American Economic Journal: Macroeconomics 2018, 10(1): 57–89
https://doi.org/10.1257/mac.20150258

Job Polarization and Structural Change†

By Zsófia L. Bárány and Christian Siegel*

We document that job polarization—contrary to the consensus—has started as early as the 1950s in the United States: middle-wage workers have been losing both in terms of employment and average wage growth compared to low- and high-wage workers. Given that polarization is a long-run phenomenon and closely linked to the shift from manufacturing to services, we propose a structural change driven explanation, where we explicitly model the sectoral choice of workers. Our simple model does remarkably well not only in matching the evolution of sectoral employment, but also of relative wages over the past 50 years. (*JEL* E24, J21, J22, J24, J31)

The polarization of the labor market is a widely documented phenomenon in the United States and several European countries since the 1980s.[1] This phenomenon, besides the relative growth of wages and employment of high-wage occupations, also entails the relative growth of wages and employment of low-wage occupations compared to middle-wage occupations. The leading explanation for polarization is the routinization hypothesis, which relies on the assumption that information and computer technologies (ICT) substitute for middle-skill and, hence, middle-wage (routine) occupations, whereas they complement the high-skilled and high-wage (abstract) occupations (Autor, Levy, and Murnane 2003; Autor, Katz, and Kearney 2006; Autor and Dorn 2013; Feng and Graetz 2015; Goos, Manning, and Salomons 2014; Michaels, Natraj, and Van Reenen 2014).

The contribution of our paper is two-fold. First, we document a set of facts that raises flags that routinization driven by ICT, although certainly playing a role from the 1980s onward, might not be the only driving force behind this phenomenon.

* Bárány: Department of Economics, Sciences Po, 28 rue des Saints-Pères, 75007 Paris, France (email: zsofia.barany@sciencespo.fr); Siegel: School of Economics, University of Kent, Canterbury, Kent, CT2 7NP, UK (email: c.siegel@kent.ac.uk). We wish to thank Árpád Ábrahám, Moshe Buchinsky, Francesco Caselli, Nicolas Coeurdacier, David Dorn, Georg Duernecker, Georg Graetz, Emeric Henry, Per Krusell, L. Rachel Ngai, Rish Singhania, Silvana Tenreyro, and Ákos Valentinyi as well as seminar and conference participants at Trinity College Dublin, UC Berkeley, Sciences Po, Stockholm School of Economics, Exeter, the Vienna Joint Macro Seminar, the 7th Nordic Summer Symposium in Macroeconomics, the European Meeting of the Econometric Society in Gothenburg, the 16th IZA/CEPR European Summer Symposium in Labour Economics, the 2013 Cologne Workshop on Macroeconomics, the 2013 Winter Meeting of the Hungarian Society of Economists, the Christmas Meetings of the German Economists Abroad in Konstanz, the German Economic Association Annual Meeting 2014, the 23rd CEPR European Summer Symposium in International Macroeconomics, University College London, the NBER Summer Institute 2016 Macro Perspectives group for useful comments.

† Go to https://doi.org/10.1257/mac.20150258 to visit the article page for additional materials and author disclosure statement(s) or to comment in the online discussion forum.

[1] See, for example, Autor, Katz, and Kearney (2006) and Autor and Dorn (2013) for the United States; Goos and Manning (2007) for the United Kingdom; Spitz-Oener (2006) and Dustmann, Ludsteck, and Schönberg (2009) for Germany; Goos, Manning, and Salomons (2009, 2014) for Europe.

Second, based on these facts, we propose a novel perspective on the polarization of the labor market, one based on structural change.

Our analysis of US data for the period 1950–2007 reveals some novel facts.[2] First, we document that polarization defined over occupational categories both in terms of employment and wages has been present in the United States since the 1950s, which is long before ICT could have played a role. Second, we show that at least since the 1960s the same patterns for both employment and wages are discernible in terms of three broad sectors: low-skilled services, manufacturing, and high-skilled services. Moreover, we confirm previous findings that a significant part of the observed occupational employment share changes are driven by sectoral employment shifts. Additionally, we show that sectoral effects contribute significantly to occupational wage changes. Therefore understanding the sectoral labor market trends is important even for the occupational trends.

Based on these facts, we propose a structural change driven explanation for these sectoral labor market trends. We introduce a Roy-type selection mechanism (Roy 1951) into a multi-sector growth model, where each sector values a specific skill. Individuals, who are heterogeneous along a range of skills, optimally select which sector to work in. As long as the goods produced by the different sectors are complements, a change in relative productivities increases labor demand in the relatively slow growing sectors, and wages in these sectors have to increase in order to attract more workers.

In particular, we assume that there are three types of consumption goods: low-end service, manufacturing, and high-end service goods.[3] We break services into two as they are comprised of many different subsets, e.g., dry cleaners versus banking, which seem hardly to be perfect substitutes in consumption, as would be implied by having a single-service consumption in households' preferences. In our model, we therefore treat low- and high-end services as being just as substitutable with each other as they are with manufacturing goods.

A change in relative productivities does not only affect relative supply, but through prices it also affects relative demand. Given that goods and the two types of services are compliments, as relative labor productivity in manufacturing increases, labor has to reallocate from manufacturing to both service sectors. To attract more workers into both low- and high-skilled services, their wages have to improve relative to manufacturing. Since in the data we see that manufacturing jobs tend to be in the middle of the wage distribution, this mechanism leads to a pattern of polarization in terms of sectors, which is driven by the interaction of supply and demand for sectoral output.

We calibrate the model to quantitatively assess the contribution of structural change—driven by unbalanced technological progress—to the polarization of wages and employment. Taking measured labor productivity growth from the data

[2] Analyzing the data until more recent years does not affect our findings; we chose 2007 as the final year to exclude the potential impact of the financial crisis.

[3] Buera and Kaboski (2012) also split services into low- and high-skilled: their selection is based on the fraction of college-educated workers in the industry. Their main interest is linking the rising skill premium to the increasing share of services in value added, and they emphasize the home versus market production margin. Our focus is very different: sectoral wages.

and using existing estimates for the elasticity of substitution between sectors, we find that our model predicts between 33 and 59 percent of the relative average wage gain of high- and low-skilled services compared to manufacturing, and between 62 and 99 percent of the change in employment shares. For this exercise, we quantify the adjustment of labor productivity growth needed to correct for selection effects in the calibrated model. Without these adjustments, productivity growth is understated in the expanding sectors, and is overstated in the shrinking sector; according to our model this would lead to an overstatement of annual productivity growth rate differentials by between 27 and 35 percent.

This paper builds on and contributes to the literature both on polarization and on structural change. To our knowledge, these two phenomena until now have been studied separately.[4] However, according to our analysis of the data, polarization of the labor market and structural change are closely linked to each other, and according to our model, industrial shifts can lead to polarization.[5] Our theory highlights a particular connection between structural change and occupational structure. Structural change leads to the sector with the highest productivity growth to shrink in terms of employment, and to experience lower wage growth than the other sectors of the economy; the occupation that is used the most intensively in this sector also experiences employment and wage losses. In the period 1950 to 2007 around half of routine employment was in the manufacturing sector (and around 80 percent of manufacturing hours were in routine jobs). Thus, when manufacturing started to shrink after 1950, this led to a "hollowing out" pattern, as routine workers were in the middle both in terms of skills and wages.

The structural change literature has documented for several countries that as income increases employment shifts away from agriculture and from manufacturing toward services, and expenditure shares follow similar patterns (Kuznets 1957; Maddison 1980; Herrendorf, Rogerson, and Valentinyi 2014). In particular, the employment and expenditure share of manufacturing has been declining since the 1950–1960s in the United States, while those in services have been increasing. From an empirical perspective, we add to this literature by documenting that in the United States the employment patterns are mimicked by the path of relative average wages. The economic mechanisms put forward in the literature for structural transformation combine specific features of preferences with some form of technological progress. Some papers assume non-homothetic preferences, such that changes in aggregate income—coming from technological progress—lead to a reallocation of employment across sectors (Kongsamut, Rebelo, and Xie 2001; Boppart 2014). Other papers focus on differential total factor productivity (TFP) growth across sectors (Ngai and Pissarides 2007) or on changes in the supply of an input used by different sectors with different intensities (Caselli and Coleman 2001, Acemoglu and Guerrieri 2008).

[4] Acemoglu and Autor (2011) and Goos, Manning, and Salomons (2014) look at the contribution of between-industry shifts to the polarization of occupational employment, but do not analyze the effect of structural change on the polarization of the labor market.

[5] While we focus in the main text on the link between industrial and occupational structure since 1950–1960, we show in online Appendix A.10, using data over 1850–1940, that there is also a close connection over much longer time series, see Figure A-7 and Table A-9.

We build on the model of Ngai and Pissarides (2007) closely, with one important modification: we explicitly model sectoral labor supply. As our goal is to study the joint evolution of employment and wages, we introduce heterogeneity in workers' skills, who endogenously sort into different sectors. In order to meet increasing labor demands in certain sectors—driven by structural change—the relative wages of those sectors have to increase. Since we model the sector of work choice, we can analyze the effects of structural change on relative sectoral wages, which is not common in models of structural change.[6] Another modification of Ngai and Pissarides (2007) is that we do not model capital, as our interest is in the heterogeneity of labor supply. The change in relative sectoral labor productivity can be driven by differential sectoral TFP changes or by capital accumulation and different sectoral capital intensities.[7] We stay agnostic about the origin of the differential labor productivity growth across sectors. As Goos, Manning, and Salomons (2014) point out, it is possible that part of this since the 1980s or 1990s is driven by different routine intensities and ICT. While the spread of ICT is not likely to be driving the differential sectoral productivity growth pre-1980, other forms of mechanization could have had a stronger impact in the manufacturing sector than in services over the longer time horizon that we study.

Ours is not the first paper to consider sectoral choice in a model of structural change. The setup of Matsuyama (1991) is similar, where agents have different efficiencies across sectors, but focuses on the theoretical possibility of multiplicity of stationary steady states. Caselli and Coleman (2001) study the role of falling costs of education in the structural shift from agriculture to manufacturing, and they derive predictions about the relative wages in the farm and non-farm sector. Focusing on cross-country differences, Lagakos and Waugh (2013) show that self-selection can account for gaps in productivity and wages between agriculture and non-agriculture. Buera and Kaboski (2012) analyze the relation between the increasing value added share of the service sector and the increasing skill premium, without exploring their model's implications for sectoral employment or wages, whereas this is the focus of our paper.

The polarization literature typically focuses on employment and wage patterns after the 1980s or 1990s. We contribute to this literature by documenting that in the United States the polarization of occupations in terms of wages and employment has started as early as the 1950s. As mentioned before, the leading explanation is routinization linked to ICT. While the spread of ICT is a convincing explanation for the polarization of labor markets after the mid-1980s, it does not provide an explanation for the patterns observed earlier.[8] But it is conceivable that similar factors, not linked to ICT, but to other forms of mechanization, might have contributed to polarization earlier. Another explanation suggested in the literature is consumption spillovers.

[6] A notable exception is Caselli and Coleman (2001).

[7] For example, if ICT is used more intensively in the manufacturing sector, and ICT becomes cheaper, then this would show up as an increase in the relative productivity of manufacturing workers.

[8] Another explanation is the increasing off-shorability of tasks (rather than finished goods), as first emphasized by Grossman and Rossi-Hansberg (2008). It has been argued that it is largely the middle-earning jobs that are off-shorable, but the evidence is mixed (Blinder 2009, Blinder and Krueger 2013, Acemoglu and Autor 2011). Just as for the ICT routinization hypothesis, this mechanism could have explanatory power from the 1980s onward.

This argument suggests that as the income of high-earners increases, their demand for low-skilled service jobs increases as well, leading to a spillover to the lower end of the wage distribution (Manning 2004, Mazzolari and Ragusa 2013). We do not incorporate such a mechanism in our model, as we strive for the most parsimonious setup featuring structural change, which does a good job in replicating the basic sectoral labor market facts since the 1960s.

