistently concluded that changing technology has the greatest effect on the demands for skills made by the labor market. Autor, Katz, and Kearney (2006) found that the growth in wage inequality during the 1980s was caused by the increased accessibility of computers. As firms were able to purchase more computers at cheaper prices, they were able to automate more routine tasks usually assigned to middle-skill workers, such as clerical work. This automation of middle-skill work by new technology is commonly referred to as skill-biased technological change, or SBTC, since the technological advances made and utilized in the labor force have, over the past 50 years, been complementary to highly-skilled workers who complete cognitive and nonroutine tasks. Autor and Dorn (2013) find that in regions of the United States where there was a relatively larger share of routine work, SBTC led to the growth of wages for workers on both the low end of the skill distribution and the high end, since the tasks completed by those workers are manual, cognitive, or both, and therefore are harder to automate than middle-skill tasks. Michaels, Natraj, and Van Reenen (2010) also find evidence that new technologies led to increased demand for high- and low-skilled workers while decreasing demand for middle-skilled workers and establishing a connection between education and skill level. In particular, information and communication technologies (ICT) has been the main source for polarization, as acquiring internet access and a greater number of computers requires hiring people who can use and maintain those computers effectively. Michaels, Natraj, and Van Reenen note that workers of different educational backgrounds tend to cluster into different jobs based on the skills they require. Workers with higher educational attainment can complete abstract or cognitive work, allowing them to fill high-skill jobs, while those with lower educational attainment cannot, which forces them into middle- and low-skill work.

Bárány and Siegel theorize that as productivity in a sector increases, the need for workers in that sector decreases, which in turn creates an excess supply of those workers who ultimately depress their wages (2019). This creates an incentive for some workers to change sectors to earn now relatively higher wages, which is the cause of polarization. Their analysis suggests this theory to be accurate, as they find that the structural changes of the economy and the changes in average wages across sectors are caused by unbalanced technological growth in manufacturing.

On the other hand, some research suggests that automation is not the primary cause of job polarization, and that instead trade, or some other factor has had the greater effect on the demand for skilled labor. Lu and Ng (2013) suppose that an increase in competition in manufacturing from international sources has caused polarization more so than new technologies. As import competition increases, domestic manufacturers shift away from demanding workers who can complete routine tasks and instead demand workers who can complete nonroutine tasks. This allows the firms to become more competitive by improving the quality of their products, rather than through the quantity foreign producers can offer. An interesting finding in this paper is that the changes in skill demand for domestic manufacturing would have taken place even if the United States had not opened trade with low-wage countries and only maintained trade with other developed nations, which is in contrast with popular beliefs about why the demand for middle-skill jobs has decreased.

When looking specifically at manufacturing plants in the United States, Dunne and Troske (2005) determine that while technology has changed the labor market on a macroscopic scale, new technologies adopted by firms do not change the mix of skills demanded by those firms. That is, the firms adopting new technologies are not replacing their workers outright.

Instead, the firms adopting new technology hire new workers at a faster rate than firms that do not adopt new technology at all.

As mentioned above, all of these papers focus on some broad subset of the labor market, whether it be low-skilled or middle-skilled workers, the “middle-skill sector” or the manufacturing sector, but none follow an individual industry over the past few decades. This is what I attempt to determine for the automobile manufacturing industry. However, I am not particularly interested in whether polarization in this industry is due to trade or automation since most evidence seems to point towards the latter. Instead, I intend to explore how these large-scale trends are manifested on a small scale, given the findings of the literature discussed above. The task-based theory of labor markets developed by David Autor in 2013 is the framework I use to answer this question, which I will elaborate on in Section III.

III. Theory

David Autor (2013) explains how the standard theory for the demand and supply of labor is insufficient in describing the role of technology plays in shifting supply and demand in his essay “The ‘Task-Approach’ to Labor Markets: An Overview.” He states that assuming some combination of capital and labor are capable of producing some output is too simplistic. Additionally, the typical model considers technology an exogenous variable. Unlike the typical theory, Autor describes capital and labor as imperfectly substitutable goods, and incorporates technological change in order to show its effects internally.

In the same essay, Autor (ibid.) breaks up the production process into a few components: factors of production, skills, and tasks. Factors of production include all kinds of machinery and workers, who are categorized as either low-skilled, middle-skilled, or high-skilled based on their human capital. Skills are defined as a set of abilities that labor or capital possesses that allow them to complete a task. Tasks, then, are the unit of production for this theory. When a task is completed, there is some output produced. Therefore, factors of production which possess skills use those skills to complete tasks, which then create some output.

