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Is Job Polarization a Recent Phenomenon? Evidence from Sweden, 1950–2013, and a Comparison to the United States

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Is Job Polarization a Recent Phenomenon?

Evidence from Sweden, 1950–2013, and a Comparison to the United States[*]

November 16, 2017

Magnus Gustavsson[♦]

Abstract

In this paper, I first show that Swedish job polarization is—contrary to common belief—a long-run phenomenon: the share of middle-wage jobs has declined relative to the highest- and lowest-paid jobs since at least the 1950s. Based on previous results for the US, I then demonstrate that the same major employment shifts across routine and nonroutine jobs drive long-run job polarization in both Sweden and the US. In particular, the shrinking manufacturing sector, with the subsequent decline of routine manual (blue-collar) jobs, stands out as the main explanation for why job polarization is a long-run phenomenon. However, consistent with the hypothesis of routine-biased technological change, both countries display across-the-board declines of routine jobs from around the 1980s, as well as polarizing employment patterns not only between but also within industries. But despite these trend breaks, Sweden actually experienced a stronger job-polarization process—a more pronounced hollowing out of the job-wage distribution—in the pre- than in the post 1980-era.

Keywords: Automation; Industrial Composition; Routine-Biased Technological Change; Routinization; Structural Change

JEL Classifications: J21; J23; N10; N30; O33

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1. Introduction

The phenomenon of declining employment in middle-wage jobs relative to the highest- and lowest-paid jobs has attracted wide attention in recent years. This interest is primarily due to the fit between this job-polarization pattern, documented for both the US and Western European countries since the 1980s, and the whopping fall in the price of computer technology over the same period (see Acemoglu and Autor, 2011). In essence, according to the popular hypothesis of 'Routine Biased Technological Change' (RBTC henceforth), advances in computer-based technology causes routine (middle-wage) jobs to be replaced by machines or exported abroad, resulting in job polarization.[1]

The literature on job polarization seldom analyzes data for periods prior to the 1980s though, which combined with the focus on RBTC often leaves the impression of job polarization as a new phenomenon uniquely tied to the rise of the "computer age". As an illustrative example of this view, Jaimovich and Siu (2015, p.2), in their much-noticed analysis of jobless recoveries in the US labor market, begin by stating that "In the past 25 to 30 years, the US labor market has seen the emergence of two new phenomena: *job polarization* and *jobless recoveries*." (italics in original).

However, recent research by Foote and Ryan (2015) and Bárány and Siegel (2017) show that for the US, job polarization has been present since at least the 1950s. That is, in the US, the relative employment decline of routine jobs began well before the fall in the price of computer power gained real speed in the 1980s.

In addition, the results in Bárány and Siegel (2017) imply that job polarization could be a long run rather than a recent phenomenon for most Western European

[1] Studies that document job polarization and support RBTC as an important explanation from the 1980s onwards include, but are not limited to: Goos, Manning, and Salomons (2009, 2014), Acemoglu and Autor (2011), and Michaels, Natraj, and Van Reenen (2014) based on cross-national evidence; Autor, Katz, and Kearney (2008) and Autor and Dorn (2013) for the US; Goos and Manning (2007) for the UK; Spitz-Oener (2006) and Dustmann, Ludsteck, and Schönberg (2009) for Germany; and Adermon and Gustavsson (2015) and Heyman (2016) for Sweden.

countries as well. Bárány and Siegel's (2017) main conclusion is that persistent post-war employment shifts from manufacturing to service industries drives long-run job polarization in the US. But since this kind of structural change characterizes most developed countries (e.g. Herrendorf, Rogerson, and Valentinyi, 2014), the US results suggest that long-run job polarization could also characterize most developed countries. That is, since manufacturing industries disproportionately use jobs intensive in routine tasks while nonroutine tasks dominate in service industries (e.g. personal and business services), the general decline of manufacturing across developed countries could translate into common long-run patterns of job polarization.

In this paper, I present results that support the idea of job polarization as a long run rather than a recent phenomenon. Based on data for the 63 years spanning 1950-2013, I show that declining employment in middle-wage routine jobs relative to both high- and low-wage nonroutine jobs is a long-run trend not only in the US but also in Sweden, present since at least the 1950s. Drawing on previous US results in Foote and Ryan (2015) and adaptions of Acemoglu and Autor's (2011) US data, I further demonstrate that Sweden and the US display common trends in the underlying employment patterns that point towards structural change as the main driver of long-run job polarization. However, the common US-Sweden results are also consistent with RBTC as an additional driver of job polarization in more recent decades.

In more detail, consistent with the structural-change explanation, I find that shifts in the industrial composition working against employment in routine manual (blue-collar) jobs explain most of the job polarization in both Sweden and the US prior to the 1980s, but also remains important thereafter. Consistent with RBTC as an additional force in more recent decades, I show that the relative decline of middle-wage jobs is more across-the-board in both Sweden and the US from around the 1980s, with dwindling employment in white-collar routine jobs and altering job structures within industries also contributing significantly to the observed job polarization. But despite these trend breaks, summary measures suggest that

Sweden actually experienced a stronger job-polarization process—a more pronounced hollowing out of the job-wage distribution—in the pre- than in the post 1980-era.

To the best of my knowledge, this paper is the first study of long-run job polarization for a European country, going as far back as 1950, and thus the first to be able to make a cross-country comparison between a European country and the US over the full period 1950–2013. The two previous European studies that extend furthest back in time are Goos and Manning (2007) for the UK and the period 1975–1999 and Adermon and Gustavsson (2015) for Sweden and the period 1975–2005. Both these studies report a pattern of job polarization over their full sample periods, but they do not investigate if job polarization actually began in the 1970s or later. Acemoglu and Autor (2011) and Goos, Manning and Salomon's (2014) documentations of a common pattern of job polarization in the US and Western European countries—although covering a large number of countries—only include data from the early 1990s onwards.

A US-Sweden comparison is well suited to shed light on potentially strong, general cross-country drivers of job polarization, like structural change and RBTC. Institutions, policies and the overall functioning of the labor market differs across the two countries in a number of marked and important aspects; see, for instance, Edin and Topel (1997) and Cahuc and Zylbergberg (2014).[2] Hence, if long-run job polarization in the US and Sweden were only driven by country-specific institutions and/or economic policies, I would arguably not find such similar trends for the two countries as is the case in this paper.

The rest of this paper proceeds as follows. The next section describes the data and the empirical methodology. It starts with a description of the data sources, followed by an explanation of the basic ideas behind the hypothesis of RBTC and the

[2] Sweden has a long tradition of powerful labor unions and coordinated collective bargaining, whereas the US is at the opposite end of the spectrum, with highly decentralized wage bargaining. Though there are differences within the two countries over time, Sweden also generally have, among other things, markedly higher taxes, stronger employment protection, a much more compressed wage structure, and more generous unemployment and social benefits.

applied classification of occupations into routine and nonroutine jobs. The section ends with a discussion of alternative measures of job polarization. Section 3 contains the empirical results. It first presents results for changes in the job structure in Sweden and compare the findings to previous US evidence. This is followed by a comparison of the importance of shifts in industrial compositions for the observed job polarization in the two countries. The paper ends with concluding remarks.

2. Data and Methodology

2.1 Data

The main data source for this paper is the Swedish longitudinal database LINDA. From 1960 onwards, it contains cross-representative samples of 3.3 percent of the Swedish population; see Edin and Fredriksson (2000) for details. LINDA builds on information from Statistics Sweden's registers and surveys. As individuals and employers are obligated by law to respond in their respective surveys, response rates are never below 97 percent and close to 99 percent in most cases.

Information on individuals' occupations, which are used to classify employment into routine versus nonroutine jobs (see below), are available in LINDA in 1960, then every fifth year for the period 1970-1990, and then annually from 1998 onwards. Up to 1990, this information is from the Swedish Population and Housing Census ("Folk- och bostadsräkningen", FoB). From 1998 onwards, it is collected by Statistics Sweden through employers.

The data used for analyses of employment in different occupations in 1950 is not based on microdata, but from tabulated values in the official report of the Swedish Population and Housing Census of 1950; see Statistics Sweden (1953). These tabulated values are based on all individuals born on the 15th each month, which makes up a sample of around 3 percent of the Swedish population.

To get consistent samples over time, all analyses based on LINDA are for individuals 18 to 65 years old. For 1950 and the tabulated values, however, the

information pertain to individuals aged 15 and above.[3] To be comparable to the majority of previous US studies, like among other, Acemoglu and Autor (2011), Foote and Ryan (2015), and Bárány and Siegel (2017), I only include individuals working in non-agricultural occupations or industries. Like these US studies, I also exclude individuals in military occupations. Resulting sample sizes for the used microdata range from 79,344 individuals in 1960 to 121,688 individuals in 2013.

2.2 RBTC and the Classification of Routine Jobs

Following Autor, Levy and Murnmane's (2003) seminal paper on RBTC,[4] computer-based technology can primarily, at least cost-effectively, replace human labor in 'routine' tasks—tasks that can be expressed by rules or step-by-step procedures—but not (as yet) in 'nonroutine' tasks. Routine tasks are, by definition, "codifiable". That is, they follow sufficiently precise, well-understood procedures to be fully specified as a series of instructions to be executed by a machine (or, alternatively, can be sent electronically—outsourced—to foreign work sites). As first highlighted by Goos and Manning (2007) based on UK data and later confirmed for the US by Autor, Katz and Kearney (2008), routine tasks are most frequent in middle-wage jobs.

For nonroutine jobs, the impact of advances in computer technology depends on whether they belong to the subcategories 'manual' ("brawns") or 'cognitive' ("brains") tasks—two groups found at the opposite end of the occupational-wage distribution. Nonroutine cognitive tasks characterize many of the highest paid jobs, such as managerial, professional, and technical occupations. They require analytics, problem solving, intuition, persuasion, and creativity. As these tasks typically draw heavily on information (in a broad sense), they are

[3] From 1998 onwards, occupation data is only available for individuals 18 to 65 years old. For most other years, it is available for individuals aged 16 and above. Performing the analysis in this paper for individuals aged 16 and above instead, in the years where this is possible, does not noticeable affect any results.

[4] The following description of RBTC draws on Acemoglu and Autor (2011) and Autor (2013).

complemented when the price of accessing, organizing, and manipulating information falls, causing an increase in the demand for these jobs, *ceteris paribus*.

Nonroutine manual tasks, on the other hand, require interpersonal and situation adaptability, visual recognition and basic in-person interactions. Even though such skills generally come naturally to humans, the demands for flexibility and physical adaptability mean that computer-based technologies neither can replace humans nor increase human productivity in these tasks. Nonroutine manual tasks typically dominate in the lowest paid jobs: being a busser in a crowded nightclub, preparing meals, doing janitorial work or working as a cleaner are all activities intense in nonroutine manual tasks.

According to Nordhaus (2007), the large absolute decline in the price of computer power began in the 1980s. From then on, the price continued to fall by 60 to 75 percent *annually*, thus causing a large exponential increase in the amount of computer power received per dollar. Following the arguments of Autor, Levy and Murnane (2003), this should create large incentives for employers to substitute computer-based technology for human labor in jobs dominated by routine tasks. Since routine jobs typically are middle-wage jobs, RBTC hence predicts declining employment in middle-wage jobs relative to both high-wage (nonroutine cognitive) and low-wage (nonroutine manual) jobs following the large fall in the price of computer technology from the 1980s onwards—i.e. job polarization.[5]

To capture the heterogeneous impact of RBTC across routine and nonroutine occupations, I employ the job-task classification developed by Acemoglu and Autor (2011). Based on 10 major, non-agricultural occupation groups in the 1990 US Census, they classify occupation into one of the categories 'routine jobs', 'nonroutine cognitive jobs', or 'nonroutine manual jobs'; this classification into three job-task groups has also been used by, among others, Jaimovich and Siu (2015), Cortes (2016), Bárány and Siegel (2017), and Boehm (2017). However Acemoglu and

[5] Presumed that wages can be thought of as a single-index of worker skills, this sets it apart from the more traditional hypothesis of "Skill-Biased Technological Change" (SBTC), where technological progress simply should yield increased demand for higher paid jobs relative to lower paid jobs.