The remainder of the paper is organized as follows. Section I lays out our empirical findings, Section II our theoretical model, Section III the quantitative results, and Section IV concludes.

I. Polarization in the Data

Using US census data between 1950 and 2000 and the 2007 American Community Survey (ACS), we document the following three facts: (i) polarization in terms of occupations—contrary to the consensus—started as early as the 1950–1960s, (ii) wages and employment have been polarizing in terms of broadly defined industries as well, (iii) a significant part of employment and wage polarization in terms of occupations is driven by industry-level changes. The focus of our quantitative model is fact (ii). We document fact (i) as most of the literature documents polarization in terms of occupations. The employment part of fact (iii) has been documented in the literature using shift-share decompositions (Acemoglu and Autor 2011, Goos, Manning, and Salomons 2014), here we confirm it for our classification, data, and time horizon. We also conduct a similar decomposition for wages and show that a significant part of relative occupational wage changes are driven by industry effects. We report fact (iii) to convince the reader whose main interest is in occupations, that for the full picture one needs to consider industries as well. In what follows we document each of these facts in detail.

A. *Polarization in Terms of Occupations*

In the empirical literature, polarization is mostly represented in terms of occupations. We document polarization in terms of two occupational classifications. We start from the finest balanced occupational codes possible, and then go to ten broad occupational categories.

Following the methodology used in Autor, Katz, and Kearney (2006); Acemoglu and Autor (2011): and Autor and Dorn (2013), we plot the smoothed changes in log real wages and employment shares for occupational percentiles, where occupations are ranked according to their 1980 mean hourly wages.[9] The novelty in these graphs is that we show these patterns going back until 1950, rather than focusing only on the post-1980 period.[10] In both graphs, each of the four curves represent changes that occurred over a different 30-year period. The top panel in Figure 1 shows that

[9] We split occupations into 100 groups, each representing 1 percent of employment in 1980. We smooth changes in log real hourly wages and employment shares with a locally weighted regression using a bandwidth of 0.8.

[10] For comparability with the literature, we rank occupations based on their mean hourly wage in 1980. However, given that we look at a longer horizon than most of the literature, we also plot these changes against a different

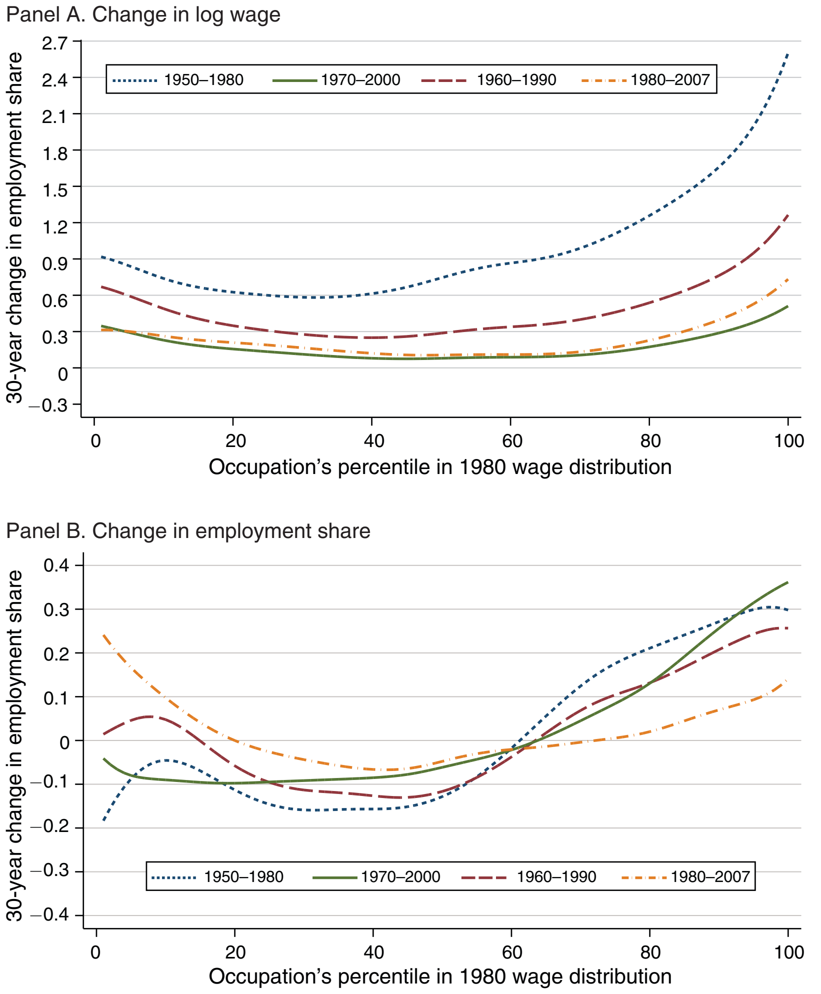

Figure 1. Smoothed Changes in Wages and Employment

Notes: The data is taken from IPUMS US census data (provided by Ruggles et al. 2010) for 1950, 1960, 1970, 1980, 1990, 2000, and the American Community Survey (ACS) for 2007. The sample excludes agricultural occupations/industries and observations with missing wage data; the details are given in online Appendix A. Balanced occupation categories (183 of them) were defined by the authors based on Meyer and Osborne (2005), Dorn (2009), and Autor and Dorn (2013). The horizontal axis contains occupational skill percentiles based on their 1980 mean wages (see online Appendix for details). In panel A, the vertical axis shows for each occupational skill percentile the 30-year change in log hourly real wages, whereas, in panel B, it shows the 30-year change in employment shares (calculated as hours supplied).

there has been polarization in terms of real wages in all 30-year periods, since the real wage change is larger for low- and for high-ranked occupations than it is for middle-ranked occupations. The polarization of real wages is most pronounced in the first two 30-year intervals, but it is clearly discernible in the following ones as well from the slight U-shape of the smoothed changes. The bottom panel shows the smoothed employment share changes. The picture shows that employment did

ranking of occupations, one based on the 1950 mean hourly real wages. The patterns look the same, see Figure A-1 and the discussion in online Appendix A.

not move monotonically toward higher wage occupations, instead it seems that middle-earning occupations lost the most in terms of employment. Thus, employment polarization is present in the sense that the employment share in low- and high-wage occupations increased more (or decreased less) than in middle-wage occupations. Polarization in terms of employment is most pronounced in the last 30 years (1980–2007), but it seems to be present even in the earlier periods.[11]

We focus on 30-year windows for two reasons. First, most of the literature documents polarization over periods longer than two decades. Second, we link polarization to structural change, which is a long-run phenomenon. One concern with showing 30-year windows, as in Figure 1, is that they stay silent on the exact timing of when polarization started. To address this, we show the decade-by-decade version of this in Figure A-2 in online Appendix A. This figure shows that these patterns do not necessarily hold for a decade-by-decade analysis, neither in the earlier nor in the later part of the sample. In some decades the top gains, whereas in others the bottom gains, but it is never the middle that grows the most in terms of employment shares.[12] However, between 1960 and 1970 there is clear evidence of polarization, therefore the early polarization patterns in the 30-year windows are not solely driven by changes after 1980.

A set of balanced occupational categories is needed to generate Figure 1. Meyer and Osborne (2005) develop a set of harmonized occupational codes for the 1950 to 2000 census and the ACS data. Dorn (2009) aggregates Meyer and Osborne (2005) to achieve the finest possible balanced set of categories from 1980 onward. We base our categories on Meyer and Osborne (2005) and Dorn (2009) to similarly achieve the finest possible balanced set of occupations from 1950 onward. One concern with this approach is that despite the efforts of these authors, their harmonized and/or balanced categories are not truly comparable across census years, and the reader might worry, that looking at a longer horizon, as we do, only exacerbates this problem. However, the biggest change in occupational classification occurred with the implementation of the Standard Occupational Classification (SOC) based occupation codes in the 2000 census, when the hierarchical structure of occupational codes was drastically modified. While in previous census years certain smaller occupation categories disappeared or entered, the main structure of occupations remained the same.[13] Therefore looking at longer horizons does not worsen the comparability issue relative to existing literature, which typically focuses on the post-1980 period.

Nonetheless, to minimize the comparability issues of fine occupational categories arising from the reclassifications across census years, we aggregate up these fine categories to a coarser set of occupations. For these coarser categories there is less of a concern about the consistency over time. The bar charts in Figure 2 show ten broad occupational groups percentage changes in total hours worked and in the

[11] When ranking occupations in terms of the initial 1950 wage distribution, i.e., the initial wage distribution, as is commonly done in this literature, employment polarization is much more noticeable since the 1960s, see Figure A-1 in online Appendix A.

[12] The fact that over ten-year windows the polarization patterns do not hold for a very fine classification of occupations is in line with the evidence in Acemoglu and Autor (2011), see their Figure 10. Nonetheless, with a coarser classification of occupations, one sees polarization decade-by-decade, see Figure 2.

[13] See the documentation of the Integrated Public Use Microdata Series (IPUMS) Census data.

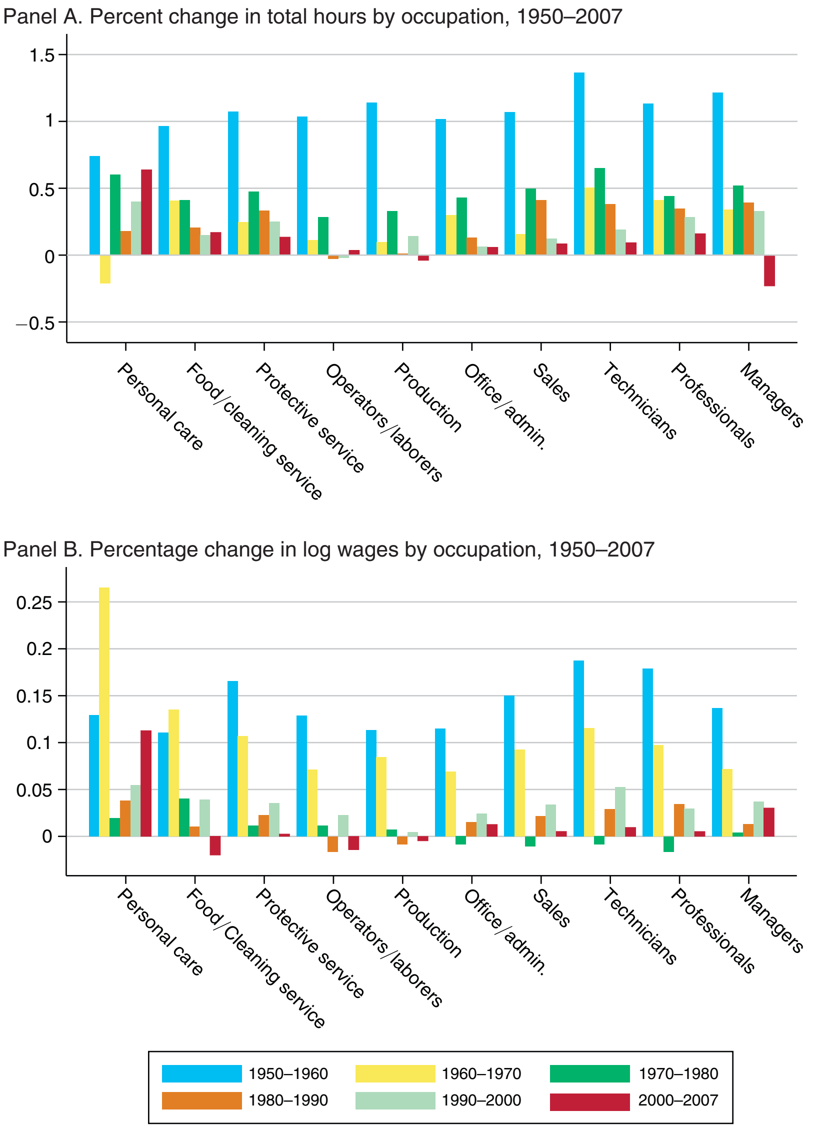

Figure 2. Polarization in Broad Occupational Categories

Note: These bar graphs show for ten broad occupational categories, as defined in Acemoglu and Autor (2011), the decade-by-decade percentage change in hours worked (panel A) and in the mean log wages (panel B).

mean log wages over ten year intervals. This categorization follows Acemoglu and Autor (2011), who show with this methodology the employment changes post 1980. We follow their ranking of occupations: the right three groups are the most educated and highest paid occupations, the four in the middle are middle-skilled, while the three on the left are the least educated and lowest paid occupations.