According to Autor (ibid.), tasks are assigned to the various factors of production according to the principle of comparative advantage, so that the most productive input is used to complete tasks. Whenever a new task is created, it is assigned to the level of labor with the most appropriate skillset, rather than machinery, since labor is more capable of solving problems and learning to complete new tasks. Meanwhile, older tasks are undergoing or are finished being codified by the workers who are assigned to them. Once a task is codified, it is possible for it to be automated. In this theory, capital is able to complete a task quicker and more frequently than labor but can be limited in its use, depending on the relative cost of labor to capital.

Automation's effect on the supply and demand of labor is found in the wages received by each of the different skill levels. For example, if a machine were created that is able to complete a task that is normally done by a middle-skill worker, and if the use of machinery is relatively cheaper than hiring middle-skill workers, then firms will substitute towards the capital and away from middle-skill labor, reducing the demand for this kind of labor. This depresses the wages of the middle-skilled workers. Simultaneously, workers who do not fall in the middle-skill category become more productive because of the new automation, which in turn increases the demand for their skills, further increasing their wages beyond the relative increase caused by the depression of middle-skill wages. Autor calls this phenomenon skill-biased technological change, or SBTC.

Assuming that Autor's theory of labor supply and demand holds true, it is reasonable to believe that the decreasing shares of differently skilled jobs found by Tuzemen and Willis (2013) can be attributed to automation of middle-skilled tasks, and therefore middle-skilled jobs. If SBTC has taken place between 1980 and 2017, it should be detectable by analyzing the share of each skill level in a sector or industry, as well as in the wages paid to workers in different skill levels.

In Section IV, I will discuss how this theory has informed my hypothesis and shaped my empirical model. Additionally, I will discuss the source for my data and how it will be analyzed.

IV. Data and Empirical Model

I tested my first hypothesis using data from the American Community Survey, it is possible to measure the effects of SBTC in the automobile manufacturing industry and all other manufacturing by looking at the change in the share of skilled work. This can be achieved by categorizing all workers into one of the three skill levels as mentioned in Section III above. Skill levels can be determined by the types of tasks completed by a worker. Unfortunately, the ACS does not provide data on what tasks a worker completes or which skill level they can be categorized as. It does, however, provide data on a respondent's occupation, given as a census code (referred to here as an ACS occupation code), which can be cross-referenced with information from a different source: The Dictionary of Occupational Titles (DOT). The DOT provides information on tasks commonly completed by workers in a given occupation acquired through survey responses. At the bottom of each entry in the DOT are various crosswalk values, including ACS occupation codes, which allowed me to search for appropriate job titles' entries in the DOT.

Using the crosswalks provided by each DOT entry, a list of these entries was compiled that correspond to an ACS occupation code. Each entry contained a list of up to twenty tasks. To limit the number of tasks that needed to be sorted, I selected up to five entries to represent the ACS occupation code, as some codes had a large number of relevant occupations. Each task in an entry was then counted as either manual, routine, or abstract depending on what was written about each task. Autor (2013) gives an idea of how researchers define abstract, routine, and manual tasks, which I used as guidelines for categorization. First of all, abstract tasks were noted as those that "may require creativity, hypothesis formation, problem solving or persuasion" (23). Secondly, routine tasks "are readily codifiable for purposes of machine performance," and follow very exact rulesets in controlled environments (ibid.). Finally, manual tasks are those "which may require physical flexibility and adaptability, visual recognition, or non-scripted communications" (ibid.).

In some instances, DOT entries were crosswalked to more than one ACS occupation code, which led to a few different challenges. The first kind of challenge I faced was that the only entry equivalent to a particular ACS occupation code was already used to analyze another ACS occupation code. If this was the case, the new ACS occupation code would be placed in the same category (abstract, routine, or manual) as the code that shared a DOT entry with. In the second situation, some, but not all of the DOT entries were used for other ACS occupation codes. In this case, only "new" entries' tasks would be sorted to represent an ACS occupation code. A few ACS occupation codes had no related DOT entries. To accurately categorize such a code, workers were categorized based on their educational attainment. Additionally, the ACS data was reduced to only include those workers who were working at least 30 hours a week for 50 weeks in the previous year, and only those ACS occupation codes with more than 100 workers were analyzed.

Finally, once all available tasks for each ACS occupation code's relevant DOT entries were sorted, notes were made on which ACS codes needed to be combined with one another and which needed to be classified by education. I labelled each ACS code as either abstract, routine, or manual, depending on which of the three had a plurality of tasks. For example, the code for plumbers, which was comprised of seven abstract tasks, thirteen routine tasks, and fifteen manual tasks, would be classified as a "manual" job. If ACS occupation codes had a tie for largest task group or did not have tasks at all, they would be sorted based on the most common education level of the workers, so that college graduates and above were considered abstract, those who graduated high school and had less than a Bachelor's degree were considered routine, and anyone below a high school diploma were considered manual.