Autor (2011) also propose—and show—that it can be informative to further divide routine jobs into the two subgroups 'routine manual jobs'—blue-collar occupations—and 'routine cognitive jobs'—white-collar occupations. Like Acemoglu and Autor (2011), and also Foote and Ryan (2015), I use this additional division of routine jobs into the manual and cognitive subcategories in order to provide additional information on the potential underlying causes for employment changes in 'routine jobs' as a whole.

The division of occupations into just four job-task categories is admittedly coarse. However, Acemoglu and Autor (2011) demonstrate that this division corresponds well to what you get based on more detailed occupation classifications and detailed job-task measures along the lines available in the US database O*NET. Three other advantages with using this classification are as follows. First, it offers maximum transparency and replicability, and thus a straightforward comparison to results from previous US studies. Second, the division of 10 major US occupation groups into four job-task groups makes it straightforward to construct a corresponding division based on Swedish occupations coded at the 2-digit ISCO-88 level. This, in turn, makes translation of Statistics Sweden's different historical occupation classifications over time largely unproblematic. That is, even though detailed occupation codes might be impossible to translate into a corresponding single detailed code across different years, such detailed codes close to always remain in the same broad occupation group, such as those captured by the broader 2-digit ISCO-88 codes; see Bihagen (2007) for a detailed discussion and investigation of this for Sweden.[6] Third, the use of four broad task-groups is what makes it possible to incorporate the tabulated statistics from the Swedish 1950 Housing and Population Census into the analysis; this is further described in Appendix A.

[6] Older Swedish occupational codes have been translated to 2-digit ISCO-88 codes by using the official crosswalks provided by Statistics Sweden and the crosswalks developed by Erik Bihagen; see Bihagen (2007). All do-files and underlying documentations of the translations are available on request.

Table 1. *Job-task classification; occupations ordered by 1970 median earnings*

Occupational groups		**ISCO-88/SSYK 96**
Nonroutine Cognitive		
1.	Professionals	21–24
2.	Managers	12–13
3.	Technicians and Associate Professionals	31–34
Routine Manual		
4.	Production, Craft and Repair	71–74
5.	Operators, Fabricators and Laborers	81–83, 93
Routine Cognitive		
6.	Office and Administrative Support	41
7.	Sales	42, 52
Nonroutine Manual		
8.	Personal Care and Personal Service; Protective Service	51
9.	Food and Cleaning Service	91

Note: The four job-task groups correspond to the classification in Acemoglu and Autor (2011). Numbers in the first column corresponds to ranking of occupations in 1970 by median earnings, based on a sample of 104,973 individuals aged 18-65. The last column states the 2-digit ISCO-88 occupation codes for each occupation category.

Table 1 displays the resulting division of Swedish occupations into the four routine- and nonroutine-job groups based on the microdata for the period 1960–2013. The numbers in the first column correspond to the ranking of median annual earnings for each occupation group in 1970, which is the first year in the data with combined information on individuals' annual earnings and occupations; information on individuals' annual labor income is based on information from official tax reports. In Sweden, like reported for the US in Acemoglu and Autor (2011), nonroutine cognitive jobs are highest paid (highest median earnings), followed by routine manual and routine cognitive jobs, while nonroutine manual jobs contain the lowest paid occupations.[7]

Beginning in 1970, Table 2 further displays cross-sectional differences in median earnings between the four job-task groups in every tenth year. Though the

[7] Differences in median earnings between each of the nine job groups are statistically significant, with the exception of the difference between Managers and Professionals. A ranking for more detailed occupations, based on 2-digit ISCO-88 codes, is available in Table A5 in Appendix E.

Table 2. *Differences in median log earnings between job-task groups*

	1970	**1980**	**1990**	**2000**	**2010**
Nonroutine cognitive	0.924	0.553	0.472	0.511	0.471
	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)
Routine manual	0.625	0.350	0.335	0.346	0.306
	(0.006)	(0.004)	(0.003)	(0.004)	(0.004)
Routine cognitive	0.392	0.177	0.136	0.148	0.106
	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
Nonroutine manual	-	-	-	-	-
Pseudo R^2	0.068	0.087	0.099	0.128	0.109
N	104,973	121,257	123,686	111,566	119,422

Note: The table contains estimated differences in median log earnings relative to nonroutine manual jobs based on cross-sectional samples from LINDA for individuals aged 18-65 for every tenth year between 1970 and 2010. Estimates are based on Koenker and Bassett (1978) quantile regressions. Standard errors are in parentheses.

size of the pay differentials vary over time, their order is stable, with median earnings of nonroutine cognitive jobs in the top, nonroutine manual jobs in the bottom, and routine jobs in the middle. Changes in the magnitude of these pay differentials also correspond roughly well to what is known about historical changes in the Swedish wage structure, with a very strong and primarily union driven wage compression during the 1970s followed by a slight rebound during the 1990s (Edin and Topel, 1997; Fredriksson and Topel, 2010).

2.3 Measures of Job Polarization

The empirical analysis focuses on changes over time in shares of total non-agricultural employment across routine and nonroutine jobs.[8] This displays how recent changes in the routine/nonroutine job composition—often attributed to RBTC—differ to changes in earlier decades. As the earnings ranking of these job-task

[8] As measures of hours worked are unavailable in the Swedish data for 1950, 1960 and 1985, calculated employment shares are based on the number of employed individuals in each occupation. However, weighting employment shares with hours worked, for the years where this is possible, yields no visible changes in how employment shares evolve over time across the four job-task groups. For levels, including information on hours causes the employment shares in nonroutine manual and routine cognitive jobs to decrease by roughly two percentage points whereas shares in routine manual and nonroutine cognitive jobs increase by the same amount. All results are available on request.

categories are stable over time, it also informs on employment changes across broad groups of low-, middle- and high-wage jobs, and thus about the presence of job polarization. This methodology, where relative employment changes in Acemoglu and Autor's (2011) routine and nonroutine job categories are used to make inference about job polarization, is also employed in, among others, Acemoglu and Autor (2011), Jaimovich and Siu (2015), Foote and Ryan (2015), and Bárány and Siegel (2017).

Another common way to investigate job polarization, for instance used in Goos and Manning (2007), is to classify jobs into wage-quintile groups based on the employment-weighted job-wage distribution in a base year—with the first year in the sample being the common choice of base year—and then compare changes in employment shares across quintile groups. As a complement to the Swedish-specific part of the analysis and as an additional check of the strength in the connection between relative employment changes across Acemoglu and Autor's (2011) four job-task groups and job polarization, I also present Swedish results based on the wage-quantile methodology. However, since this analysis requires—at least if to be meaningful—a more detailed classification of jobs than what is available in the tabulated data from 1950, it is only based on data from 1960 onwards.

In the wage-quantile analysis, I employ a division of jobs into wage-quartile (four) groups. To assign jobs into these four wage groups, I first use LINDA data from 1970 to obtain median annual earnings in 2-digit ISCO-88 occupations (1970 being the first year with information on both individuals' occupation and annual earnings). Next, I use the 1970 median earnings and the employment shares in each occupation in 1960—i.e. the chosen base year—to assign each occupation into a unique quartile group. That is, jobs in 1970 with the lowest median earnings that together employ 25 percent of the individuals in 1960 are classified as being in the first wage-quartile group. Jobs with the second lowest median earnings in 1970 that also holds 25 percent of the employed individuals in 1960 are classified as belonging to the second wage-quartile group, and so forth up to the fourth quartile group. I then calculate changes in employment shares for all jobs within each quartile group

as a whole between 1960 and 2013, as well as for each specific decade (with the last "decade" being the period 2000–2013).[9] With this division, the second and third wage-quartile groups can be thought of as "the broad middle" of the job-wage distribution.

One potential issue with this wage-quantile methodology is however, as shown by Adermon and Gustavsson (2015), the potentially wide sample distributions associated with the estimated employment changes across the wage-quantile groups. In particular, jobs with very dynamic employment located close to the thresholds for dividing jobs into wage-quantile groups can have a large effect on the final results depending on which side of the threshold they, by chance, are assigned to (i.e. depending on the particular sample used). Like Adermon and Gustavsson (2015), I therefore check the reliance of the estimates by using a bootstrap procedure to approximate the finite sample distribution of the calculated statistics; this is further described in Appendix B.

3. Results

3.1 Tasks and Job Polarization in Sweden

Figure 1 displays shares of total Swedish nonagricultural employment in routine and nonroutine jobs between 1950 and 2013. As can be seen, all four job-task groups display major changes in their employment shares over these 63 years, but the dynamics of nonroutine cognitive and routine manual jobs are particularly striking.[10] Routine manual jobs make up over 50 percent of nonagricultural employment in 1950 to make a whopping and almost linear decrease to less than 20 percent in

[9] Note, however, that since each occupation is assigned into a unique quartile-group in 1960 and some occupations hold a large share of total employment, each quartile group does not contain 25 percent of the employed population in 1960. Instead, the employment shares for quartile group 1 up to quartile group 4 are 0.32, 0.18, 0.26, and 0.24, respectively; see Table A5 in Appendix E for details.

[10] Based on the microdata from 1960 onwards, Table A1 in Appendix E contains standard errors for the decennial changes depicted in Figure 1; all these are, with the exception of the non-economically significant change for routine cognitive jobs during the 1960s, statistically significant.

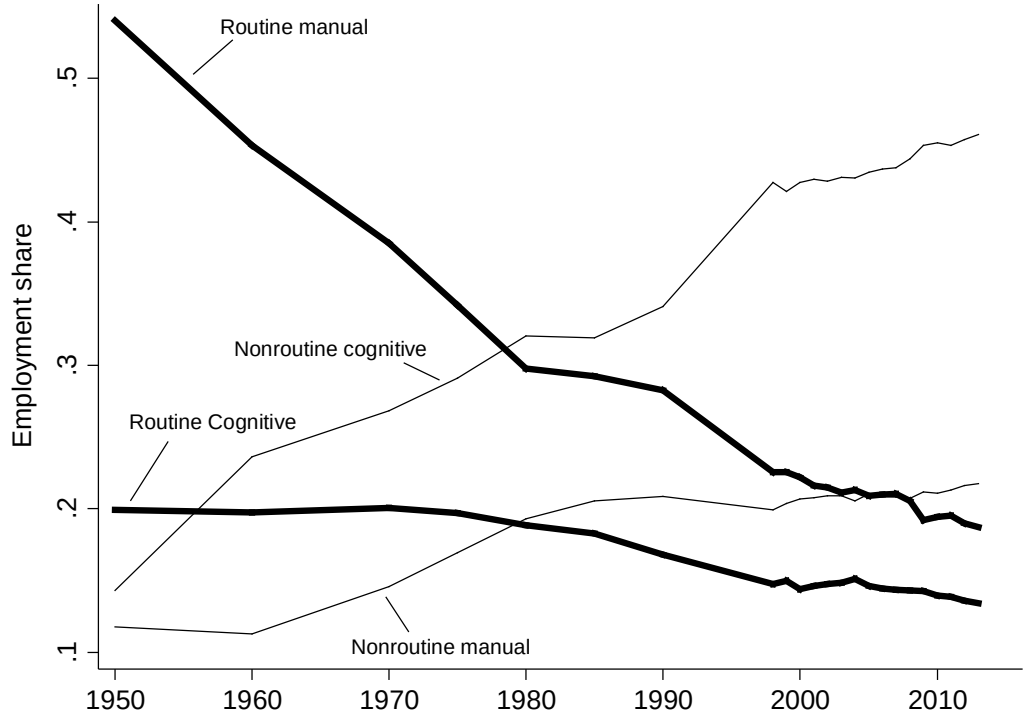

Fig. 1. Employment shares in routine and nonroutine jobs in Sweden, 1950–2013

Notes: The figure depicts shares of total nonagricultural employment (y-axis) in Sweden for four-job task groups; see Table 1. The time series are based on data from 1950, 1960, 1970, 1975, 1980, 1990, and 1998–2013.