We expand on Acemoglu and Autor (2011) in two ways: (i) by showing the trends in decennial employment growth from 1950 onward (in the top panel), and (ii) by also showing wage growth (bottom panel). While over 1950–1960, there is no clear pattern in the employment growth of these broad occupational categories, from 1960 onward there is a U-shaped pattern. Total hours worked grew by more for occupations at the higher and at the lower end of the skill distribution than for those in the middle. A similar pattern is evident in the wage growth rates. Over each ten year period, wage growth was the lowest in middle-skilled occupations. We conclude that even when grouping occupations into broad categories following the methodology of Acemoglu and Autor (2011), there is evidence of employment and wage polarization as early as 1960.[14]

B. *Polarization in Terms of Sectors*

Next we document the polarization of employment and wages in terms of three broad industries or sectors: low-skilled services, manufacturing, and high-skilled services.

Our classification for the manufacturing sector also includes mining and construction, as is common in the structural change literature (e.g., Herrendorf, Rogerson, and Valentinyi 2013). As mentioned in the introduction, we split the remaining (service) industries into two categories based on consumption side considerations: within sectors the industries should be close substitutes, whereas across sectors they should be complements. The categorization is also guided by differences on the production side; in low-end services workers have much less education and earn much lower wages than in high-end services. For this reason we refer to them as low-skilled and high-skilled services.[15] As a result of the combined production- and consumption-side considerations, we classify as low-end services the following industries: personal services, entertainment, low-skilled transport, low-skilled business and repair services, retail trade, and wholesale trade. High-end services comprise of professional and related services, finance, insurance and real estate, communications, high-skilled business services, utilities, high-skilled transport, and public administration.

Figure 3 documents the patterns of polarization both in terms of employment shares and wages for the above defined sectors between 1950–1960 and 2007. The bottom panel shows the path of employment shares: high-skilled services increase continuously, low-skilled services increase and manufacturing decreases from 1960 onward.[16] In terms of wages, we plot the sector premium in high-skilled and low-skilled services compared to manufacturing, as well as their 95 percent confidence intervals. These sector premia are the exponents of the coefficients on sector dummies, which come from a regression of log wages where we also control for gender, race, and a polynomial in potential experience.[17] We plot these rather than the relative average wages because in our quantitative exercise we do not aim to

[14] In Figure A-3 in online Appendix A, we document polarization in terms of occupations in an even coarser classification. Following Acemoglu and Autor (2011), we classify occupation groups into three categories: manual, routine, and abstract. Again, we find that the middle-earning group, the routine workers, lost both in terms of relative average wages and employment share to the benefit of manual and abstract workers.

[15] See Figure 3, as well as Figure A-4 and Table A-1, in online Appendix A.

[16] Between 1950 and 1960, manufacturing employment increased, and low-skilled service employment fell.

[17] See Table A-2 in online Appendix A.3 for details of the regression.

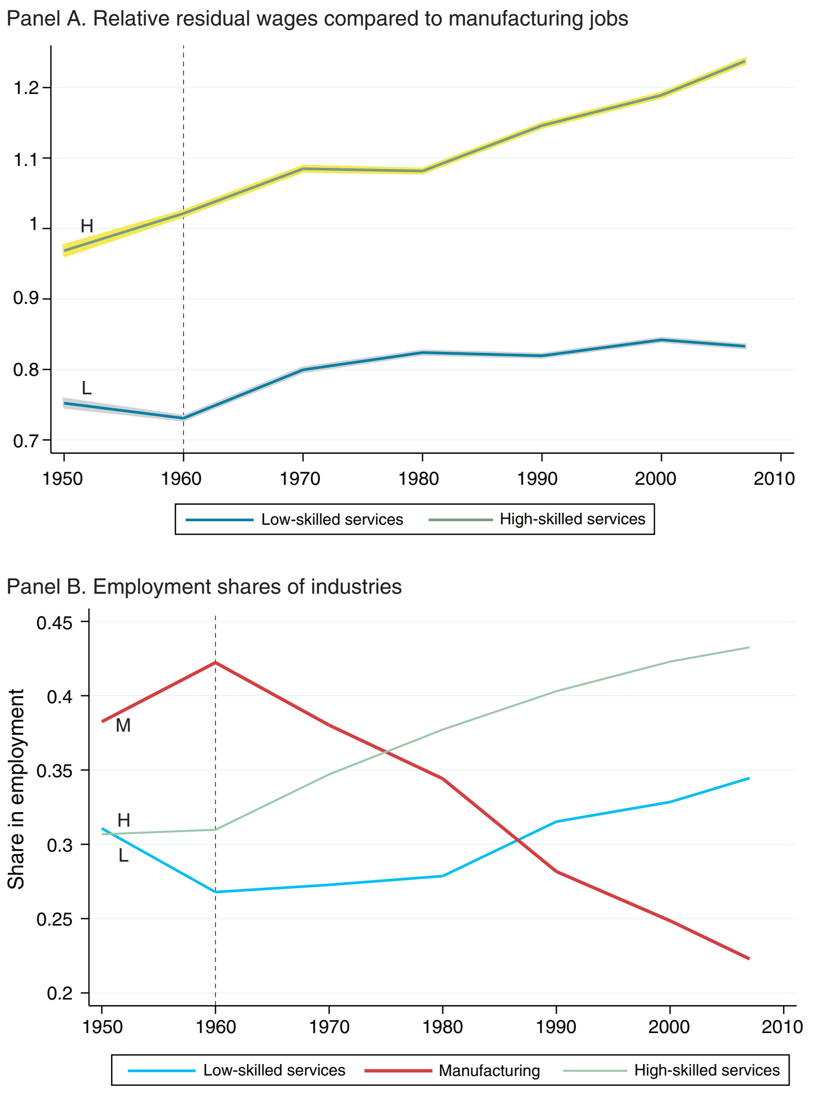

Figure 3. Polarization for Broad Industries

Notes: The data used is the same as in Figure 1. Each worker is classified into one of three sectors based on their industry code (for details of the industry classification, see text and online Appendix A.2). Panel A shows relative wages: the high-skilled service and the low-skilled service premium compared to manufacturing (and their 95 percent confidence intervals), implied by the regression of log wages on gender, race, a polynomial in potential experience, and sector dummies. Panel B shows employment shares, calculated in terms of hours worked. The dashed vertical line represents 1960, from when on manufacturing employment has been contracting.

explain sectoral wage differentials that are potentially caused by age, gender, or racial composition differences and the differential path of these across sectors.[18]

[18] One might be concerned that the employment share changes are driven by changes in the age, gender, or race composition of the labor force. To assess this, we generate counterfactual industry employment shares by fixing the industry employment share of each age-gender-race cell at its 1960 level, and allowing the employment shares of the cells to change. This exercise confirms that to a large extent the employment share changes are not driven by the compositional changes of the labor force. See Figure A-6 in online Appendix A.6.

As the graph shows, low-skilled service workers earn less, whereas high-skilled service workers earn more than manufacturing workers. Since the 1960s, both low- and high-skilled service workers have been gaining in terms of wages compared to manufacturing workers.[19] To summarize, from 1960 onward there is clear polarization in terms of these three sectors: the low- and high-skilled service workers gained in terms of employment and wages at the expense of the middle-earning, middle-skilled, manufacturing workers.

C. *Polarization across Occupations Linked to Industry Shifts*

To quantify the contribution of sectoral employment shifts to each occupation's employment share path, we conduct a standard shift-share decomposition.[20] The overall change in the employment share of occupation o between year 0 and t, $\Delta E_{ot} = E_{ot} - E_{o0}$, can be expressed as

$$\Delta E_{ot} = \underbrace{\sum_i \lambda_{oi} \Delta E_{it}}_{\equiv \Delta E_{ot}^B} + \underbrace{\sum_i \Delta \lambda_{oit} E_i}_{\equiv \Delta E_{ot}^W}, \tag{1}$$

where $\lambda_{oit} = L_{oit}/L_{it}$ denotes the share of occupation o, industry i employment within industry i employment at time t, $E_{it} = L_{it}/L_t$ denotes the share of industry i employment within total employment at time t, Δ denotes the change between period 0 and t, and the variables without a time subscript denote the average of the variable between period 0 and period t. The term ΔE_o^B represents the change in the employment share of occupation o that is attributable to changes in industrial composition, i.e., structural transformation, while ΔE_o^W reflects changes driven by within sector forces.

Table 1 shows for three broad occupational categories the total employment share change and its decomposition between 1950 or 1960 and 2007 into a between-industry and a within-industry component. We use either 3 occupational and 3 sectoral categories, or similarly to Acemoglu and Autor (2011), 10 occupations and 11 industries to be sure that our results are not driven by the coarse categorization. This decomposition indicates that a significant part of the occupational employment share changes are driven by shifts in the industrial composition of the economy between 1950 and 2007. Between-industry shifts are the most important in manual occupations, and the least important in abstract occupations, where they still account for at least a quarter of the total change.

The magnitude of the role of between-industry shifts in our analysis is similar to that in Acemoglu and Autor (2011) and Goos, Manning, and Salomons (2014).[21]

[19] These trends are very robust, they hold in the raw data (see the left panel in Figure A-4 in online Appendix A.3) as well as when constructing the sector premia using different specifications of the log wage regression (see Table A-4 in Appendix A.4).

[20] An alternative way is to calculate how much occupational employment shares would have changed, if industry employment shares would have remained at their 1960 level. See Figure A-6 in Appendix A.6.

[21] Acemoglu and Autor (2011) use US Census data between 1960 and 2000, and the ACS 2008 data. Their focus is the declining importance of between-industry shifts from 1960–1980 to 1980–2007. We find some support for this in our decade-by-decade analysis shown in Table A-5 in online Appendix A.6. The relatively smaller contribution

Table 1—Decomposition of Changes in Occupational Employment Shares

	Employment shares			
	3 × 3		10 × 11	
	1950–2007	1960–2007	1950–2007	1960–2007
Manual				
Total Δ	2.98	5.68	2.98	5.68
Between Δ	2.30	3.07	3.13	4.38
Within Δ	0.67	2.61	−0.15	1.30
Routine				
Total Δ	−19.79	−19.14	−19.79	−19.14
Between Δ	−5.66	−6.32	−9.73	−10.01
Within Δ	−14.13	−12.82	−10.06	−9.13
Abstract				
Total Δ	16.81	13.46	16.81	13.46
Between Δ	3.35	3.24	6.60	5.63
Within Δ	13.46	10.21	10.21	7.83

Notes: Same data as in Figure 1. For each occupational category, the first row presents the total change, the second presents the between-industry component, and the third presents the within-industry component over the period 1950 or 1960 to 2007. The first two columns use 3 occupations and 3 sectors, the last two use 10 occupations and 11 industries. The 10 occupations are the same as in Figure 2, while the 11 industries are: personal services, entertainment, and low-skilled business and service repairs; low-skilled transport; retail trade; wholesale trade; extractive industries; construction; manufacturing; professional and related services and high-skilled business services; finance, insurance, and real estate; high-skilled transport and public utilities (incl. communications); and public administration.