Once the ACS occupation codes had been sorted into different skill levels based on the tasks most frequently completed or education levels, each worker was assigned their skill level based on their given ACS occupation code: high-skill for those in abstract jobs, middle-skill for those in routinized jobs, and low-skill for those in manual jobs. Then, the distribution of skill levels was computed for two groups in two time periods. First, relative shares were computed within automobile manufacturing alone in 1980 and then again in 2017. This process was repeated for the second group, made up of all other workers in the manufacturing sector in 1980 and 2017. Once these values were found, I used an index of dissimilarity to show how much of each skill level must adjust in the 2013-2017 period to match the original 1980 distribution for both groups. These indices were calculated with the following formula:

$$\frac{1}{2}\sum_{n=1}^{3}\left|\frac{v_n}{V} - \frac{m_n}{M}\right|$$

Where v_n is the number of workers with skill level n in the 2013-2017 period, m_n is the number of workers in 1980 categorized as skill level n, V is the total number of workers in 2013-2017, and M is the total number of workers in 1980.

To test my second hypothesis, that wages have grown for high- and low-skilled workers while falling for middle-skilled workers, I looked at two different years. Tuzemen and Willis (2013) note that polarization has been a gradual process over time but found that the rate at which jobs and wages have become polarized accelerates during recessions. With this in mind, I chose to compare the same two groups, automobile manufacturing and all other manufacturing, in two periods on either end of the Great Recession: 2005 and 2015. I estimated wages using the following regression:

$$LNWAGE = \alpha_1 + \beta_1(HIGHSKILL) + \beta_2(MIDDLESKILL) + \beta_3(AGE) + \beta_4(AGESQUARED) + \beta_5(FEMALE) + \beta_6(HISP) + \beta_7(NONWHITE)$$

If β_1 in 2015 is greater than β_1 in 2005, and β_2 in 2015 is less than β_2 in 2005, then wage polarization will be considered to have occurred. Table 1 provides a brief description of the variables used in this regression.

Table 1: Variable Definitions for Regression

Variable	Description
Dependent Variable	
LNWAGE	Natural log of real wages. Real wages computed using the consumer price index with 2015 as the base year.
Independent Variable	
HIGHSKILL	1 if person’s job is classified as abstract.
MIDDLESKILL	1 if person’s job is classified as routine.
AGE	Age of person.
AGESQUARED	AGE*AGE
FEMALE	1 if person is female.

HISP	1 if person is Hispanic.
NONWHITE	1 if person is nonwhite.

V. Results and Discussion

a. Skill Distributions

Between 1980 and the period of 2013-2017, automobile manufacturing saw a large increase in abstract jobs, as predicted by my hypothesis. However, the concurrent decrease in job share did not come from a loss of routinized jobs, as would be expected. Instead, the share of routine jobs not only remained stable, but increased slightly between the two periods. The share of manual jobs in automobile manufacturing decreased by roughly 12% between the two periods. Meanwhile, the changes in the rest of manufacturing are more in line with expectations, though still quite similar to automobile manufacturing. Just as in the other group, the share of abstract jobs increased with a simultaneous decrease in manual jobs. However, routine jobs decrease alongside manual jobs, though not with the same magnitude. The indices of dissimilarity for both groups are quite similar, 12.25% and 12.74% for automobile manufacturing and all other manufacturing respectively. The results here do not support my hypothesis that there was a large decrease in routine work between 1980 and 2013-2017

Table 2 shows the fraction of the labor force in automobile manufacturing and all other manufacturing that each skill level makes up in 1980 and 2013-2017.

Table 2: Distributions of Employment Across Skill Groups for Automobile Manufacturing and All Other Manufacturing

	Automobile Manufacturing			All Other Manufacturing		
	Abstract	Routine	Manual	Abstract	Routine	Manual
1980	21.50%	42.07%	36.43%	27.18%	34.28%	38.54%
2013-2017	33.17%	42.64%	24.19%	39.92%	31.42%	28.66%
Index of Dissimilarity		12.25%			12.74%	

However, the methodology employed in this study has a few drawbacks and limitations. In terms of data quality, the Dictionary of Occupational Titles' tasks were sometimes worded in an ambiguous way that made it challenging to confidently sort it into one group or another. Similarly, some DOT entries not only were a solitary ACS occupation code crosswalk, but also had very few tasks listed, as few as only 2 tasks from one entry on one occasion. This may have prevented jobs from being categorized in the appropriate group. Methodologically, future research would benefit from a more rigid definition of what constitutes an abstract, routine, or manual task in order to sort tasks more thoroughly and accurately. In addition, it may be the case that 1980 was too late a year to look for change in skill distribution, so perhaps an earlier decade would paint a more accurate picture of the changes in manufacturing.

b. Wages and Polarization

As discussed above, another way of determining job polarization's presence is by observing the change in wages over time. Using the equation given in Section IV, I estimated the effects having a routinized job on an individual's wages while controlling for age, race, sex, and Hispanic heritage. Four groups similar to those in the previous analysis were utilized for the regression: Automobile Manufacturing in 2005, All Other Manufacturing in 2005, Automobile Manufacturing in 2015, and All Other Manufacturing in 2015. The results of the wage regressions are presented in Table 3.