2013. Nonroutine cognitive jobs display close to a mirror image, with a threefold increase from 15 percent of employment in 1950 to over 45 percent in 2013.

The two other job-task groups in Figure 1, routine cognitive and nonroutine manual jobs, contain a smaller share of employment and—unlike nonroutine cognitive and routine manual jobs—display time-varying trends. The employment share for routine cognitive jobs, i.e. the other and smaller middle-wage group besides routine manual jobs, is constant up to 1975 to decrease thereafter. The employment share for the lowest paid jobs—nonroutine manual jobs—displays a noticeable increase from 1960 to mid-1980s, stays roughly constant up to the late 1990s after which it again increases but a markedly slower pace.

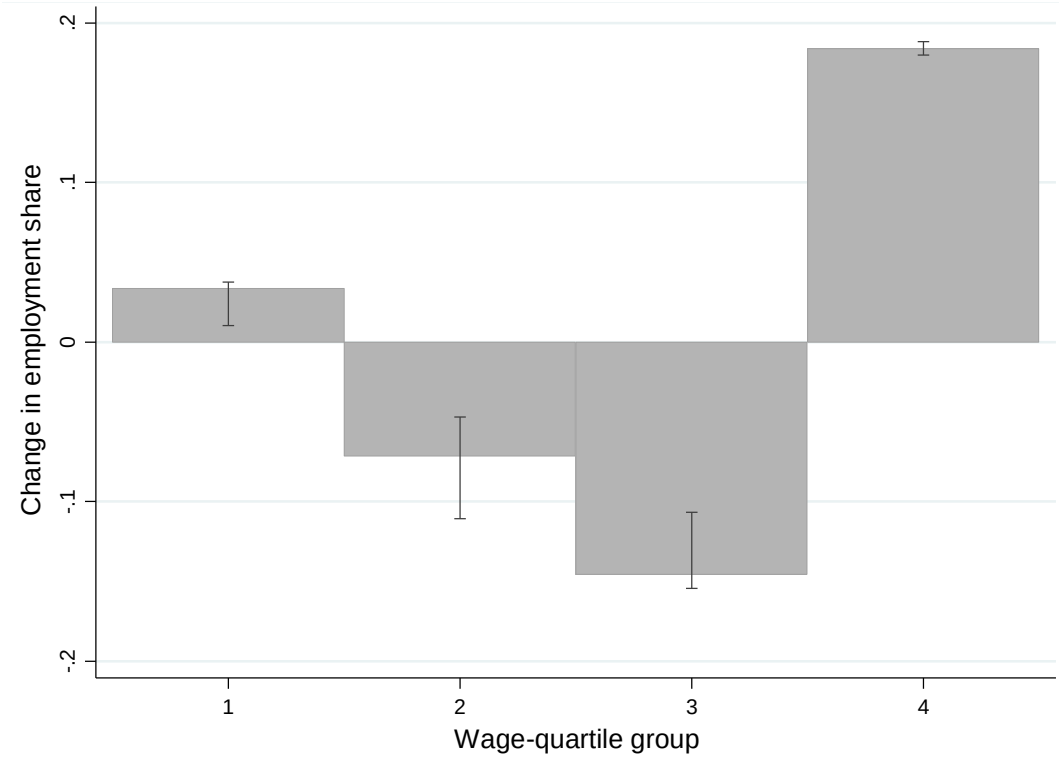

Fig. 2. Changes in employment shares by wage-quartile groups in Sweden, 1960–2013

Notes: Confidence bands for each quartile group display bootstrapped 95-percent confidence intervals. Employment shares correspond to shares of total nonagricultural employment. Wage-quartile groups are based on 1970 median annual earnings in occupations classified according 2-digit ISCO-88 and employment shares in 1960; see the main text for details.

Figure 2 displays the changing job composition in terms of employment changes across wage-quartile groups from 1960 to 2013; that is, when jobs are categorized according to their wage ranking rather than their task content. The changes for each wage-quartile group is both economically and statistically significant—see the bootstrapped confidence intervals—and their pattern make up a "textbook example" of job polarization. The share of employment in the middle of the job-wage distribution, captured by the second and third quartiles, is 22 percentage points lower in 2013 than in 1960. At the same time, both the highest and lowest quartile-groups display noticeable increases in their employment shares.

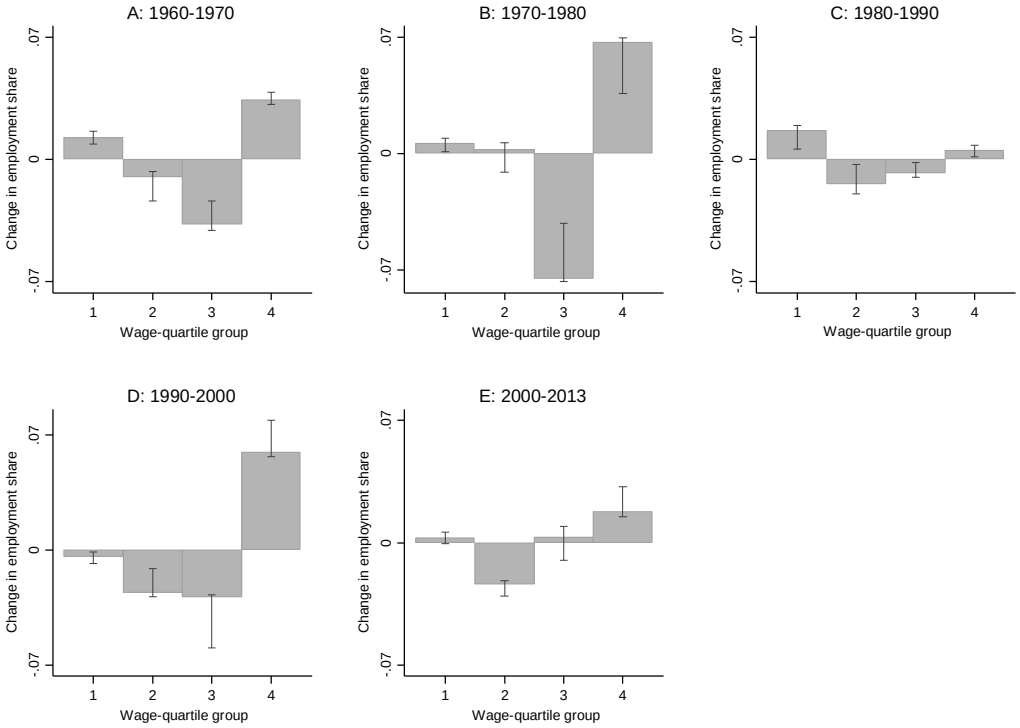

Fig. 3. Decennial changes in employment shares by wage-quartile groups in Sweden, 1960–2013

Notes: Confidence bands for each quartile group display bootstrapped 95-percent confidence intervals. Employment shares correspond to shares of total nonagricultural employment. Wage quartile groups are based on 1970 median annual earnings in occupations classified according 2-digit ISCO-88 and employment shares in 1960; see the main text for details.

Figure 3 extends Figure 2 by depicting decennial changes in employment shares across the wage-quartile groups. Job polarization is visible in all decades, but the largest changes occur in the 1960s, 1970s and 1990s; differences in the magnitude of job polarization over time are further investigated in connection to US-Sweden comparison in the next subsection.[11]

[11] Adermon and Gustavsson (2015) have previously performed a similar analysis as in Figure 3, but for the shorter period 1975-2005. Even though their analysis relies on a more detailed occupation classification combined with detailed information on industries, plus the use of 1975 as the base year in the division of jobs into job-wage groups, the results in Figure 3 match their results closely.

There is a strong correspondence between the decline of employment in routine jobs relative to nonroutine jobs displayed in Figure 1 and the Swedish job-polarization patterns depicted in Figures 2 and 3. To summarize, 11 occupations (out of 23) at the 2-digit ISCO-88 classification have a lower employment share in 2013 than in 1960. Of these 11 occupations, 10 are routine occupations (in total, there are 12 routine occupations). These declining routine occupations are, in turn, primarily located in the two middle-quartile groups in Figures 2 and 3; the shares of routine jobs in quartile-groups 1-4 are 65, 77, 100, and 18 percent, respectively. The expanding nonroutine manual occupations are, on the other hand, only located in the first (lowest-paid) quartile group, with 35 percent of its employment. Non-routine cognitive jobs are primarily located in the highest-paid group, i.e. in the fourth quartile group, making up 82 percent of its employment in 1960. Hence, the larger the share of routine jobs within a wage-quartile group, the larger its decline in terms of shares of total nonagricultural employment. A detailed account of the wage ranking and employment share dynamics of occupations at the 2-digit ISCO-88 classification is available in Table A5 in Appendix E.

3.2 Common US-Sweden Employment Patterns

First, it should be noted that, based on the "wage-quantile group"-methodology, the US, like Sweden, display a long-run pattern of job polarization. Bárány and Siegel (2017, p.8) for the US and data for the period 1950–2007, based on results from methods corresponding closely to those underlying Figures 2 and 3, state that "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.".

However, detailed cross-country comparisons of job polarization based on wage-quintile groups should be done with care, at least in connection to investigations of RBTC. In particular, differences in initial job compositions across countries may result in markedly different sets of occupations within each country's wage-quantile groups.

To get a clean and robust US-Sweden comparison, I henceforth focus on shares of employment across routine and nonroutine jobs. To do this, I use Foote and Ryan's (2015) estimates of employment shares in Acemoglu and Autor's (2011) routine and non-routine job categories in the US between 1950 and 2013; these estimates where kindly provided by Christopher Foote and Richard Ryan. Their study is, to the best of my knowledge, the only for the US that both covers the entire period 1950–2013 and divides routine jobs into the subgroups manual and cognitive. Their estimates are based on data from the Current Population Survey in the form of tabulated values on occupational employment provided by the Census Bureau and Bureau of Labor Statistics; see Foote and Ryan (2015) for details.[12]

Figure 4 compares changes in the composition of routine and nonroutine jobs in Sweden and the US between 1950 and 2013. The trends for nonroutine cognitive and routine manual jobs are very similar across the two countries; both the US and Sweden display a marked and continuously falling employment share in routine manual jobs combined with a close to mirror-image growth in nonroutine cognitive jobs. For routine cognitive jobs, on the other hand, US-Sweden trends are similar only from the late 1980s onwards, with both countries then displaying downward trends. For the low-wage, nonroutine manual jobs, Sweden experienced a noticeably stronger growth up to the late 1980s, and it is only from the late 1990s that Sweden and US display similar increases.