Goos, Manning, and Salomons (2014) argue that part of the between-industry shifts can be driven by routinization, which is a within-industry phenomenon. Since routinization has a bigger impact on industries where routine labor is used more intensively, employment might shift away from these industries. While this is a valid concern, routinization, linked to ICT, is not likely to be driving the faster productivity growth observed between the 1950s and 1980s. We also conduct an alternative shift-share decomposition where we use sectoral value added shares instead of sectoral employment shares. Even though the importance of the between industry component is somewhat smaller than in the standard shift-share decomposition, it is nonetheless a substantial share of the overall change.[22] We also decompose relative occupational wage changes into an occupation-driven component and an industry-driven component. We define the relative average wage of occupation o as the ratio of the occupation's average wage relative to the average wage in routine occupations:[23]

$$rw_{ot} \equiv \sum_i \frac{L_{iot}}{L_{ot}} \frac{w_{it}}{w_{rt}} \frac{w_{iot}}{w_{it}} = \sum_i \chi_{iot} rw_{it} p_{iot},$$

of between-industry shifts in later periods might be due to routinization kicking in after the 1980s, thus providing an extra force for within-industry reallocation of labor. Nonetheless, we find that even in the 1980–2007 period, between-industry shifts explain a significant part of occupational employment share changes. Goos, Manning, and Salomons (2014) use data for 16 European countries between 1993 and 2010, and attribute a roughly equal role to between- and within-industry shifts in all occupations.

[22] See online Appendix A.7 for details.

[23] It is clear that the wage has to be a relative wage, otherwise the decomposition picks up the general upward trend in wages, and assigns it to the component, which includes a wage change. Since we are interested in the path of manual and abstract wages relative to routine wages, it is natural to normalize by the average wage in routine occupations.

where $\chi_{iot} = L_{iot}/L_{ot}$ is employment in industry i and occupation o in period t relative to employment in occupation o in period t, $rw_{it} = w_{it}/w_{rt}$ is the ratio of the average wage in industry i in period t relative to the average wage of routine occupations in period t, and $p_{iot} = w_{iot}/w_{it}$ is the premium of occupation o in industry i in period t. In this three-way decomposition, the *industry effect* is itself composed of two parts: the first part captures changes coming from workers within an occupation moving across industries with different wages (L_{iot}/L_{it}). The second part captures that each industry's relative average wage path (w_{it}/w_{rt}) influences the overall relative average wage of the occupation. The *occupation effect* is driven by the change in the occupational premium within each industry (w_{iot}/w_{it}).

Table 2 shows the change in manual and abstract wages relative to routine wages, and their decomposition into an industry and an occupation component, between 1950 or 1960 and 2007. This table confirms that both manual and abstract occupations have been gaining in terms of wages relative to routine jobs. The decomposition shows that between half and two-thirds of the gain in relative manual wages is driven by industry effects, by the reallocation of manual labor to higher paying industries, or by faster wage growth in industries where more manual workers are employed. For the increase in relative abstract wages the results are even more striking: all of the gain is driven by industry effects.[24]

To summarize, first we document that polarization defined over occupational categories both in terms of employment and wages has been present in the United States since the 1950s. Second we show that the same patterns are discernible in terms of three broad sectors: low-skilled services, manufacturing, and high-skilled services. Finally, we show that over the last six decades a significant amount of the employment share changes and relative wage changes in occupations are driven by the (employment) shifts across industries.

In the remainder of the paper, we present a simple model of sorting and structural change to jointly explain the sectoral shifts in employment and the changes in average sectoral wages. We then calibrate the model to quantitatively assess how much of the polarization of sectoral employment and wages it can explain over the last fifty years, when feeding in sectoral labor productivity from the data.

II. Model

In order to illustrate the mechanism that is driving the polarization of wages and employment, we present a parsimonious static model, and analyze its behavior as productivity levels increase across sectors. The key novel feature of our model is that we assume that each sector values different skills in its production process. Relaxing the assumption of the homogeneity of labor allows us to derive predictions, not only about the employment and expenditure shares, but also about the relative average wages across sectors over time.

[24] In general, there are three ways of conducting a three-way decomposition depending on which element one separates first. The other decompositions give virtually the same results, see online Appendix A.8. The decomposition of the decade-by-decade wage changes shows broadly similar patterns, see Table A-8 in online Appendix A-9.

Table 2—Decomposition of Changes in Relative Occupational Wages

	Relative wages			
	3 × 3		10 × 11	
	1950–2007	1960–2007	1950–2007	1960–2007
Manual/Routine				
Total Δ	0.289	0.310	0.289	0.310
Industry Δ	0.180	0.148	0.225	0.218
Occupation Δ	0.108	0.162	0.064	0.093
Abstract/Routine				
Total Δ	0.327	0.240	0.327	0.240
Industry Δ	0.310	0.254	0.376	0.317
Occupation Δ	0.016	−0.014	−0.050	−0.077

Notes: Same data as in Figure 1. For each occupational category, the first row presents the total change, the second presents the industry component, and the third presents the occupation component over the period 1950 or 1960 to 2007. The first two columns use 3 occupations and 3 sectors, columns three and four use 10 occupations and 11 industries.

We assume that the economy is populated by heterogeneous agents, who all make individually optimal decisions about their sector of work. Every individual chooses their sector of work to maximize wages, in a Roy-model type setup. We assume that individuals are ex ante heterogeneous in their efficiency units of labor in low-skilled services, manufacturing, and high-skilled services, and, thus, endogenously sort into the sector where the return to their labor is the highest.

Furthermore these individuals are organized into a stand-in household, which maximizes its utility subject to its budget constraint.[25] Households derive utility from consuming high- and low-skilled services and manufacturing goods.

The economy is in a decentralized equilibrium at all times: individuals make sectoral choices to maximize their wages, the stand-in household collects all wages and maximizes its utility by optimally allocating this income between low-skilled services, manufacturing goods and high-skilled services. Production is perfectly competitive, wages and prices are such that all markets clear. We analyze the qualitative and quantitative role of technological progress in explaining the observed sectoral wage and employment dynamics since the 1960s.

A. *Sectors and Production*

There are three sectors in the model: high-skilled services (H), manufacturing (M), and low-skilled services (L). All goods and services are produced under perfect competition, and each sector uses only labor as an input into production. The technology to produce in each sector is

$$Y_j = A_j N_j \quad \text{for} \quad j \in \{L, M, H\}, \tag{2}$$

[25] We make the assumption of a stand-in household purely for expositional purposes. Given that the preferences we use are homothetic (see Section IIB), the resulting sectoral demands are equal to the aggregation of individual demands.

where A_j is productivity and N_j is the total amount of efficiency units of labor (efficiency labor for short) hired in sector J for production. Sector J firms are price takers, therefore the equilibrium wage per efficiency unit of labor (unit wage for short) in this sector has to satisfy

$$\omega_j = \frac{\partial p_j Y_j}{\partial N_j} = p_j A_j \quad \text{for} \quad j \in \{L, M, H\}. \tag{3}$$

Note that the wage of a worker with a efficiency units of sector J labor when working in sector J is $a\omega_j$.

B. *Labor Supply and Demand for Goods*

The stand-in household consists of a measure one continuum of different types of members. Each member chooses which one of the three market sectors to supply his one unit of raw labor in. The household collects the wages of all its members and decides how much low-skilled services, manufacturing goods, and high-skilled services to buy on the market.

Sector of Work.—We assume that every member of the household works full time in one of the three market sectors. Since every member can work in any of the three sectors, and each member's utility is increasing in his own wages (as well as in all other members' wages), it is optimal for each worker to choose the sector that provides him with the highest wages.

Individuals are heterogeneous in their endowment of efficiency units of labor, $\mathbf{a} \in \mathbb{R}^3_+$, which is drawn from a time invariant distribution $f(\mathbf{a})$. This is an innate ability distribution, and as such is prior to any form of human capital that a worker might accumulate, for example, by acquiring education. Even though we do not model this explicitly, one could think of our model as having a reduced-form educational choice in the following sense. If a worker, given their ability, selects a sector, say H, to work in, they will get education, or other qualifications, as necessary to enter that sector.[26]

The endowment, $\mathbf{a}$, determines each individual's productivity in sectors L, M, and H. We assume that each dimension of ability corresponds to one sector, such that $a_l \equiv \mathbf{a}(1)$ denotes the individual's efficiency units of labor in low-skilled services, $a_m \equiv \mathbf{a}(2)$ in manufacturing, while $a_h \equiv \mathbf{a}(3)$ denotes his efficiency units in high-skilled services. Therefore the wage of an individual with $\mathbf{a} = (a_l, a_m, a_h)$ efficiency units of labor if working in sector J is $a_j\omega_j$. Given wage rates ω_l, ω_m, and ω_h per efficiency unit of labor, the optimal decision of any agent can be characterized as follows.

[26] Given that high-skilled services is the most intensive sector in college-educated workers, the increase in college education that the United States has witnessed over the last decades is in line with our model, as it generates an increase in the demand for high-skilled services, providing a link from structural change to educational attainment (see, for example, also Buera, Kaboski, and Rogerson 2015).

RESULT 1: *Given unit wage rates ω_l, ω_m, and ω_h, the optimal sector choice of individuals can be characterized by two relative unit wages:*

$$\frac{\omega_l}{\omega_m} \quad \textit{and} \quad \frac{\omega_h}{\omega_m}.$$

It is optimal for an individual with (a_l, a_m, a_h) efficiency units of labor to work in:

- *sector L if and only if*

$$a_l \geq \frac{1}{\frac{\omega_l}{\omega_m}} a_m \quad \textit{and} \quad a_l \geq \frac{\frac{\omega_h}{\omega_m}}{\frac{\omega_l}{\omega_m}} a_h. \tag{4}$$

- *sector M if and only if*

$$a_m \geq \frac{\omega_l}{\omega_m} a_l \quad \textit{and} \quad a_m \geq \frac{\omega_h}{\omega_m} a_h. \tag{5}$$

- *sector H if and only if*

$$a_h \geq \frac{\frac{\omega_l}{\omega_m}}{\frac{\omega_h}{\omega_m}} a_l \quad \textit{and} \quad a_h \geq \frac{1}{\frac{\omega_h}{\omega_m}} a_m. \tag{6}$$

Figure 4 shows this endogenous sorting behavior. The left panel shows that for a given efficiency in high-skilled services, a_h^0, individuals who have relatively low efficiency in both manufacturing and low-skilled services sort into H (the horizontally striped area), those with relatively higher efficiency in low-skilled services sort into L (the dotted area), while those with relatively higher efficiency in manufacturing sort into M (the vertically striped area). The middle and right panel show the same for a given manufacturing and low-skilled service efficiency. The comparative statics of optimal sorting with respect to changes in the relative unit wages is straightforward.

The optimal sector of work choices of individuals determine the effective labor supplies in the three markets:

$$N_l\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right) = \int_0^{\infty} \int_0^{\frac{\omega_l}{\omega_m} a_l} \int_0^{\frac{\frac{\omega_l}{\omega_m}}{\frac{\omega_h}{\omega_m}} a_l} a_l f(a_l, a_m, a_h)\, da_h\, da_m\, da_l, \tag{7}$$

$$N_m\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right) = \int_0^{\infty} \int_0^{\frac{1}{\frac{\omega_l}{\omega_m}} a_m} \int_0^{\frac{1}{\frac{\omega_h}{\omega_m}} a_m} a_m f(a_l, a_m, a_h)\, da_h\, da_l\, da_m, \tag{8}$$

$$N_h\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right) = \int_0^{\infty} \int_0^{\frac{\frac{\omega_h}{\omega_m}}{\frac{\omega_l}{\omega_m}} a_h} \int_0^{\frac{\omega_h}{\omega_m} a_h} a_h f(a_l, a_m, a_h)\, da_m\, da_l\, da_h. \tag{9}$$

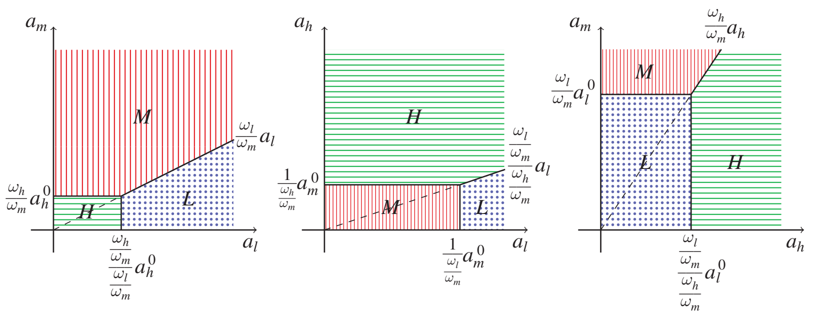

FIGURE 4. OPTIMAL SECTOR OF WORK

Notes: This figure depicts the optimal sector of work choices as a function of ω_l/ω_m and ω_h/ω_m from these perspectives. The left panel shows, for a given a_h^0 value, the optimal sector choice for all $\{a_l, a_m\}$ pairs. The middle panel shows, for a given a_m^0 value, the optimal sector choice for all $\{a_l, a_h\}$ pairs. The right panel shows, for a given a_l^0 value, the optimal sector choice for all $\{a_h, a_m\}$ pairs. The dotted areas are where L is the optimal sector, the vertically striped areas show where M is optimal, and the horizontally striped areas show where H is optimal.