Table 3: Regression Results: Dependent = Natural Log of Real Wage (2015 base)

Panel A: Automobile Manufacturing

	Automobile Manufacturing in 2005		Automobile Manufacturing in 2015	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
(Constant)	9.395***	.059	9.155***	.055
HIGHSKILL	.473***	.012	.554***	.013
MIDDLESKILL	-.030***	.011	-.050***	.013
AGE	.059***	.003	.063***	.003
AGESQUARED	-.001***	.000	-.001***	.000

FEMALE	-.303***	.011	-.229***	.012
HISP	-.262***	.020	-.165***	.019
NOTWHITE	-.041***	.013	-.074***	.013
Adjusted R-Squared	.287		.327	
Sample Size	12,564		11,359	

Panel B: All other Manufacturing

	All Other Manufacturing in 2005		All Other Manufacturing in 2015	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
(Constant)	9.187***	.018	9.120***	.019
HIGHSKILL	.543***	.004	.597***	.004
MIDDLESKILL	-.063***	.004	-.071***	.004
AGE	.067***	.001	.065***	.001
AGESQUARED	-.001***	.000	-.001***	.000
FEMALE	-.295***	.003	-.260***	.004
HISP	-.246***	.005	-.245***	.005
NOTWHITE	-.091***	.004	-.095***	.004
Adjusted R-Squared	.326		.314	
Sample Size	135,381		126,401	

***indicates significance at the ρ<.001 level; **indicates significance at the ρ<.01 level; *indicates significance at the ρ<.05 level.

I hypothesized that when comparing wages in two periods before and after a recession, that high skill jobs and low skill wages will have grown more than middle skill. This can be interpreted above from the coefficients for both *HIGHSKILL* and *MIDDLESKILL*, where if the former's coefficient has increased over 2005-2015 and the latter's coefficient has decreased over the same interval. In comparing the automobile manufacturing groups, high-skill jobs were found to pay more than middle-skill jobs in both periods. The coefficients changed as expected, as high-skill's coefficient increased from 0.473 to 0.554, and middle-skill's coefficient decreased from -0.030 to -0.050. A similar change was observed in all other manufacturing industries with high-skill increasing from 0.543 to 0.597 and middle-skill decreasing from -0.063 to -0.071.

VI. Conclusion

The phenomenon of job polarization has been observed over the past half century as middle-skill, routinized jobs have experienced shrinking wages while also taking up a decreasing share of the job market. Much empirical work has gone into unravelling the effects that technological change and free trade have on the domestic job market. They have found that technological change has had the greatest effect through the process of skill-biased technological change, which can be analyzed through Autor's task-based theory of labor markets. He states that technological change in the form of automation has the comparative advantage in routinized jobs, inducing employers to demand capital to complete routinized tasks over labor. This increase in productivity from automation also increases the productivity of those workers who engage in abstract tasks, which in turn increases their wages and demand for their work. Wages can be seen changing most dramatically during the course of a recession, as was found by Tuzemen and Willis.

I explored how Autor's task-based model could explain the changes in employment shares in the manufacturing sector, paying particular attention to automobile manufacturing, an industry traditionally believed to be primarily comprised of workers, as well as all other manufacturing. I found that in automobile manufacturing, contrary to expectations, the share of routinized jobs did not decrease between 1980 and 2013-2017, while there was a large decrease in manual-classified jobs. This may have been due to limitations in the data or the definitions used to classify each task may have been too broad. The rest of the manufacturing sector's skill distributions changed more in line with theory, but contrary to my hypothesis that manual jobs would increase in number.

The results of the wage analysis were consistent with expectations and the trends theorized by Autor. Using the findings of Tuzemen and Willis (2013) to analyze wages in two periods on either end of a recession, it was found that the wages of high-skill workers increased and the wages of middle-skilled workers decreased in both automobile manufacturing and the overall manufacturing industry. Despite this similarity, the automobile manufacturing industry may not serve as an appropriate “model industry” for the manufacturing sector. It has seen growth in routine jobs where the rest of the sector has seen a decrease.

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