To further quantify and make US-Sweden comparisons of both the magnitude of job polarization and the employment-share dynamics of each job-task group underlying the overall job polarization, I next use simple expressions of the form:

$$(1) \qquad \Delta(E_{Rout} - E_{NonrM})^t = \Delta E^t_{RoutM} + \Delta E^t_{RoutC} - \Delta E^t_{NonrM} \ ,$$

[12] Up to 1983, the tabulated values are from printed publications. From 1983 onwards, the values are from the BLS website. I convert Foote and Ryan's (2015) original quarterly estimates to annual estimates by averaging the quarterly estimates for each year.

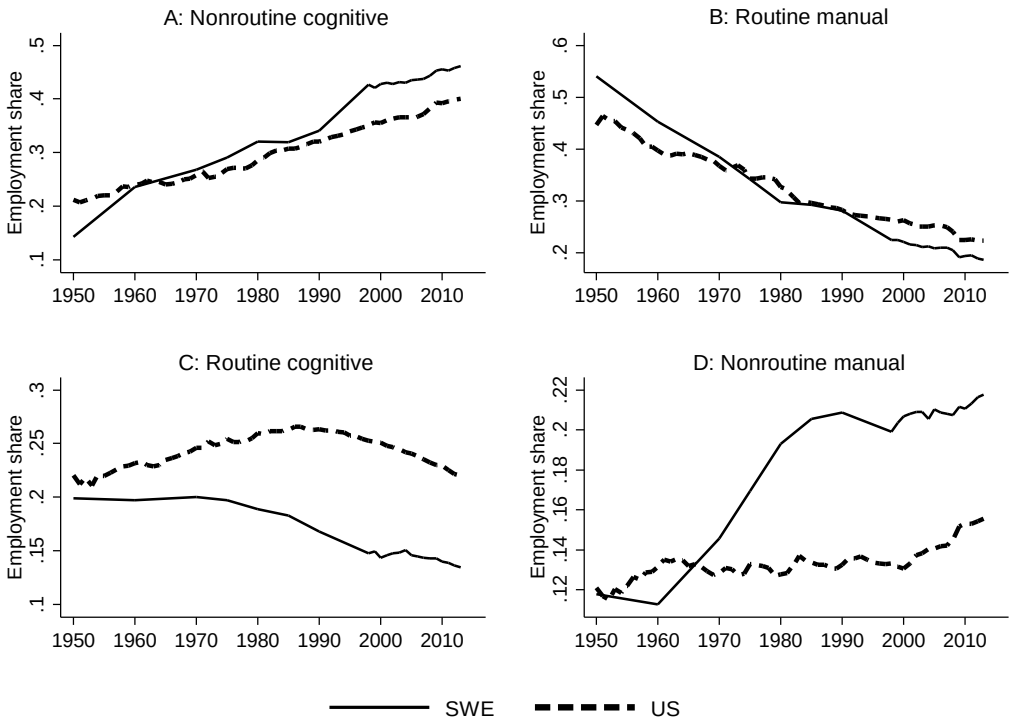

Fig. 4. Employment shares in routine and nonroutine jobs, 1950–2013: Sweden vs. the US

Notes: Employment shares correspond to shares of total nonagricultural employment. Annual time series data for the US are from Foote and Ryan (2015, Figure 4, p.381).

where $\Delta(E_{Rout} - E_{NonrM})^t$ denotes changes in the employment-share differential between routine jobs (cognitive and manual jobs grouped together) and nonroutine manual jobs during the time interval $t = t_1 - t_0$, and where the right hand side further divides routine jobs into the two subgroups manual and cognitive. The corresponding measure is calculated for change in employment-share differentials between routine jobs and nonroutine cognitive jobs, i.e. $\Delta(E_{Rout} - E_{NonrC})^t$.

Since routine jobs are typical middle-wage jobs while nonroutine manual and cognitive jobs are at the lower and upper end of the wage ranking, respectively, I use the left-hand sides of expressions along the lines of (1) as summary measures of overall job polarization—the extent to which middle-wage jobs decline relative to low- and high-wage jobs, respectively.

As quantitative measures of how the employment-share dynamics for each job-task group contributes to the relative decline of routine jobs as a whole, i.e. to the observed job polarization, I use the percentage contribution of each of the three right-hand side terms to the change in the left-hand side of equation (1). That is, I divide each of the three terms, including their signs, e.g. $-\Delta E^{t}_{NonrM}$, with the value of the left-hand-side term (and multiply by 100).

Table 3 presents the resulting calculations for decennial changes as well as changes over the two longer-run periods 1950–1980 and 1980–2010. The division into before and after 1980 marks the middle in the investigated period, but it can also be viewed as a rough approximation of before and after the "computer age". The use of 1980 as a break also corresponds well to the trend breaks in the decennial changes, as visible in Table 3.

Turning to the results, Table 3 shows that Swedish job polarization, as summarized by the values of $\Delta(E_{Rout}-E_{NonrM})^{t}$ and $\Delta(E_{Rout}-E_{NonrC})^{t}$, actually was larger in the pre- than in the post-1980 period (see the rows denoted "1950–1980" and "1980–2013"). Of course, this is not the only way to quantify job polarization. An alternative is the percentage-based measures of job polarization proposed by Adermon and Gustavsson (2015). They consider percentage changes in the ratios of employment in middle-wage jobs and low-/high-wage jobs, respectively. In my application, this corresponds to calculating percentage changes over time in the ratios (E_{Rout}/E_{NonrM}) and (E_{Rout}/E_{NonC}). However, such calculations also clearly display a stronger job-polarization process in Sweden in the pre-1980 compared to the post-1980 period.[13] Yet another alternative is to base the calculations on changes for the wage-quartile groups in Figures 2 and 3. That is, in the calculations, replace employment shares in routine jobs (E_{Rout}) with the sum of employment

[13] For Sweden and the period 1950-1980, the decline in (E_{Rout}/E_{NonrM}) is 60 percent and the decline in (E_{Rout}/E_{NonC}) is 71 percent. For the period 1980-2013, the corresponding numbers are, respectively, 41 and 54 percent.

Table 3: *Employment-share dynamics and the relative decline of routine jobs in Sweden and the US, 1950–2013*

	Total change in		% explained by			
	$(E_{Rout} - E_{NonrM})$	$(E_{Rout} - E_{NonrC})$	ΔE_{RoutM}	ΔE_{RoutC}	$-\Delta E_{NonrM}$	$-\Delta E_{NonrC}$
Sweden						
1950-1960	-.083		104.05	2.14	-6.19	
1960-1970	-.098		69.53	-3.22	33.69	
1970-1980	-.147		59.81	8.01	32.18	
1980-1990	-.052		29.32	40.11	30.57	
1990-2000	-.083		73.21	29.31	-2.52	
2000-2013	-.055		63.17	17.23	19.60	
1950-1980	*-.328*		*73.93*	*3.16*	*22.90*	
1980–2013	*-.189*		*58.31*	*28.74*	*12.95*	
1950-1960		-.182	47.61	0.98		51.42
1960-1970		-.097	70.28	-3.26		32.97
1970-1980		-.152	57.81	7.74		34.45
1980-1990		-.056	27.08	37.04		35.88
1990-2000		-.171	35.27	14.12		50.61
2000-2013		-.078	44.74	12.20		43.06
1950–1980		*-.431*	*56.31*	*2.41*		*41.28*
1980–2013		*-.305*	*36.18*	*17.84*		*45.98*
US						
1950-1960	-.048		102.78	-24.72	21.95	
1960-1970	-.012		238.70	-114.26	-24.44	
1970-1980	-.027		152.89	-50.50	-2.39	
1980-1990	-.045		97.65	-8.39	10.74	
1990-2000	-.031		65.89	40.38	-6.27	
2000-2013	-.094		40.82	32.94	26.25	
1950-1980	*-.087*		*137.50*	*-45.35*	*7.86*	
1980–2013	*-.170*		*60.41*	*23.32*	*16.27*	
1950-1960		-.064	76.60	-18.43		41.82
1960-1970		-.033	87.33	-41.80		54.47
1970-1980		-.056	73.80	-24.37		50.58
1980-1990		-.076	58.20	-5.00		46.80
1990-2000		-.067	30.11	18.46		51.43
2000-2013		-.115	33.66	27.16		39.18
1950-1980		*-.153*	*77.93*	*-25.71*		*47.77*
1980–2013		*-.258*	*39.96*	*15.42*		*44.62*

Notes: Total change in $(E_{Rout} - E_{NonrM})$ denotes changes in the employment-share differential between routine jobs (routine manual plus routine cognitive jobs) and nonroutine manual jobs. Total change in $(E_{Rout} - E_{NonrC})$ denotes changes in the employment-share differential between routine jobs (routine manual plus routine cognitive jobs) and nonroutine cognitive jobs. The next four columns display the percentage contribution to these changes from altering employment shares in routine manual, routine cognitive, nonroutine manual, and nonroutine cognitive jobs, respectively; see the main text for details. Estimates for the US are based on Foote and Ryan (2015, Figure 4, p.381).

shares in the second and third wage-quantile groups and replace E_{NonrM} and E_{NonrC} by employment shares in the first and fourth wage-quartile groups, respectively. Again, such calculations clearly point towards a stronger Swedish job-polarization process—a more pronounced hollowing out of the job-wage distribution—in the pre- than in the post-1980 period.[14] For the US, however, regardless of method, the calculated magnitude of job polarization is always largest in the post-1980 period.[15]

In terms of the employment-share dynamics underlying the observed job polarization, Table 3 further show that for the pre-1980 period, routine manual jobs explain 74 percent of the decline of Swedish routine jobs as a whole relative to nonroutine manual jobs. Routine cognitive jobs, on the other hand, only account for 3 percent. For the US, the corresponding numbers are 137 percent for routine manual jobs and a negative 45 percent for routine cognitive jobs (a negative value as the employment share for these jobs actually increases during this period). In the post 1980-period, declining employment in routine manual jobs still accounts for the majority of the decline of routine jobs as a whole relative to nonroutine manual jobs, 58 and 60 percent for Sweden and the US, respectively. However, declining employments shares for the other subcategory of routine jobs, routine cognitive jobs, now explain a significant fraction, with 28 and 23 percent for Sweden and the US, respectively.

By construction, the larger importance of routine manual jobs compared to routine cognitive jobs in the pre- than in the post-1980 period also carries over to

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[14] Since estimates for wage-quartile groups only are available from 1960 onwards, the pre-1980 period is considerable shorter than the post-1980 period. I therefore base the conclusions on calculated average annual changes over these two periods. The average change in the employment-share differentials between the two middle (second and third) quantile groups and the lowest (first) and highest quantile groups are, respectively, 0.69 and 1.11 percentage points for the period 1960–1980, and 0.34 and 0.55 percentage points for the period 1980–2013. Based on Adermon and Gustavsson's (2015) measures (see footnote 13), the average annual decline in the ratios of employment shares the two middle quantile groups and the lowest and highest quantile groups are, respectively 1.86 and 3.29 percent for the period 1960–1980, and 1.23 and 1.75 percent for the period 1980–2013.

[15] Based on Adermon and Gustavsson's (2015) percentage-based measures of job polarization, the declines for the US in the ratios (E_{Rout} / E_{NonrM}) and (E_{Rout} / E_{NonC}) are, respectively, 17 and 35 percent for the period 1950–1980 and 38 and 46 percent for the period 1980–2013. For US results based on wage-quantile groups, see Bárány and Siegel (2017)

the decline of employment in routine jobs relative to employment in the high-wage, nonroutine cognitive jobs. However, for this measure, the comparison group also holds explanatory power, i.e. nonroutine cognitive jobs, as its expanding employment share accounts for over 40 percent of the relative decline of routine jobs relative to nonroutine cognitive jobs in both Sweden and the US and in both the pre- and post-1980 periods.