The effective labor supply in sector J is the total amount of sector J efficiency units, a_j, supplied to that sector. This is not measurable in the data, but we observe hours worked, which corresponds to the raw labor supply or employment share in the model. These employment shares are the mass of individuals who supply their labor in the given sectors:

$$L_l\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right) = \int_0^{\infty} \int_0^{\frac{\omega_l}{\omega_m}a_l} \int_0^{\frac{\frac{\omega_l}{\omega_m}}{\frac{\omega_h}{\omega_m}}a_l} f(a_l, a_m, a_h)\, da_h\, da_m\, da_l, \tag{10}$$

$$L_m\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right) = \int_0^{\infty} \int_0^{\frac{1}{\frac{\omega_l}{\omega_m}}a_m} \int_0^{\frac{1}{\frac{\omega_h}{\omega_m}}a_m} f(a_l, a_m, a_h)\, da_h\, da_l\, da_m, \tag{11}$$

$$L_h\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right) = \int_0^{\infty} \int_0^{\frac{\frac{\omega_h}{\omega_m}}{\frac{\omega_l}{\omega_m}}a_h} \int_0^{\frac{\omega_h}{\omega_m}a_h} f(a_l, a_m, a_h)\, da_m\, da_l\, da_h. \tag{12}$$

In a similar vein, ω_l, ω_m, and ω_h are the sectoral unit wages, which are in general also not observed in the data, but sectoral average wages are. These are simply the total earnings in a sector divided by the mass of people working in the sector, or equivalently the unit wage times the average worker efficiency ($\overline{a}_j = N_j/L_j$) in the given sector:

$$\overline{w}_j = \frac{\omega_j N_j}{L_j} \equiv \omega_j \overline{a}_j \qquad \text{for} \qquad j \in \{L, M, H\}. \tag{13}$$

Demand for Consumption Goods and Services.—Household members derive utility from low-skilled services, manufacturing goods, and high-skilled services.

The household allocates total income earned by household members to maximize the following utility:

$$\max_{C_l, C_m, C_h} u\left(\left[\theta_l C_l^{\frac{\varepsilon-1}{\varepsilon}} + \theta_m C_m^{\frac{\varepsilon-1}{\varepsilon}} + \theta_h C_h^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}\right)$$

subject to

$$p_l C_l + p_m C_m + p_h C_h \ \leq \ \omega_l N_l + \omega_m N_m + \omega_h N_h,$$

where u is any monotone increasing function; $\omega_l L_l + \omega_m N_m + \omega_h N_h$ are the total wages of household members; and p_l, p_m, and p_h are the prices of the low-skilled services, the manufacturing goods, and the high-skilled services.

The household's optimal consumption bundle has to satisfy

$$\frac{C_l}{C_m} \ = \ \left(\frac{p_l}{p_m}\frac{\theta_m}{\theta_l}\right)^{-\varepsilon}, \tag{14}$$

$$\frac{C_h}{C_m} \ = \ \left(\frac{p_h}{p_m}\frac{\theta_m}{\theta_h}\right)^{-\varepsilon}. \tag{15}$$

C. *Competitive Equilibrium and Structural Change*

A competitive equilibrium is given by relative unit wage rates $\{\omega_l/\omega_m, \omega_h/\omega_m\}$, prices $\{p_l, p_m, p_h\}$, and consumption demands $\{C_l, C_m, C_h\}$, given productivities $\{A_l, A_m, A_h\}$, where individuals, households, and firms make optimal decisions, and all markets clear.

Using goods market clearing in all sectors ($Y_j \ = \ C_j$ for $j \ \in \ \{L, M, H\}$), where the supply is given by (2), and the market clearing unit wage rates, (3), in the household's optimality conditions, (14) and (15), we obtain the following:

$$\frac{A_l}{A_m}\frac{N_l}{N_m} \ = \ \left(\underbrace{\frac{\omega_l}{\omega_m}\frac{A_m}{A_l}}_{=p_l/p_m}\frac{\theta_m}{\theta_l}\right)^{-\varepsilon},$$

$$\frac{A_h}{A_m}\frac{N_h}{N_m} \ = \ \left(\underbrace{\frac{\omega_h}{\omega_m}\frac{A_m}{A_h}}_{=p_h/p_m}\frac{\theta_m}{\theta_h}\right)^{-\varepsilon}.$$

The left-hand side is the relative supply, while the right-hand side is the relative demand for low- and, respectively, high-skilled services compared to manufacturing. A change in the relative productivity affects both the relative supply and the relative demand.

An increase in relative manufacturing productivity compared to low-skilled service productivity (A_m/A_l) has two direct effects: (i) it reduces the relative supply of low-skilled services, (Y_l/Y_m), and (ii) through an increase in the relative price of low-skilled services (p_l/p_m), it lowers the relative demand for low-skilled services. If low-skilled services and manufacturing goods are complements, $\varepsilon < 1$, the effect through relative prices is the weaker one, and relative supply falls by more than relative demand. To restore equilibrium, the relative supply of low-skilled services has to increase and/or its relative demand has to fall compared to manufacturing.

In order for the relative supply to increase, the efficiency units of labor hired in low-skilled services have to increase relative to manufacturing, which requires a rise in the relative unit wage, ω_l/ω_m. At the same time, a rise in the relative unit wage also increases the relative price of low-skilled services, thus lowering the relative demand. Similarly, an increase in A_m/A_h, through its effect on relative supply and relative demand requires a rise in ω_h/ω_m.

Using the optimal sorting of individuals, (7), (8), and (9), we obtain the following expressions, which allow us to formally analyze the comparative static properties of the equilibrium:

$$\frac{N_l\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right)}{N_m\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right)} \left(\frac{\omega_l}{\omega_m}\right)^{\varepsilon} = \left(\frac{A_m}{A_l}\right)^{1-\varepsilon} \left(\frac{\theta_m}{\theta_l}\right)^{-\varepsilon}, \tag{16}$$

$$\frac{N_h\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right)}{N_m\left(\frac{\omega_l}{\omega_m}, \frac{\omega_h}{\omega_m}\right)} \left(\frac{\omega_h}{\omega_m}\right)^{\varepsilon} = \left(\frac{A_m}{A_h}\right)^{1-\varepsilon} \left(\frac{\theta_m}{\theta_h}\right)^{-\varepsilon}. \tag{17}$$

These two equations implicitly define the relative unit wages, ω_l/ω_m and ω_h/ω_m, and in turn these fully characterize the equilibrium of the economy.

PROPOSITION 1: *When manufacturing goods and the two types of services are complements* $(\varepsilon < 1)$, *then faster productivity growth in manufacturing than in the two types of services* $(dA_m/A_m > dA_h/A_h = dA_l/A_l)$ *leads to a change in the optimal sorting of individuals across sectors. In particular,* ω_l/ω_m *and* ω_h/ω_m *unambiguously increase, while* ω_l/ω_h *can rise or fall. This results in an unambiguous increase in efficiency labor in L and in H, and a reduction in efficiency and raw labor in M.*

PROOF:

Total differentiation of (16) and (17). See online Appendix B for details. ∎

Proposition 1 confirms the results of Ngai and Pissarides (2007) in terms of efficiency labor, rather than raw labor or employment shares: when sectoral outputs are complements in consumption, effective labor inputs need to increase in the sectors that become relatively less productive. As manufacturing productivity grows the fastest, efficiency labor has to move out of manufacturing into both low- and high-skilled services. Since individuals optimally sort into the sector with the highest return for them, this implies that the equilibrium relative unit wages have to adjust. Proposition 1 states what these adjustments entail. The adjustment to the new equilibrium requires sector *M* to be squeezed from both sides, ω_l/ω_m and ω_h/ω_m have to increase. This is very intuitive: sector M has to shrink, while sectors L and H have to expand, which requires sector M unit wages to fall both relative to sector H and sector L unit wages. This implies that in sector M not only efficiency units of labor, but also the raw employment (share) falls, while the employment share of overall services expands. It is worthwhile to note that these results hold for any underlying distribution of efficiency units of labor, $f(a_l, a_m, a_h)$. However, in general, it is ambiguous whether the boundary between L and H shifts up or down (ω_l/ω_h increases or decreases), and, thus, also whether the employment share of both L and H increases. Since, in general, the boundary between sectors L and H changes, one of the sectors loses workers to the other sector, which might imply that the employment share of one of the service sectors falls. The effective employment of both service sectors unambiguously increases, as their gain from sector M always outweighs their potential loss to the other service sector.

In terms of relative average wages, in general, it is not possible to sign the changes predicted by the model. The reason is self-selection; the workers leaving manufacturing are the ones that have a relatively low efficiency. As a consequence, the average efficiency in manufacturing increases when its employment share decreases. This tends to increase the average wage in manufacturing compared to the other sectors, offsetting to some extent the direct effect of the falling relative manufacturing unit wage. Without further assumptions, it is conceivable that the indirect effect through the average efficiency might overturn the direct effect of changing unit wages. To see this, consider the average low- (high)-skilled service wage relative to the average manufacturing wage (from (13)):

$$\frac{\overline{w}_j}{\overline{w}_m} = \frac{\omega_j \frac{N_j}{L_j}}{\omega_m \frac{N_m}{L_m}} = \frac{\omega_j}{\omega_m} \frac{\overline{a}_j}{\overline{a}_m} \qquad \text{for} \qquad j \in \{L, H\}.$$

From Proposition 1 we know that ω_j/ω_m increases. Due to the changing nature of self-selection, average efficiency in M increases, while in J it decreases, thus, in general, the change in average low- (high)-skilled service wages relative to average manufacturing wages is ambiguous. In general, the overall direction of change of the relative average wages depends on the exact form of the underlying distribution. We explore the change in relative average wages in more detail in the quantitative analysis, and in all our simulations the relative average wages (for both L and H to M) move in the same direction as the relative unit wages.

Since the structural change literature focuses on employment shares and value added shares, we also investigate our model's implications for relative value added. We can show that relative sectoral value added shares increase in the sectors with lower productivity growth if the sectoral outputs are complements in consumption.

PROPOSITION 2: *When manufacturing goods and the two types of services are complements* ($\varepsilon < 1$), *then faster productivity growth in manufacturing than in the two types of services* ($dA_m/A_m > dA_h/A_h = dA_l/A_l$) *increases the relative value added in both high- and low-skilled services compared to manufacturing:*

$$d\frac{p_h Y_h}{p_m Y_m} > 0 \qquad \textit{and} \qquad d\frac{p_l Y_l}{p_m Y_m} > 0.$$

These results can be understood by considering the following. In this model, sectoral value added is equal to the sectoral wage bill: $p_i Y_i = p_i A_i N_i = \omega_i N_i$. Proposition 1 tells us for $j \in \{L, H\}$ that ω_j/ω_m increases, that N_j increases, and N_m falls. Both relative unit wages and effective labor changes increase the value added output of sector J relative to sector M.