So far, the US numbers have been based on Foote and Ryan's (2015) estimates, which in turn are based on tabulated statistics from CPS. A natural question is therefore if estimates based on these tabulated values differ from US estimates based on other data sources. To check this, I also use Acemoglu and Autor's (2011) estimates based on US Census data from 1959 up to 1999 (available every tenth year) and Census American Community Survey for 2007. Figure A2 in Appendix E repeats Figure 2 but also adds Acemoglu and Autor's (2011) estimates. Though there are some differences in the levels of some of Acemoglu and Autor's (2011) and Foote and Ryan's (2015) series (around 2-3 percentage points), changes over time are close to identical and display the same main trends.[16] Hence, the similarities of the long-run trends in the composition of routine and nonroutine jobs across the US and Sweden holds regardless of whether one compares the Swedish evidence to Foote and Ryan's (2015) CPS estimates or Acemoglu and Autor's (2011) Census estimates. Given this, the next subsection further utilizes Acemoglu and Autor's (2011) estimates to make US-Sweden comparisons of the importance of between- versus within-industry shifts in employment for the changing job compositions.

To summarize the results from this subsection, declining employment in middle-wage jobs relative to the highest- and lowest-paid jobs is a long-run phenomenon in both the US and Sweden. Both countries do however display falling

[16] Part of these differences could be due to how the data is collected. However, it is also likely that different choices regarding how to harmonize breaks in US occupation classifications over time, in combination with different lengths of the time series, explain part of the differences; see Acemoglu and Autor (2011) and Foote and Ryan (2015) for details on this.

employment shares in a broader set of middle-wage jobs in more recent decades, with a negative trend for not only routine manual jobs but also for routine cognitive jobs.

3.3 The Role of Structural Change

According to Bárány and Siegel (2017), the overrepresentation of routine jobs in the manufacturing sector in combination with persistent employment shifts from manufacturing to service industries can explain why US job polarization is a long-run phenomenon. They argue that such general between-industry shifts in employment account for a majority of US job polarization during the 1950s and 1960s and a substantial part in later decades. As this kind of structural change is present across the developed world (e.g. Herrendorf, Rogerson, and Valentinyi, 2014), it has the potential to explain why job polarization is a long-run phenomenon in Sweden as well.

Popular explanations for persistent employment shifts from the manufacturing to the service sector do not, unlike RBTC, stress automation of certain types of jobs. Rooted in the macroeconomic literature on economic growth, one popular explanation for this 'structural transformation' is instead non-homothetic consumer preferences, such that increases in aggregate income give rise to disproportionate increases in consumer demand for services (e.g. Kongsamut, Rebelo, and Xie, 2001; Boppart, 2014). Another is unequal total factor productivity growth across sectors combined with a sufficient low (below one) demand elasticity of substitution across sectors' final goods (e.g. Baumol, 1967; Ngai and Pissarides, 2007; Bárány and Siegel, 2017). Note that in models related to the former explanation, technological progress does not replace but rather complement human labor, but with the resulting increase in labor productivity being largest (or only occurring) in the manufacturing sector.[17]

[17] The resulting fall in the cost of the manufacturing sector's final goods will increase consumer demand for these goods but not by enough to keep in work all those previously employed in the sector. At the same time, as consumers view manufacturing and service goods as complements, the demand for the

With RBTC, on the other hand, employment shifts *within* rather than between industries should be the main driver of job polarization. That is, when firms replace routine workers with computer-based technology, the employment composition of routine and nonroutine workers shifts within industries (and firms), and these shifts give rise to the job polarization observed at the aggregate level; see Acemoglu and Autor (2011).[18]

However, Goos, Manning and Salomons (2014) raise a caveat to the interpretation of RBTC as only a within-industry phenomenon. They argue that RBTC, in addition to within-industry job polarization, also could give rise to important between-industry shifts in employment along the lines predicted by traditional macro models of structural transformation.[19] Because of this possibility, I focus not only on the relative magnitude of between- and within-industry shifts for the observed long-run job polarization, but also on their altering trends over time. That is, if structural change is the main driver of job polarization during the earliest decades of the data, but RBTC becomes economically significant with the large scale computerization of the workplace from around the 1980s, one expects to see an increase in the explanatory power of within-industry shifts around this time; I return to this issue in connection with the empirical results.

It should also be recognized that exogenous changes in labor supply, rather than structural change or RBTC, could potentially explain the Swedish job-polarization pattern. In Appendix C, I therefore use standard Blinder-Oaxaca decompositions to investigate and discuss the explanatory power of shifts in the gender and age composition for changes in the Swedish job composition. The

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service sector's final good will also increase, resulting in an increased demand for labor in the service sector.

[18] Of course, disproportional declines of routine workers within industries could also be important prior to recent advances of computer-based technology. Feng and Graetz (2016), for instance, argue that automation and mechanization may have been inherently biased against middle skill workers since at least the mid-1800s.

[19] In short, since RBTC has a bigger impact on industries that use routine jobs more intensively (manufacturing), these industries will use less employment to produce a given level of output, why employment might shift away from these industries.

conclusion from this exercise is that age and gender explain neither short- nor long-run patterns of job polarization in Sweden.[20] Given this, I henceforth focus on the potential role of within- versus between-industry shifts in employment.

Similar to working with occupation classifications, employing industry classifications from 1950 onwards invokes dealing with several shifts in Statistics Sweden's industrial coding schemes over time. To obtain the most robust translation of industries over time possible for Sweden and to be able to include tabulated data from 1950, I employ the broad 1-digit SNI-69 industry classification, which is identical to the international 1-digit ISIC rev.2 classification.[21] This gives seven consistent nonagricultural industries.[22]

Figure 5 provides an overview of the Swedish industrial composition from 1950 to 2013 in terms of employment shares in the six largest industries; the graph omits the industry "Mining and Quarrying" since it accounts for less than one percent of employment. Based on the available microdata, Figure 6 further displays the composition of routine and nonroutine jobs within each of these six industries between 1960 and 2013. Combined, these figures show that Swedish industries with disproportionately large shares of routine occupations also indeed display persistent negative trends in their overall employment shares, while industries that rely more heavily on nonroutine occupations tend to display positive trends. In particular, routine manual jobs dominate in the two manufacturing industries "Manufacturing"

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[20] The same also holds for the expansion of Swedish public sector employment up to the 1980s; the equivalent of Figure 1 but divided by public and private sector employment displays a clear pattern of job polarization within both sectors over the period 1960–2013. These graphs are available on request.

[21] Translations of different industry classifications are based on Statistics Sweden's official crosswalks; all used do-files are available on request. The crosswalk between 1960 and 1970 is however less detailed than crosswalks for later shifts. While it allows for a translation of the 1960 classifications into 1-digit SNI69 codes, it prevents a translation beyond 1970, as this would require a more detailed classification of SNI69 than what is possible to assign to the 1960 codes. Moreover, it is possible to map tabulated values for industries from the 1950 FoB into the 1-digit level of SNI69, but not beyond this. For these reasons, I use the 1-digit SNI69 classification for the whole period 1950–2013.

[22] This actually gives eight industries, but I merge the industry "Electricity, Gas, and Water" with the industry "Transport and Communication". The former on average employ 0.6 percent of the population and display minor changes over time. By this, the content of the resulting Swedish industry "Transport and Communication" corresponds more closely to the US industry "Transport and Utilities", which aids a comparison to the US evidence.

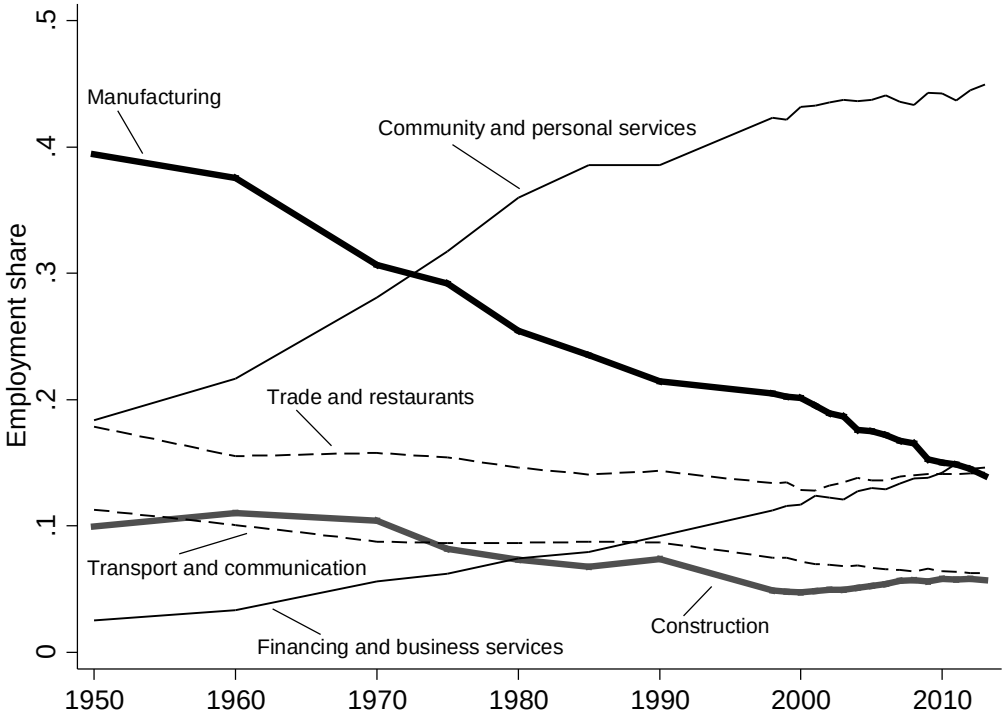

Fig. 5. Employment shares in Swedish industries, 1950–2013

Notes: Employment shares correspond to shares of total nonagricultural employment. Industries are classified according to 1-digit ISIC rev.2. The industry "Mining and quarrying" is omitted due to its small employment share.

and "Construction", which both, and in particular the former, display downward trends in their share of employment. The two major service industries, "Community and Personal Service" and "Financing and Business Services", which both are overrepresented in terms of shares of nonroutine cognitive jobs and the former also in terms of nonroutine manual jobs, instead display the most notable increases in employment shares. Overall, these graphs are consistent with structural change as one important driver of long-run job polarization in Sweden.

In order to quantify the relative importance of between- versus within-industry employment shifts and to be able to make a clear as possible US-Sweden comparison of changes over time, I next use standard shift-share decompositions. In these, employment-share shifts across the four job-task categories are due to either

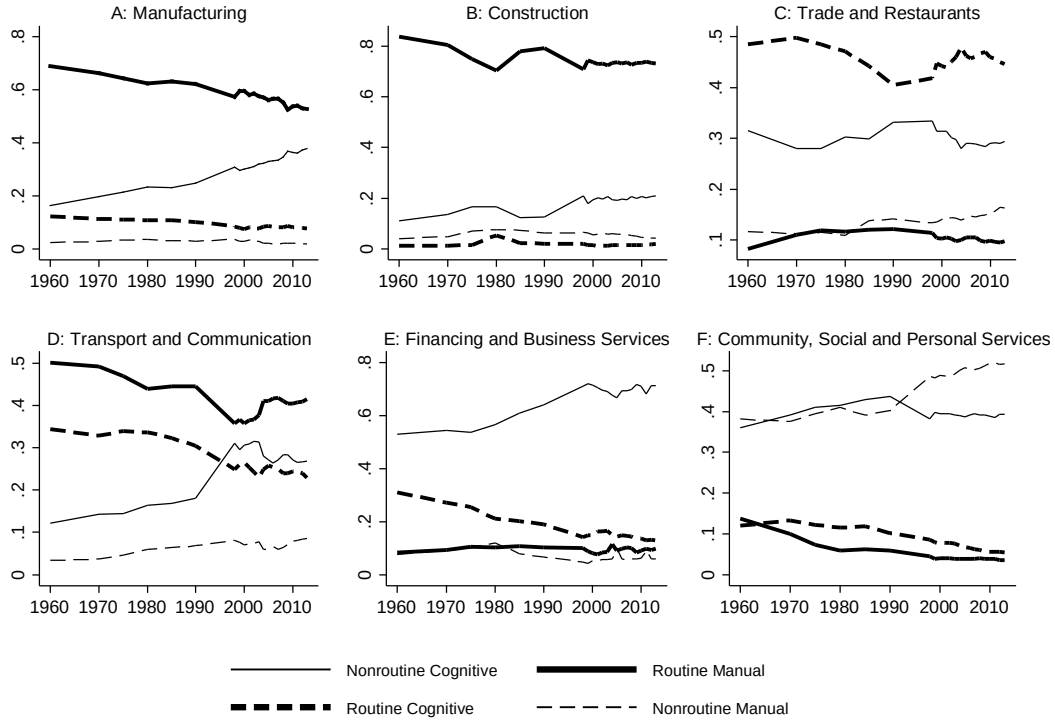

Fig. 6. Shares of routine and nonroutine jobs within Swedish industries, 1960–2013

Notes: Shares of routine and nonroutine jobs (y-axis) corresponds to the share of total employment within each industry. Industries are classified according to 1-digit ISIC rev.2. The industry "Mining and Quarrying" is omitted because of its small employment share.

within- or between-industry shifts in employment. Following Acemoglu and Autor (2011), the change in the overall share of employment in job-task group *j* over time interval $t = t_1 - t_0$, is expressed as

$$(2) \qquad \Delta E_j^t = \sum_k \Delta E_k^t \lambda_{jk} + \sum_j \Delta \lambda_{jk}^t E_k \equiv \Delta E_B^t + \Delta E_W^t ,$$

where ΔE_B^t is the part of the change in job-tasks group *j*'s share of employment attributable to changes in industrial composition—between-industry shifts in employment across industries—and ΔE_W^t is the part attributable to within-industry changes in the composition of the four job-task groups. In the calculation of these two components, ΔE_k^t is the change in industry *k*'s employment share during time

interval *t*, $E_k = (E_k^{t_1} + E_k^{t_0})/2$ is the average employment share of industry *k* over *t*, $\Delta\lambda_{jk}^{t}$ is the change in job-task group *j*'s share of industry *k* employment during *t*, and λ_{jk}^{t} is job-task group *j*'s average share of industry *k* employment during *t*.

To the best of my knowledge, there exists no published shift-share analysis for total nonagricultural employment in the US spanning a sufficient long period that also divide Acemoglu and Autor's (2011) routine classification into the subgroups manual and cognitive.[23] However, based on the same exact underlying Census data and working samples as used in the gender-specific analyses by Acemoglu and Autor (2011), David Autor kindly provided (thorough his webpage) detailed enough data on employment in US industry-occupation cells for me to be able to perform their shift-share analysis without the division by gender. That is, a US shift-share decomposition for the four job-task groups and their shares of total nonagricultural employment.[24]

One difference between the US and Swedish decompositions is that Acemoglu and Autor (2011) use eleven industries whereas the Swedish data allows for at most seven industries (in order to get a robust industry classification over time).[25] Although the industry classification, at the broad level used here, is very similar across the two countries and the difference in the number of industries is small, using more industries could produce larger between-industry components. To keep the clean link between the presented US results and Acemoglu and Autor's

[23] Foote and Ryan's (2015) estimates are based on tabulated aggregated values, which prevent a shift-share analysis. Bárány and Siegel's (2017) shift-share analysis does not separate routine jobs into the subgroups manual and cognitive; as shown in Figure 4, this separation holds valuable information for the US-Sweden comparison. Acemoglu and Autor (2011) only present shift-share analyses divided by gender, i.e. analyses for the share of total female employment (i.e. summing to 100 percent) in the four job-tasks groups as well as a corresponding analysis for male employment shares.

[24] The data was downloaded from https://economics.mit.edu/faculty/dautor on June 27, 2017. The used data is the same as used by Acemoglu and Autor (2011) to produce Table 6, p. 1102. On the webpage, this dataset was labeled "census-cells-ind-occ-1960-2008".

[25] The 11 US industries are: "Extractive Industries", "Construction", "Manufacturing, Transportation and Utilities", "Wholesale Trade", "Retail Trade", "Finance, Insurance, and Real Estate", "Business Services", "Personal Services and Entertainment", "Professional Services", and "Public Administration".

Table 4. *Shift-share decompositions of changes in employment shares (percentage points) for routine and nonroutine jobs in Sweden, 1960–2013*

	Time period				
	1960-1970	**1970-1980**	**1980-1990**	**1990-2000**	**2000-2013**
Nonroutine cognitive					
Total Δ	3.20	5.23	2.01	8.67	3.34
Industry Δ	2.23	2.15	1.06	2.07	1.24
Within Δ	0.97	3.08	0.95	6.60	2.10
Routine manual					
Total Δ	-6.82	-8.78	-1.51	-6.05	-3.48
Industry Δ	-4.96	-5.17	-2.26	-3.20	-2.60
Within Δ	-1.86	-3.61	0.75	-2.84	-0.88
Routine cognitive					
Total Δ	0.32	-1.18	-2.07	-2.42	-0.95
Industry Δ	0.32	0.05	0.10	-0.52	0.49
Within Δ	-0.00	-1.22	-2.17	-1.90	-1.43
Nonroutine manual					
Total Δ	3.30	4.72	1.58	-0.21	1.08
Industry Δ	2.41	2.98	1.10	1.65	0.87
Within Δ	0.89	1.75	0.48	-1.86	0.21

Notes: The table contains decomposition of changes in shares of total nonagricultural employment (percentage points) for four job-task groups into components due to changes in industry composition and changes in job shares within industries. The decomposition employs seven industries categorized according to 1-digit ISIC rev.2.

(2011) original study, I nevertheless retain their original US industry classification in the main analysis. In Appendix D, however, I also present the US shift-share decompositions based on seven broader industry groups, obtained by collapsing the eleven US industries into seven groups that arguably corresponds more closely to the seven Swedish industries. As it turns out, this yields only minor changes in the US decompositions and does not alter any conclusions. Further details on the data underlying the US results are available in Acemoglu and Autor (2011).

Based on the Swedish microdata from 1960 onwards, Table 4 presents decennial shift-share decompositions. Corresponding results for the US, based on Census data for 1959 up to 2007, are displayed in Table 5.

For Sweden and the growth of nonroutine cognitive jobs, Table 4 shows that between- and within-industry shifts are of roughly equal importance up to 1990

Table 5. *Shift-share decompositions of changes in employment shares (percentage points) for routine and nonroutine jobs in the US, 1959–2007*

	Time Period				
	1959-1969	**1969-1979**	**1979-1989**	**1989–1999**	**1999–2007**
Nonroutine cognitive					
Total Δ	1.54	2.70	4.24	3.61	0.99
Industry Δ	2.47	1.30	0.86	1.21	0.33
Within Δ	-0.94	1.41	3.37	2.40	0.67
Routine manual					
Total Δ	-4.47	-3.57	-5.61	-2.65	-2.21
Industry Δ	-3.33	-2.11	-2.53	-1.22	-1.26
Within Δ	-1.14	-1.46	-3.08	-1.43	-0.95
Routine cognitive					
Total Δ	2.33	0.69	1.10	-2.05	-1.22
Industry Δ	0.65	0.89	0.86	-0.22	0.03
Within Δ	1.68	-0.20	0.24	-1.84	-1.25
Nonroutine manual					
Total Δ	0.60	0.18	0.27	1.09	2.43
Industry Δ	0.20	-0.08	0.80	0.23	0.90
Within Δ	0.39	0.25	-0.53	0.86	1.53

Notes: The table contains decomposition of changes in the shares of total nonagricultural employment (percentage points) for four job-task groups due to changes in industry shares and changes in job shares within industries. The decompositions are based on the data and the eleven industries underlying the results in Acemoglu and Autor (2011, Table 6, p.1102); see the text for details.

whereas within-industry shifts dominate thereafter. The decompositions in Table 5 for the US display similar trends for this job-task group (nonroutine cognitive jobs), with the difference that within-industry shifts starts to outweigh between-industry shifts a decade earlier than in Sweden.

For Sweden and routine manual jobs, between-industry shifts consistently account for a majority of the declining employment share—only during the 1990s do shifts in job compositions within industries come close to the same relative weight as shifts in the industrial composition. For the US, between-industry shifts, like for Sweden, account for a majority of the decline of routine manual jobs prior to the 1980s. However, unlike Sweden, there is a trend break thereafter, as the relative size of the within component grows and explains roughly half of the decline during the 1980s and 1990s.

Tables 4 and 5 further show that within-industry shifts account for most of the observed decline of employment shares in routine cognitive jobs in both Sweden and the US. Both the economically significant fall in Sweden after 1975 (see Figure 1) and the corresponding fall in US from the second half of 1980s, are accounted for by altering job compositions within industries rather than shifts in the industrial composition.

Finally, the Swedish increase in the employment share of nonroutine manual jobs—the lowest-paid jobs—is primarily driven by between-industry shifts. For the US, the corresponding decennial changes are small up to the late 1980s, subsequently yielding small within- and between-industry components—where both the economical and statistical significance arguably can be questioned—,but on average, the numbers imply a larger weight to between-industry shifts. From the 1990s onwards, however, within-industry shifts clearly dominate the US growth of nonroutine manual jobs.

Taken together, the shift-share analyses display important common trends across the US and Sweden, although of different magnitudes. Up to the 1980s, the altering industry composition accounts for the great majority of shifts in the composition of routine and nonroutine jobs in both countries. In particularly, the large relative decline of routine manual jobs—the by far largest middle-wage group—is explained by changes in the industrial compositions. In more recent decades however, within-industry shifts explain a larger part of the relative decline of middle-wage routine jobs in both the US and Sweden. This trend break is more pronounced for the US, where employment shifts within industries explain a majority of the overall job polarization after the late 1980s. For Sweden, the increased explanatory power of within-industry shifts is limited to nonroutine cognitive and routine cognitive jobs. In both countries, however, between-industry shifts continue to be of economic significance after 1980.

According to Bárány and Siegel (2017), employment shifts from manufacturing to service industries is the main explanation for the long-run trend of job polarization. To what extent do such shifts account for the between-industry

components in the above shift-share decompositions? That is, part of the estimated between-industry components in Tables 4 and 5 could reflect the effect of employment-share shifts between service industries, rather than shifts from manufacturing to service industries *per se.* To investigate this further, Appendix D contains and discusses shift-share decompositions for Sweden and the US where the industry dimension is captured solely by the two broad industries/sectors manufacturing and service. In these, the manufacturing sector contains the merged industries "Manufacturing", "Construction", and "Mining and Quarrying", while the service sector contains all other industries. Though the within-industry component from such decomposition holds little economic meaning in terms of the effect of RBTC, the size of the between-industry components can be compared to those in Tables 4 and 5 and thereby inform on the relative importance of employment-share shifts from manufacturing to service industries. The main conclusion from this exercise, and consistent with Figures 4 and 5 and corresponding US graphs in Bárány and Siegel (2017), is that the majority of the between-industry shifts that drive long-run job polarization in both Sweden and the US indeed are due to persistent employment shifts from manufacturing to service industries. In particular, such shifts accounts for the great majority of the persistently negative between-industry component for Swedish and US routine manual jobs in Tables 4 and 5, which in turn accounts for the majority of the continuous decline of middle-wage routine jobs as a whole relative to the highest- and lowest-paid nonroutine jobs (as shown in Table 3).