The sectoral value added can be further expressed as $p_i Y_i = \omega_i N_i = \overline{w}_i L_i$, since the sectoral wage bill can be expressed as either sectoral unit wage times sectoral efficiency labor, or as sectoral average wage times sectoral raw labor. Using this latter expression we can show that

$$\frac{p_i Y_i}{p_j Y_j} = \frac{\overline{w}_i}{\overline{w}_j} \frac{L_i}{L_j}.$$

According to our model, relative sectoral value added has to equal the product of relative sectoral average wages and relative sectoral employment shares. This result holds even if we include capital in the model, unless one assumes either imperfect capital mobility across sectors, or different sectoral capital intensities. Since in the data the relative sectoral value added does not equal the product of relative sectoral average wages and employment shares, in our calibration we target relative average wages and sectoral employment shares, as it is the evolution of these two measures that is the focus of our paper.

III. Quantitative Results

In this section, we quantitatively assess the contribution of structural transformation to the polarization of employment and wages across sectors. To do this we consider the evolution of the competitive equilibrium in terms of employment shares and relative average sectoral wages as productivity increases in manufacturing and in both low- and high-skilled services. We calibrate our parameters to match key moments in 1960, and then feed in the exogenous process for labor productivity to generate predictions for the evolution of employment and wages. We choose 1960 as the starting point for the quantitative evaluation of the model because, as documented in Section IB, the contraction of manufacturing employment is apparent in our data from 1960 onward. We first describe the data targets and the calibration strategy, and then discuss the quantitative importance of our mechanism.

A. *Calibration*

Four of the key moments are calculated from the 1960 census data. These are the relative average sectoral wages, $\overline{w}_l / \overline{w}_m$ and $\overline{w}_h / \overline{w}_m$, and the sectoral employment shares, L_l, L_m, and L_h, which sum to one. Employment shares are calculated as share of hours worked, and relative average wages are the sector premia, both as in Section IB. The fifth moment is the dispersion of the non-transitory component of log non-agricultural wages, as in Lagakos and Waugh (2013), which we estimate from Panel Study of Income Dynamics (PSID) data from the years 1968–1975.[27]

All parameters are time-invariant, and the only exogenous change over time is labor productivity growth. The following parameters need to be calibrated: the parameters of the utility function $\theta_l, \theta_m, \theta_h, \varepsilon$, the distribution of labor efficiencies, $f(a_l, a_m, a_h)$, and the initial sectoral labor productivities, $A_l(0), A_m(0), A_h(0)$.

We proceed in two steps. First, we calibrate the underlying distribution of labor efficiencies under the assumption that the 1960 employment shares are met. Second, given the distribution of labor efficiencies, we calibrate the utility function and initial productivity parameters to match the 1960 employment shares.

The main idea behind the first step of the calibration is the following. For any given distribution, $f(a_l, a_m, a_h)$, there is a unique pair of relative unit wages, $\{\omega_l/\omega_m, \omega_h/\omega_m\}$, which results in the employment shares observed in the data in 1960. These relative unit wages in turn imply all the wages in the economy, including sectoral relative average wages and overall wage dispersion. We calibrate the parameters of the distribution to guarantee that if the observed employment shares are matched, then so are the relative average wages in 1960 and the dispersion of log wages.

For the baseline calibration we assume that labor efficiencies are drawn from a trivariate lognormal distribution. This assumption is not innocuous, but there are several reasons that support this choice. First, the lognormal distribution is particularly important in the selection literature (e.g., Roy 1951, Heckman and Sedlacek (1985), Borjas (1987), Mulligan and Rubinstein 2008). Second, empirical wage distributions are skewed to the right and typically resemble a lognormal distribution. Assuming that the underlying distribution of abilities is trivariate lognormal does not guarantee that after selection the resulting one dimensional wage distribution is also going to be lognormal. Nonetheless, under our parametrization the model generates a wage distribution that resembles those we see in reality, in particular, it has a long right tail. Third, the trivariate lognormal distribution allows for a very flexible correlation structure, the quantitative effect of which we explore.

Without loss of generality we normalize the mean of a_l, a_m, and a_h to be unity.[28] Given these assumptions, the six parameters of the variance-covariance matrix are left to be calibrated. Let σ_j denote the standard deviation of efficiency in sector J, and ρ_{jk} the correlation between sector J and sector K efficiency. In our baseline calibration we set all pairwise correlations between workers' sectoral efficiencies to 0.3. For this set of correlations—over which we conduct extensive robustness checks in Section IIIC—we calibrate the three variance parameters of the distribution to match the relative average wages in 1960 and the dispersion of log wages.[29]

[27] We rely on PSID panel data, as it is not possible to calculate this parameter in cross-sectional census data. We use data for the first eight years, which are available in the PSID, as we want to be as close to 1960 as possible, and to have a large enough sample size. See online Appendix C.1 for the details of this estimation.

[28] For the trivariate log normal distribution, numerical simulations show that the path of employment shares and of relative average wages is independent from the level of these means.

[29] We use sectoral log wage dispersion only to calibrate the variance-covariance matrix of the underlying distribution of abilities. As our interest is in the evolution of employment shares and relative average wages, we leave the analysis of the implications of structural change for overall and sectoral wage dispersion for future work.

Table 3—Calibrated Parameters

	Description	Value
ρ_{lm}	Correlation between L and M sector efficiency	0.3
ρ_{lh}	Correlation between L and H sector efficiency	0.3
ρ_{mh}	Correlation between M and H sector efficiency	0.3
σ_l^2	Variance of L sector efficiency	0.12
σ_m^2	Variance of M sector efficiency	0.30
σ_h^2	Variance of H sector efficiency	0.35
ε	CES between L, M, and H in consumption	0.002
τ_l	Relative weight on L	0.54
τ_h	Relative weight on H	0.84

Notes: The correlation values are set at 0.3, and the elasticity of substitution, ε, is taken from the literature. The remaining parameters are calibrated to match the sectoral employment shares, the relative average wages, and the overall dispersion of wages.

The parameters of the utility function and the initial labor productivities are left to be calibrated. Previous literature has found a very low elasticity of substitution between goods and services when output is measured in consumption value added terms. Ngai and Pissarides (2008) find that plausible estimates are in the range $(0, 0.3)$, while Herrendorf, Rogerson, and Valentinyi (2013) find a value of $\varepsilon = 0.002$. While neither these papers, nor others in the literature, have estimated the elasticity for our sector classification, we use $\varepsilon = 0.002$ in our baseline calibration, and conduct sensitivity analysis with respect to this parameter. Of the remaining six parameters, $\theta_l, \theta_m, \theta_h$, and $A_l(0), A_m(0), A_h(0)$ only two ratios matter for the equilibrium of this economy, as can be seen from equations (16) and (17). We calibrate $\tau_l \equiv (A_m(0)/A_l(0))^{1-\varepsilon}(\theta_l/\theta_m)^{\varepsilon}$ and $\tau_h \equiv (A_m(0)/A_h(0))^{1-\varepsilon}(\theta_h/\theta_m)^{\varepsilon}$ to match the unit wages in 1960 found in the first step of the calibration. The calibrated parameters are summarized in Table 3.

It is well-known that if individuals self-select based on their endowments of efficiency units and one cannot observe these efficiency units, then the measurement of changes in average wages or in labor productivity will be biased.[30] In our model, expanding sectors soak up, while contracting sectors shed, relatively less efficient workers. This implies that the average efficiency in manufacturing increases, while the average efficiency in low- and high-skilled services falls over time, which—if left uncorrected—leads to an overestimation of productivity growth in manufacturing relative to both types of services.[31] To understand the potential magnitude of this bias, we correct for this selection effect, and report both measured and model implied productivity growth rates.

Similarly to Ngai and Petrongolo (2014), we measure labor productivity growth by dividing the growth rate of industry-level quantity indices from the Bureau of Economic Analysis (BEA) with the growth rate of industry-level hours worked data from the census/ACS data, and aggregating it up to our three sectors. Our model output can be written as $Y_j = A_j N_j = B_j L_j$ for each sector J, where L_j is the raw

[30] Carneiro and Lee (2011) estimated the bias in the measurement of the skill premium, while Young (2014) pointed this out in the context of measuring productivity growth differentials across sectors.

[31] This is true only when manufacturing employment is shrinking, and low- and high-skilled service employment is expanding.

Table 4—Annual Average Labor Productivity Growth

	Adjusted for selection			Based on raw labor		
	A_l	A_m	A_h	B_l	B_m	B_h
1960–1970	1.0077	1.0248	1.0132	1.0068	1.0279	1.0124
1970–1980	1.0095	1.0140	1.0116	1.0093	1.0148	1.0116
1980–1990	1.0051	1.0235	1.0108	1.0042	1.0270	1.0101
1990–2000	1.0265	1.0271	1.0120	1.0270	1.0286	1.0083
2000–2007	1.0072	1.0282	1.0162	1.0062	1.0320	1.0163
1960–2007	1.0113	1.0231	1.0125	1.0109	1.0258	1.0115

Notes: Labor productivity growth rates in the last three columns are calculated by dividing industry-level quantity indices from the BEA with industry-level employment growth data taken from the census/ACS, and aggregating up to our three sectors. The first three columns give the path of model productivity growth, which for our baseline calibration result in the same measured labor productivity growth as in the data.

employment share (hours worked) and B_j the measured labor productivity, while A_j is the true productivity in the model and N_j the efficiency units of labor. To account for the difference between N_j and L_j—the selection effect—we compute the path of the A_js in the following way. Given the calibration of all of the fixed parameters of the model, we find the path of A_js such that the model implied growth in B_js is equal to the labor productivity growth measured in the data.

Table 4 shows, in the first three columns, the model implied, and in the last three columns, the measured average annual labor productivity growth in low-skilled services, manufacturing, and high-skilled services for each decade between 1960 and 2007, as well as for the entire period. According to our calculations the growth of labor productivity in manufacturing was higher than in either low- or high-skilled services in each of the decades considered. Under our calibration, the bias in the relative productivity differentials is small, but not negligible.[32] It is worth to note that both productivity growth and the relative productivity growth across sectors varied significantly decade by decade. For this reason, we evaluate the quantitative performance of the model in two ways: (i) by plugging in the average annual growth rates for the entire period; and (ii) by plugging in the decennial growth rates.

B. *Wage and Employment Dynamics*

To understand the strength of the mechanisms that we highlight, we simulate the competitive equilibrium of the economy at different productivity levels. We fix the preference and the sectoral efficiency distribution parameters at their calibrated values, and feed in the labor productivity growth shown in Table 4. Our ultimate interest is the endogenous path of employment shares and relative average wages.

Figure 5 plots the dynamics for our baseline calibration using average annual growth rates over the period 1960–2007, adjusted for selection (bottom left numbers in Table 4). The top left panel shows (in logs) the path of both the measured productivity (in the data and the model) in dotted lines, and the model productivity in

[32] Young (2014) finds that the implied bias might potentially be so large as to overturn the conventional wisdom of faster productivity growth in manufacturing. However, with our calibration this is not the case.

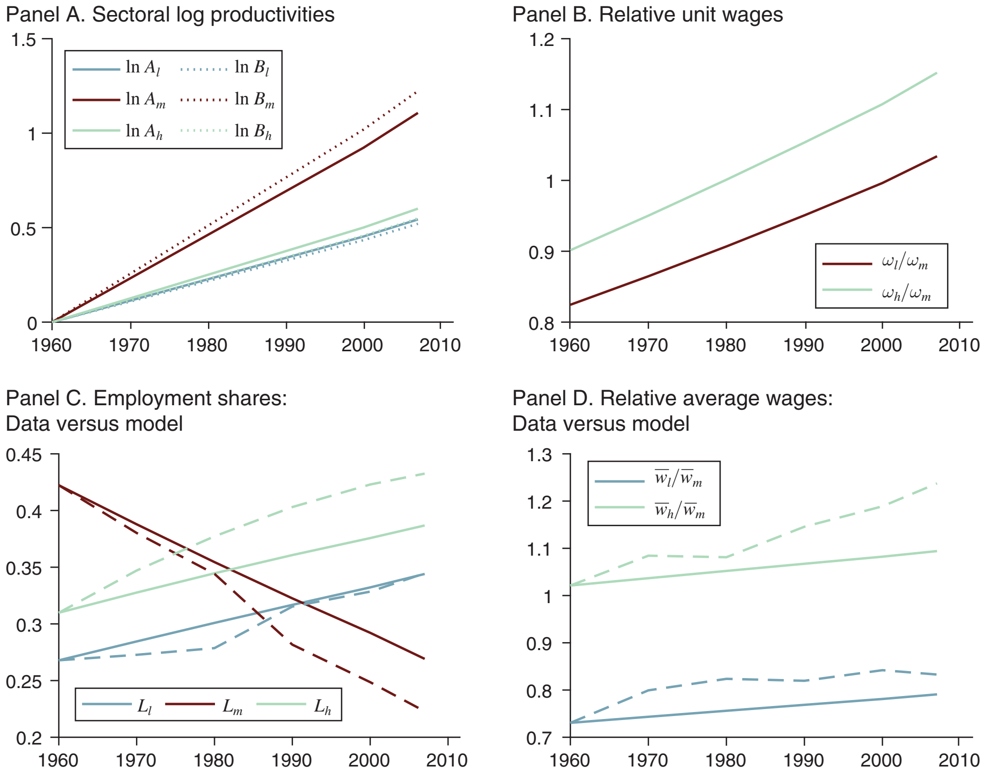

FIGURE 5. TRANSITION OF THE BENCHMARK MODEL

Notes: Panel A shows the observed average change in log labor productivity (dotted line) and model productivity (solid line). Panel B shows the endogenous response of the relative average unit wages. Panel C shows the predicted employment shares (solid line) and their actual path (dashed line), while Panel D shows the model predicted (solid line) and actual path (dashed line) of the relative average sectoral wages.

solid lines for all three sectors. Since productivity growth is highest in the manufacturing sector, but manufactured goods and both types of services are complements in consumption, the increased demand for the output of all sectors in equilibrium is met through a reallocation of labor toward low- and high-skilled services, as we showed in Proposition 1. [33] The increased demand for labor in low- and high-skilled services puts an upward pressure on the unit wages in these sectors relative to the unit wage in manufacturing, which we plot in the top right panel.

The bottom two panels show our model's predictions (solid lines) contrasted with the data (dashed lines) for our measures of interest. Not surprisingly, the model matches the 1960 employment shares (bottom left panel) and the 1960 relative average wages (bottom right panel) very well, as we targeted these measures. But the model also does well in predicting the paths of employment shares and relative

[33] In Proposition 1, we assumed that productivity growth in the two types of services was equal. In the quantitative evaluation of the model, we relax this assumption and take productivity growth from the data. Nonetheless, the results derived in the proposition hold in all our simulations.

average wages after 1960. Our baseline model predicts at least 60 percent of the change in the employment share of each sector.[34]

In our model, the relative average wage changes are driven by changes in the relative unit wages and changes in the relative average sectoral labor efficiencies. As discussed in Section IIC, these two effects, in general, go in opposite directions, however, the direct effect of the unit wages typically dominates the indirect effect that it has on average sectoral efficiencies. This is the case in our baseline calibration as well, and our model overall predicts about 33 percent of the growth in the relative low-skilled service sector wages, and 59 percent of the growth in the relative average high-skilled service sector wages compared to manufacturing.[35]

The path of employment shares and relative average wages generated by the model are very smooth compared to the data. This is not surprising, as we assumed a constant annual growth rate of sectoral labor productivity between 1960 and 2007. However, Table 4 reveals that the growth rates have varied substantially over time. Figure 6 shows the simulated model contrasted with the data when feeding in the model productivity growth rates calculated for each period. The main difference in terms of productivity growth rates is that the growth rate in low-skilled services is very low in the initial decades, and it is very high between 1990 and 2000, when it is almost the same as in manufacturing. Another important thing to note is that the growth rate in high-skilled services is also quite high between 2000 and 2007. These changing productivity differences imply that initially high-skilled service employment expands more slowly, while low-skilled services expand more rapidly, and this pattern is reversed in 1990. While the model quantitatively does worse in the initial decades, the overall predicted changes are the same.

As discussed in Section IIC, while our model qualitatively matches the *changes* in expenditure shares, a model without capital intensity differences and with perfect capital mobility across sectors cannot match the *level* of sectoral relative average wages, employment, and expenditure shares jointly. Figure 7 shows the relative value added in low- and high-skilled services compared to the value added in manufacturing in the model (solid line) and in the data (dashed line) for the time-invariant productivity growth rates. The overall increase in high-skilled services relative to manufacturing is replicated quite well, while for low-skilled services, the model over predicts the increase.[36]

C. *Robustness Checks*

In our baseline calibration we assume that the correlation between any two of the underlying sectoral efficiency draws is 0.3, that the underlying distribution of

[34] In the data, the percentage point change in the employment share of high-skilled services, manufacturing, and low-skilled services are 12, −20, and 8, in our model these numbers are 8, −15, and 8, respectively.

[35] In the data, the relative average wage of L and H compared to M workers increased by 14 and, respectively, 21 percent. In the simulation, this is 8 percent for L to M (25 percent improvement in relative unit wages and 13 percent decline in relative average efficiency), and 7 percent for H to M (28 percent increase in relative unit wages and a more than 15 percent drop in relative average efficiency).

[36] For H to M these numbers are 125 percent in the data, and 112 percent in the model, and for L to M 38 percent in the data and 120 percent in the model.

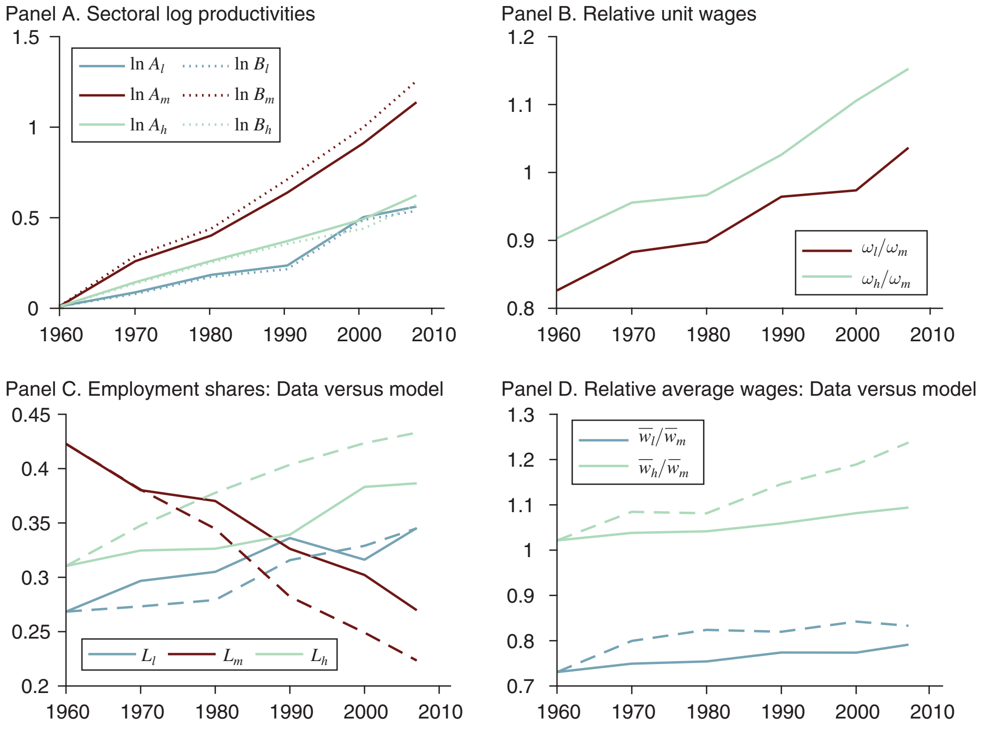

FIGURE 6. TRANSITION OF THE MODEL WITH DECENNIAL GROWTH

Note: The panels show the path of the same variables as in Figure 5, except that we feed in the change in labor productivity decade-by-decade, rather than the average for the entire period.

abilities is trivariate lognormal, and that the elasticity of substitution in consumption is 0.002. Before we analyze the sensitivity of our results to the these assumptions, we first show that given our calibration strategy the model implied path of employment shares is independent of the assumed correlations and the assumed underlying distribution of abilities.

We calibrate the diagonal elements of the variance-covariance matrix of the distribution, and a combination of the utility function parameters and of the initial model productivities to match—among other targets—the employment shares in 1960. Thus, by construction, in the initial period the model implied employment shares are the same across *all* calibrations. Moreover, the model-implied path of employment shares is independent of the underlying ability distribution. This is due to the way we correct for selection effects in the measurement of sectoral productivity growth. In particular, the A_js are such that—conditional on all fixed parameters—the model implied raw labor productivity growth (B_j) is equal to that measured in the data. This implies that the model implied growth in the B_js is also the same across *all* calibrations. This implies that as long as ε is the same across calibrations, the model implied path of employment shares is also the same, as we show below.

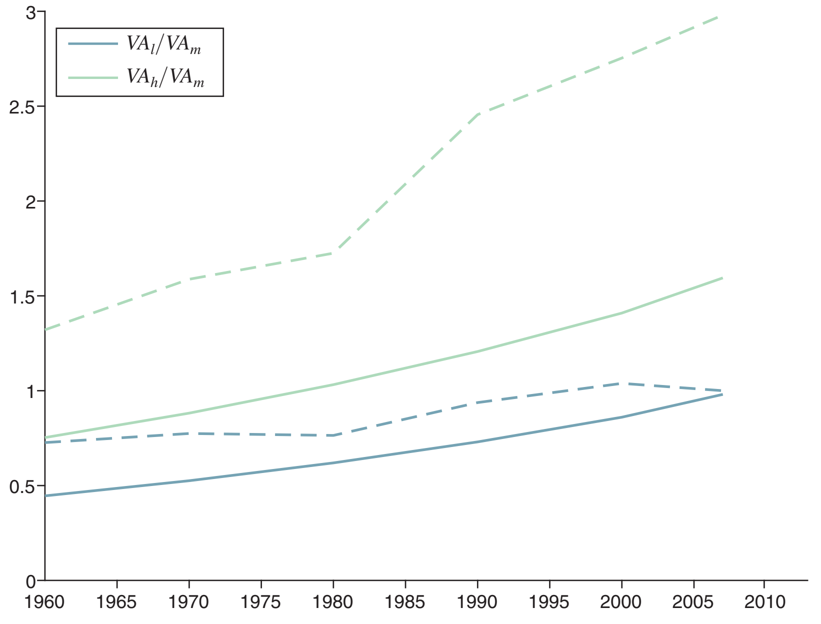

Figure 7. Transition of Relative Low- and High-Skilled Service Value Added

Note: The graph shows the value added in low- and high-skilled services relative to manufacturing as predicted by the model (solid line) and in the data (dashed line).