Overall, the estimated patterns in this subsection are consistent with structural change, in terms of persistent shifts from manufacturing to service industries, giving rise to job polarization over the long run. For Sweden, and similar to the results for the US in Table 5 as well as the conclusion for the US in Bárány and Siegel (2017), structural change appear especially important for explaining job polarization prior to the 1980s, but also matters for more recent decades. However, the increased weight of within-industry shifts combined with the common US-Sweden across-the-board decline of routine jobs from the late 1980s is also consistent with RBTC as one important additional driver of job polarization from

then on. That is, the post-1980s patterns fits well with the predictions from the hypothesis of RBTC in terms of how the massive fall in the price of computer-based technology around this time should affect employment patterns; see further Autor, Levy and Murnane (2003) and Acemoglu and Autor (2011).

Finally, and as partly discussed above, Goos, Manning and Salomons (2014) argue that RBTC, although being a within-industry phenomenon, also can give rise to a between-industry component. If so, this makes it harder to interpret and draw conclusion regarding the role of general structural change—as described by the macroeconomic/economic-growth literature—versus that of RBTC in later decades based on the relative magnitude of within- versus between-industry shifts. However, and similar to what is argued for the US by Bárány and Siegel (2017), it appears highly unlikely that a majority of the between-industry shifts in Sweden during the last decades should be due to the rise of RBTC. First, this would suggest that the drivers of between-industry shifts in previous decades came to a halt around 1980, to be replaced by RBTC as the most important cause for general employment shifts from manufacturing to service industries. With such a major change in what drives between-industry shifts in employment, one would expect to see some sort of major break in the trends of the industrial composition from around the 1980s. However, no such obvious breaks are visible for Sweden in Figure 5. Second, and a bit troublesome for the hypothesis of RBTC, there is no marked increase in the within-industry component for routine manual jobs in Sweden during the post-1980s period as a whole—that is, for the jobs overrepresented in the manufacturing sector. Instead, within-industry shifts are noticeably less important than between-industry shifts over the whole period 1960–2013. Hence, as RBTC did not give rise to a more significant decline of routine manual jobs within industries from the 1980s onwards, it can arguably not be the main driver of declining employment shares for manufacturing industries during the same period.

4. Concluding Remarks

This paper shows that job polarization in Sweden is a long-run phenomenon: employment in middle-wage jobs display significant declines relative to both higher and lower paying jobs over the whole period 1950–2013. A comparison of the job patterns underlying long-run job polarization in Sweden and the similar long-run trend recently discovered for the US shows on important cross-country similarities. In both countries, persistent shifts in the industrial composition working against routine manual (blue-collar) jobs explain most of the relative decline of middle-wage jobs prior to the 1980s. This industry factor is also important from the 1980s onwards, but both Sweden and the US then also display a broader pattern of job polarization, with dwindling employment in routine cognitive (white-collar) jobs and polarizing employment patterns also within industries.

Overall, the results in this paper are consistent with structural change—in terms of the persistent employment shifts from manufacturing to service industries present across the developed world—as the main explanation for why job polarization is a long-run phenomenon in both Sweden and the US. The common US-Sweden patterns are however also consistent with RBTC as one additional driver of job polarization in more recent decades; this conclusion is further corroborated by the large number of previous studies that support the presence of RBTC from the 1980s onwards.

The previous literature shows that job polarization is a common phenomenon across the developed world since the 1980s. Arguably, this common pattern has added weight to the popular view of advances in computer technology—and the resulting automation of jobs—as the primary, or perhaps the only, explanation for the presence of job polarization. However, the great majority of these previous studies do not investigate the potential presence of job polarization prior to the 1980s. As such, the use of Swedish data from 1950 onwards in this paper and the conclusion of declining routine jobs relative to nonroutine jobs in both Sweden and the US over the full post-war period clearly show that job polarization, *per se*, is not a new phenomenon and hence not uniquely tied to the recent

"computer age". In fact, job polarization in Sweden was actually larger in the pre- than in the post-1980 period—at least as measured in this paper.

Of course, a weakness with the cross-country comparison in this paper is the use of just two countries—albeit two countries with markedly different prerequisites. That is, we do not know if the common US-Sweden patterns of long-run job polarization are shared by most other developed countries. Neither do we know if the rapid Swedish job polarization in the pre-1980 period is an exception among European countries. In this regard, the analysis in this paper should be viewed as a first step towards obtaining more information on both country-specific and cross-country trends over a longer time span, covering both pre- and post-1980 periods. Investigations of long-run employment patterns for additional countries would therefore substantially add to our understanding of long-run job polarization and its connection to dwindling routine jobs and technological change.

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Appendix

A. The Swedish 1950 Census Classification of Occupations

The data used for analyses of employment in different occupations in 1950 is from tabulated values from the official report of the Swedish Population and Housing Census of 1950; see Statistics Sweden (1953, Table F, p. 32). The division of occupations builds on the 1949 ILO classification (International Labour Office, 1949), where nonagricultural and nonmilitary occupations are divided into 8 broad occupation categories. In the Swedish application, these are: 1. *Professional, technical and related workers*; 2. *Managerial, administrative, clerical and related workers*; 3. *Sales workers*; 4. *Workers in mine and quarry occupations*; 5. *Workers in operating transport occupations*; 6. *Craftsmen*; 7. *Production process workers and laborers not elsewhere classified* (in the Swedish data, this category is labeled "Personer tillhörande övriga yrken", i.e. labeled "Workers not elsewhere classified"); 8. *Service workers* (including protective).

The 1950 Swedish occupation groups are mapped to Acemoglu and Autor's (2011) classifications, with occupation number 1 categorized as nonroutine cognitive, occupations 2 and 3 categorized as routine cognitive, occupations 4, 5, 6, and 7 categorized as routine manual, and occupation 8 categorized as nonroutine manual. One issue here is that occupation number 2, classified as routine cognitive, also consists of managerial occupations, which should be classified as nonroutine cognitive. To adjust for this, I assume that the employment share of managerial occupations is the same in 1960 and 1950. In 1960, managerial occupations make up 5.4 percent of total employment. I therefore add this number to the 1950 employment share of nonroutine cognitive jobs and deduct it from the 1950 employment share of routine cognitive jobs.

B. The Bootstrap

The asymptotic distribution of the statistics capturing changes in employment shares for wage-quartile groups, displayed in Figures 2 and 3, is unknown, but bootstrapping offers a means to approximate its finite sample distribution (see Horowitz, 2001). To capture the temporal dependence in the data-generating process for the LINDA microdata (i.e. its longitudinal dimension), I first pool the data for 1960, 1970, and so forth every decade up to 2013, resulting in a sample of *n* individuals. In each bootstrap, I then draw, with replacement, a random sample of *n* individuals and keep all year-specific observations for each individual. This "block-bootstrap" is motivated by the fact that the estimated statistics of interest has a finite time dimension and asymptotically relies on $n \to \infty$; for details, see Horowitz (2001) and Cameron and Trivedi (2005).

To allow for the stage-by-stage nature of the estimation, I bootstrap the entire estimation procedure. That is, first, I draw a random sample of size *n* with replacement. I then estimate median wages in each job in 1970 (first-stage estimation) and classify jobs into quartile-group based on their employment in 1960 and their median earnings in 1970 (second-stage estimation). Finally, I calculate changes in employment shares over time for each quartile group (third-stage estimation). A new bootstrap sample is then drawn and all steps are performed again. This is repeated 25,000 times and the resulting empirical distribution of the estimates are used to form 95-percent confidence intervals. This way of performing the bootstrap takes account of the uncertainty associated with estimating median earnings in 1970 and the number of workers in each job in 1960, and thereby the uncertainty associated with the estimated thresholds for dividing jobs into quartile groups, as well as the uncertainty associated with the employment changes in each quartile group over time. This bootstrap approach to stage-by-stage estimation is outlined in Wooldridge (2010) and Cameron and Trivedi (2005), and applied in, for example, Dustmann and Meghir (2005) and

Adermon and Gustavsson (2015). Adermon and Gustavsson (2015) also present empirical support for the consistency of the application of the bootstrap to job polarization by performing sensitivity analyses based on the "*m* out of *n*" bootstrap procedure (see Cameron and Trivedi, 2005).

C. Age, Gender, and Shifts in the Swedish Job Composition

Sweden has witnessed a noticeable growth of female employment, with an increase from around 50 percent in 1960 to over 80 percent in 1990. Another potential factor that could affect the composition of routine and nonroutine jobs is shifts in the age structure of the Swedish working population.

To investigate the potential explanatory power of shifts in the gender and age composition, I use the micro data from 1960 onwards combined with standard Blinder-Oaxaca decompositions. For the first year in each decade, I estimate linear probability models separately for each of the four job-tasks groups with five age dummies (for ages 18-29, 30-39, 40-49, 50-59, and 60-65) and a gender dummy as explanatory variables. Based on these, I then investigate how much of the actual decennial change in the employment share for each group that potentially can be explained away by shifts in the age and gender composition while holding the estimated coefficients at their initial values for each decade.

The results, presented in Table A1, suggest that shifts in the age and gender composition cannot explain away the observed job polarization. The gender composition (i.e. the increase in female employment) can explain some of the decline in employment shares for routine manual jobs during the 1960s and 1970s and around half of the increase in nonroutine manual jobs during the same period. On the other hand, the results suggest that routine cognitive jobs potentially would have displayed a falling employment share already in the 1960s, had the gender composition been constant. Moreover, in total, the unexplained component for each job-tasks group generally accounts for the majority of the changes and display a clear and significant job-polarization pattern. Hence, age

Table A1: *Decompositions of employment-share changes (percentage points)*

	Time period				
	1960-70	**1970-80**	**1980-90**	**1990-2000**	**2000-13**
Nonroutine cognitive					
Total Δ	3.20**	5.23**	2.01**	8.67**	3.34**
	(0.16)	(0.14)	(0.14)	(0.15)	(0.21)
Due to gender	-0.59**	-0.77**	-0.35**	-0.04**	-0.02**
	(0.03)	(0.03)	(0.02)	(0.01)	(0.01)
Due to age	-0.25**	0.62**	0.04	0.70**	-0.27**
	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Unexplained component	*4.04***	*5.37***	*2.32***	*8.01***	*3.64***
	(0.20)	*(0.19)*	*(0.19)*	*(0.20)*	*(0.20)*
Routine manual					
Total Δ	-6.82**	-8.78**	-1.51**	-6.05**	-3.48**
	(0.18)	(0.15)	(0.14)	(0.14)	(0.17)
Due to gender	-2.63**	-2.71**	-1.36**	-0.29**	-0.20**
	(0.09)	(0.09)	(0.08)	(0.08)	(0.07)
Due to age	0.15**	-0.31**	-0.00	-0.41**	-0.02
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
Unexplained component	*-4.33***	*-5.76***	*-0.15*	*-5.35***	*-3.30***
	(0.21)	*(0.18)*	*(0.17)*	*(0.16)*	*(0.16)*
Routine cognitive					
Total Δ	0.32*	-1.18**	-2.07**	-2.42**	-0.95**
	(0.15)	(0.13)	(0.12)	(0.12)	(0.14)
Due to gender	1.53**	1.57**	0.72**	0.12**	0.07**
	(0.06)	(0.05)	(0.04)	(0.04)	(0.02)
Due to age	-0.05*	-0.14**	-0.01	-0.04	-0.09**
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Unexplained component	*-1.16***	*-2.61***	*-2.77***	*-2.50***	*-1.11***
	(0.18)	*(0.16)*	*(0.15)*	*(0.15)*	*(0.14)*
Nonroutine manual					
Total Δ	3.30**	4.72**	1.58**	-0.21	1.08**
	(0.13)	(0.13)	(0.12)	(0.13)	(0.17)
Due to gender	1.69**	1.91**	1.00**	0.21**	0.15**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
Due to age	0.16**	-0.18**	-0.02	-0.26**	0.16**
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Unexplained component	*1.45***	*3.00***	*0.60***	*-0.16*	*0.77***
	(0.14)	*(0.15)*	*(0.15)*	*(0.16)*	*(0.16)*

Notes: Results are for Sweden. Estimates are from Blinder-Oaxaca decompositions based on linear probability models for each job-task group, where explanatory variables are dummy variables for gender and for the age categories 18-29, 30-39, 40-49, 50-59, and 60-65. The decompositions are estimated using the *oaxaca* command for Stata by Jann (2008). Standard errors are in parentheses;* $p < 0.05$, ** $p < 0.01$.

and gender appear unlikely to be the main explanation for the Swedish long-run trend of job polarization; Bárány and Siegel (2017) reach similar conclusions for the US labor market.