The model implied labor productivity growth can directly be matched to the model implied employment shares. To see how employment is allocated across sectors, consider the social planner's problem:

$$\max_{N_{lt}, N_{mt}, N_{ht}} u\left(\left[\theta_l C_{lt}^{\frac{\varepsilon-1}{\varepsilon}} + \theta_m C_{mt}^{\frac{\varepsilon-1}{\varepsilon}} + \theta_h C_{ht}^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}\right),$$

$$\text{subject to} \quad C_{jt} = A_{jt} N_{jt} = B_{jt} L_{jt} \qquad \text{for any } j = L, M, H.$$

The social planner's problem can be formulated either as choosing the efficiency units of labor assigned to each sector given the A_js or as choosing the employment shares given the B_js.[37] The first-order conditions in terms of employment shares can be written as

$$\frac{L_{jt}}{L_{kt}} = \left(\frac{\theta_k}{\theta_j}\right)^{-\varepsilon} \left(\frac{B_{kt}}{B_{jt}}\right)^{1-\varepsilon} = \left(\frac{\theta_k}{\theta_j}\right)^{-\varepsilon} \left(\frac{B_{k0}}{B_{j0}}\right)^{1-\varepsilon} \left(\frac{\frac{B_{kt}}{B_{k0}}}{\frac{B_{jt}}{B_{j0}}}\right)^{1-\varepsilon}$$

$$= \frac{L_{j0}}{L_{k0}} \left(\frac{\frac{B_{kt}}{B_{k0}}}{\frac{B_{jt}}{B_{j0}}}\right)^{1-\varepsilon} \qquad \text{for any } t \text{ and } j, k \in \{L, M, H\}.$$

[37] Note that the path of A_js depends on the underlying distribution of abilities.

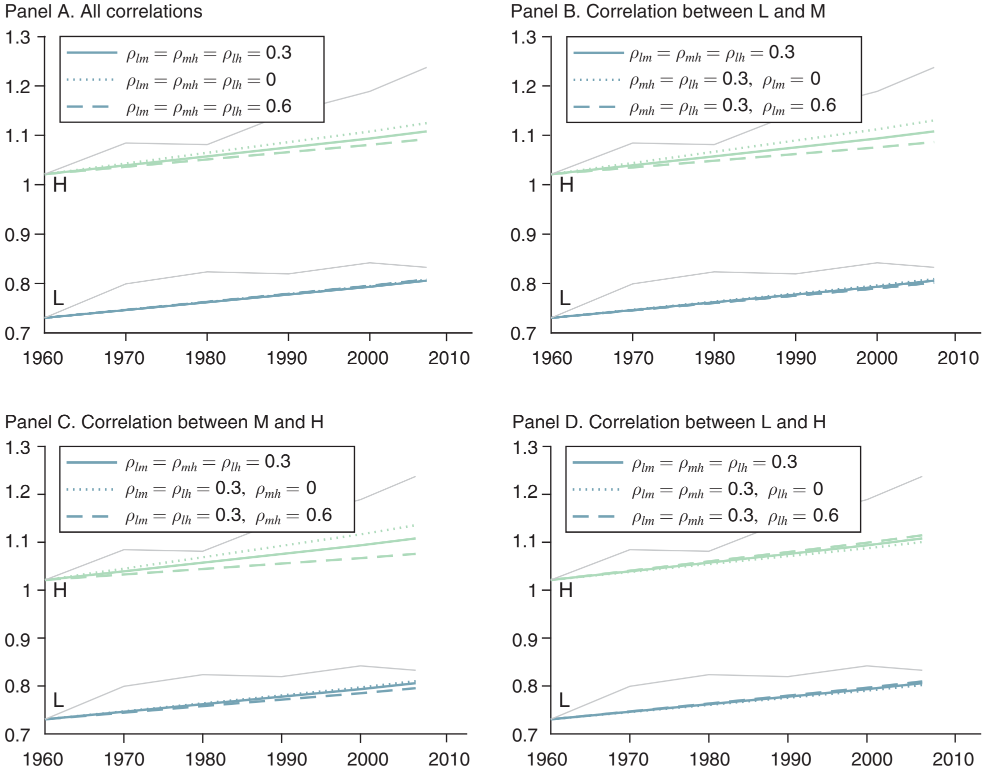

FIGURE 8. TRANSITION UNDER DIFFERENT CORRELATION STRUCTURES

Notes: The set of lines marked with H show the average wage in high-skilled services relative to manufacturing, and the set of lines marked with L show the relative average wage of low-skilled services. The thin solid line shows the data, the thicker solid line shows our baseline calibration, whereas the dotted line represents the path for a lower correlation (0), and the dashed line for a higher correlation (0.6).

The last equality makes use of the fact that for all distributions τ_l and τ_h are calibrated such that the initial L_l, L_m, and L_h are matched. This equation shows that given the growth rate of the measured labor productivity, as long as ε is the same across calibrations, the path of employment shares do not depend on the underlying distribution of sectoral efficiencies. Therefore, we only report the path of relative average wages when conducting the sensitivity analysis with respect to the sectoral efficiency distribution.

Figure 8 summarizes the sensitivity of relative average wage paths to the assumed correlation structure, along with Table A-10 in online Appendix C-2. While average wages relative to manufacturing increase in both the high- and the low-skilled service sector for all calibrations, the magnitude of these changes varies quite a bit. In Figure 8, the top left panel shows the wages for our baseline calibration (solid lines), which features a correlation of 0.3 between the underlying ability draws of any two sectors, along with one where this correlation is 0 (dotted lines) and 0.6 (dashed lines). This graph shows that while relative average high-skilled service wages increase a bit less when the correlation is higher, the path of relative wages in low-skilled services is hardly affected. Looking at the corresponding lines (top, middle bold and last) in Table A-10, we can see that the higher correlation we assume, the calibration requires a less dispersed underlying efficiency distribution. With a less dispersed and more correlated distribution, the model predicts a smaller adjustment in the relative average sectoral wages, as the model gets closer to the case of homogeneous labor (i.e., similar to Ngai and Pissarides 2007). In the limiting case, where each individual is endowed with the same amount of efficiency units of labor in all three sectors, there is no selection. In order to have positive labor supply to all three sectors, unit wages have to be equalized. As unit wages are equalized, individuals are indifferent between working in any of the three sectors. Labor supply across sectors is random, average sectoral wages are equalized, implying relative average wages are independent of the level of technology in the economy. Thus, it is not surprising that our model predicts smaller changes in relative average wages when we assume higher correlations across all three pairs of sectoral abilities.

In the other three panels of Figure 8, we show the relative average wage paths when only modifying one of the baseline correlations to 0 (dotted) and 0.6 (dashed): in the top right panel it is the correlation between sector L and M ability, in the bottom left it is between M and H, and in the bottom right it is between L and H. These graphs show that in general the relative high-skilled service wages are more sensitive to the correlation structure, but the differences in the relative average wage paths are not large.

In our baseline calibration, we assume that the underlying distribution of abilities is trivariate lognormal. At the beginning of this section we showed that the path of employment shares is independent of the assumed distribution of underlying abilities. However, the quantitative—and potentially even the qualitative—predictions regarding relative average wages are likely to be affected by not only the correlation structure, but also the functional form of the distribution. We recalibrate the model assuming a normal distribution, truncated at zero for all three abilities, for the same set of correlations as in Figure 8. As Table A-11 in online Appendix C.2 shows, our model predicts much larger changes in relative average wages when assuming that the underlying efficiencies are drawn from a truncated normal distribution. The model overpredicts the change in the relative low-skilled service wage by 35 to 79 percent, while for relative high-skilled services wages it predicts between 88 and 112 percent of the change.

In our baseline calibration, we use $\varepsilon = 0.002$ for the elasticity of substitution between goods and services (measured in value-added terms) as estimated by Herrendorf, Rogerson, and Valentinyi (2013), which is at the lower end of estimates reported by Ngai and Pissarides (2008). To see whether our results are robust to higher, yet plausible, values of this parameter, we explore how our results change when using $\varepsilon = 0.02$ or $\varepsilon = 0.2$, naturally recalibrating the other parameters to match our five targets. Figure 9 shows that qualitatively the transition paths look exactly the same. A higher elasticity of substitution implies that the effective employment in low- and high-skilled services have to increase less, and the effective employment in manufacturing has to fall less in order to meet equilibrium demands. This in turn implies less adjustment in employment shares and in relative average

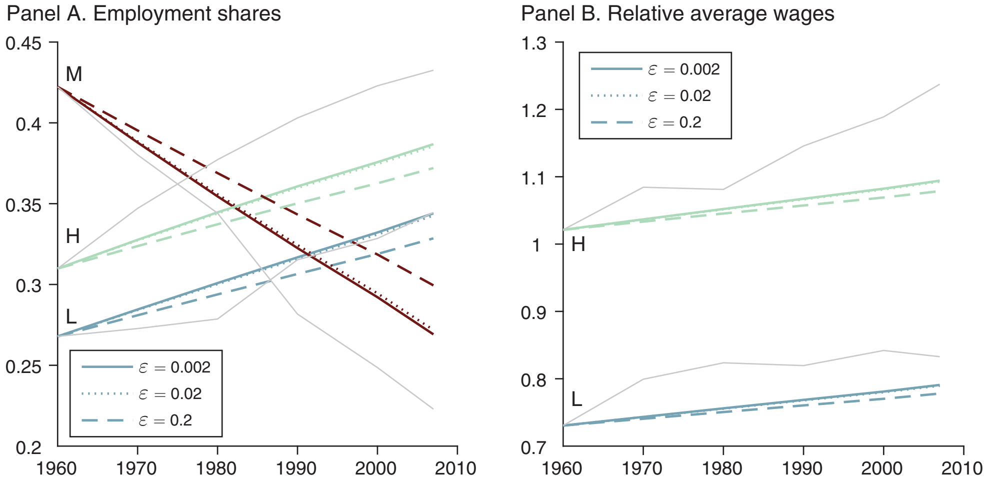

Figure 9. Transition under Different Elasticities of Substitution

Notes: The graph shows the path of employment shares (panel A) and relative average wages (panel B) for different elasticities of substitution, against the data. The thin line shows the data. The solid lines show our baseline calibration ($\varepsilon = 0.002$), whereas the dotted lines represent the path for $\varepsilon = 0.02$, and the dashed lines for $\varepsilon = 0.2$.

wages. Increasing the value of the elasticity of substitution takes the model's predictions further away from the time paths observed in the data. As can be seen in Figure 9 the transition paths look virtually the same for $\varepsilon = 0.002$ and $\varepsilon = 0.02$, while for $\varepsilon = 0.2$ the model predicts less adjustment, but it does reasonably well. This latter version of the model predicts 46 percent of the increase in L and 27 percent of the increase in H sector average wages relative to M. In terms of employment share changes, the model predicts at least half of the observed changes between 1960 and 2007.

D. *Implications for Occupational Employment Polarization*

Even though our model is about sectoral labor market allocations, we can use it to calculate the fraction of occupational employment share changes that it predicts. Fixing the within-sector occupational employment shares at the 1960–2007 period's average, we can compute how much the sectoral labor reallocation—as predicted by our model—would explain of the (between-sector) occupational employment share changes identified in the shift-share decomposition of Section IC. Our model predicts 82 percent of the manual, 72 percent of the routine, and 63 percent of the abstract occupation's between-industry employment share changes. This is equivalent to 44 percent of the total manual, 24 percent of the total routine, and 15 percent of the total abstract employment share change. However, given that our model abstracts from occupational differences within sectors, and thus by construction cannot explain any of the within-industry changes in occupational employment, we think that the model explains a quantitatively important fraction of total occupational employment share changes.

IV. Conclusions

The literature on polarization of employment and wages has typically focused on occupations. We present a set of new empirical facts that suggest that in addition to reallocations between occupations within industries, also shifts between industries contribute to the polarization of labor markets. Moreover, we show that in terms of broadly defined industries, polarization was present as early as 1950–1960 and directly linked to the decline of manufacturing employment. Based on this evidence we propose a novel explanation, one based on structural change. A methodological contribution of our paper is that we develop a multi-sector model with heterogeneous labor in Roy-style fashion, the most parsimonious setup that yet allows heterogeneity in wages. An insight from our model is that unbalanced technological progress does not only lead to structural change, the reallocation of employment across sectors, but also affects sectoral average wages. We find that higher productivity growth in manufacturing than in low- and high-skilled services increases employment and wages in both the low-skilled and the high-skilled service sector, thus leading to the polarization of the labor market. This simple model does remarkably well in predicting the sectoral wage and employment patterns of the last 50 years.

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