For completeness, Figure A1 also presents the share of Swedish routine and nonroutine jobs between 1950 and 2013 divided by gender. As can be seen, routine jobs decline relative to nonroutine jobs for both males and females over most of this period. Hence, job polarization is a long-run phenomenon for both male and female employment.

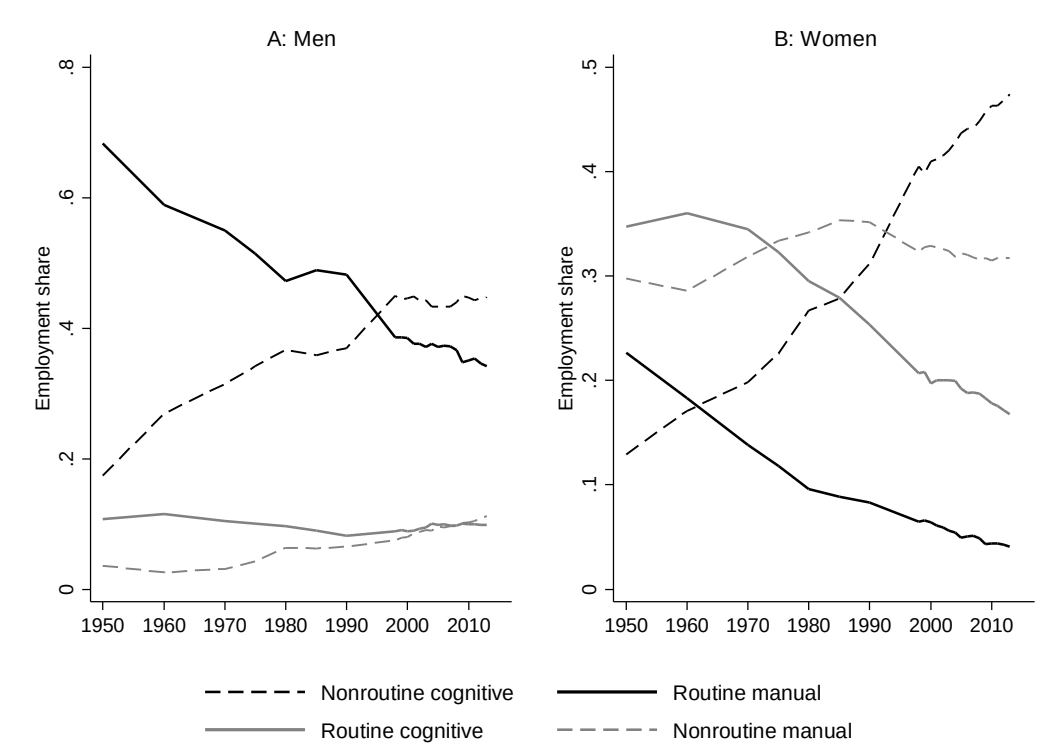

Fig. A1. Shares of employment in routine and nonroutine jobs in Sweden by gender, 1950–2013

Notes: Panel A contains shares of total male nonagricultural employment in Sweden for four-job task groups. Panel B contains shares of total female nonagricultural employment in Sweden for the same four-job task groups. The time series are based on data from 1950, 1960, 1970, 1975, 1980, 1990, and 1998–2013

D. Additional Shift-Share Decompositions

Shift-Share Decomposition for the US Based on Seven Industries

The Swedish shift-share decompositions in the main text are based on a classification into seven different industries, whereas the US decomposition employs a classification into eleven industries. To shed light on whether this difference affects any conclusions, I here present US shift-share decompositions based on seven broader industry groups, obtained by collapsing the eleven US industries into seven classifications that arguably corresponds more closely to the Swedish industries.

As in the main analysis, the decompositions for the US are based on the data used in Acemoglu and Autor (2011, Table 6, p.1102), but with their elven industries transformed into seven industries by: 1) merging the industries "wholesale trade" and "retail trade", in order to more closely correspond to the Swedish industry "trade and restaurants"; 2) merging the industries "finance, insurance, and real estate", "business services", and "professional services", in order to more closely correspond to the Swedish industry "financing and business services"; and finally 3) merging the industries "personal services and entertainment" and "public administration", in order to more closely correspond to the Swedish industry "community and personal services".

Table A2 contains the results. A comparison of these to the main results for the US presented in Table 5 shows that no main conclusions are altered by employing a classification of seven instead of eleven industries.

Shift-Share Decomposition for Sweden and the US Based on Two Industries

To further investigate the importance of employment shifts from manufacturing to service industries for the relative decline of middle-wage jobs, Tables A2 and A3 contain shifts-share decompositions for the US and Sweden where all industries are collapsed into one of these two broad sectors. Here, the manufacturing industry/sector contain the industries "Manufacturing",

Table A2: *Shift-share decompositions for the US, 1959–2007; seven industries*

	Time period				
	1959-1969	**1969-1979**	**1979-1989**	**1989–1999**	**1999–2007**
Nonroutine cognitive					
Total Δ	1.54	2.70	4.24	3.61	0.99
Industry Δ	1.93	1.25	1.16	1.15	0.37
Within Δ	-0.39	1.46	3.08	2.46	0.63
Routine manual					
Total Δ	-4.47	-3.57	-5.61	-2.65	-2.21
Industry Δ	-3.25	-2.18	-2.75	-1.36	-1.14
Within Δ	-1.21	-1.39	-2.86	-1.29	-1.06
Routine cognitive					
Total Δ	2.33	0.69	1.10	-2.05	-1.22
Industry Δ	0.98	0.52	0.89	0.11	0.18
Within Δ	1.35	0.17	0.21	-2.16	-1.40
Nonroutine manual					
Total Δ	0.60	0.18	0.27	1.09	2.43
Industry Δ	0.34	0.41	0.70	0.10	0.60
Within Δ	0.26	-0.23	-0.43	0.99	1.83

Notes: The table contains decompositions of changes in shares of total nonagricultural employment (percentage points) for four job-task groups into components due to changes in industry composition and changes in job shares within industries. The decompositions are based on the data underlying the results in Acemoglu and Autor (2011, Table 6, p.1102); but with the original eleven industries collapsed into seven industries; see the main text for details.

"Construction", and "Mining and Quarrying", whereas all other industries are assigned to the service sector. Though the within-industry component from these shift-share analyses hold little economic meaning, the estimates of the between-components can be compared to those in the main decompositions in Tables 4 and 5 and thereby shed light on the importance of overall shifts from manufacturing to service industries. This is especially relevant for routine manual jobs, as the between-industry component, as estimated in the main analysis in Tables 4 and 5, is what primarily explains the continuous trend of declining employment shares for middle-wage routine jobs as a whole.

For Sweden and routine manual jobs, the between-industry component for the 1960s in Table A2 is −4.12 percentage points. In Table 4, based on seven

Table A3: *Shift-share decompositions for Sweden, 1960–2013; two industries*

	Time period				
	1960-1970	**1970-1980**	**1980-1990**	**1990-2000**	**2000-2013**
Nonroutine cognitive					
Total Δ	3.20	5.23	2.01	8.67	3.34
Industry Δ	1.22	1.28	0.68	0.75	0.94
Within Δ	1.98	3.95	1.32	7.92	2.41
Routine manual					
Total Δ	-6.82	-8.78	-1.51	-6.05	-3.48
Industry Δ	-4.12	-4.46	-2.19	-2.17	-2.66
Within Δ	-2.70	-4.32	0.67	-3.87	-0.81
Routine cognitive					
Total Δ	0.32	-1.18	-2.07	-2.42	-0.95
Industry Δ	1.40	1.31	0.50	0.41	0.47
Within Δ	-1.09	-2.49	-2.57	-2.83	-1.42
Nonroutine manual					
Total Δ	3.30	4.72	1.58	-0.21	1.08
Industry Δ	1.50	1.86	1.01	1.00	1.26
Within Δ	1.80	2.86	0.57	-1.21	-0.18

Notes: The table contains decompositions of changes in shares of total nonagricultural employment (percentage points) for four job-task groups into components due to changes in industry composition and changes in job shares within industries. The industry dimension is captured by the two broad sectors *manufacturing* and *service*, where the former consist of the industries "Mining and Quarrying", "Manufacturing", and "Construction", and *service* contains all other industries.

different industries, the corresponding estimate is −4.96 percentage point. This suggest that 83.1 percent (−4.12/−4.96=0.831) of the between component for routine manual jobs in Table 4 for the 1960s is accounted for by employment shifts from manufacturing to service industries. Performing corresponding calculations for Sweden and each following decade gives even higher numbers, with the exception of the 1990s where the number is 67.8 percent. Similar results apply for the US, with 71.5 percent of the negative between-industry component for routine manual jobs for the 1960s in Table 5 being due to shifts from manufacturing to service industries, and with higher numbers for the following decades.

Table A4: *Shift-share decompositions for the US, 1960–2013; two industries*

	Time period				
	1959-1969	**1969-1979**	**1979-1989**	**1989–1999**	**1999–2007**
Nonroutine cognitive					
Total Δ	1.54	2.70	4.24	3.61	0.99
Industry Δ	0.63	0.43	0.67	0.35	0.31
Within Δ	0.91	2.27	3.57	3.26	0.68
Routine manual					
Total Δ	-4.47	-3.57	-5.61	-2.65	-2.21
Industry Δ	-2.38	-1.63	-2.55	-1.32	-1.10
Within Δ	-2.09	-1.94	-3.06	-1.33	-1.11
Routine cognitive					
Total Δ	2.33	0.69	1.10	-2.05	-1.22
Industry Δ	0.90	0.65	1.07	0.56	0.44
Within Δ	1.43	0.04	0.03	-2.61	-1.66
Nonroutine manual					
Total Δ	0.60	0.18	0.27	1.09	2.43
Industry Δ	0.85	0.55	0.81	0.41	0.35
Within Δ	-0.26	-0.37	-0.53	0.68	2.08

Notes: The table contains decompositions of changes in shares of total nonagricultural employment (percentage points) for four job-task groups into components due to changes in industry composition and changes in job shares within industries. The decompositions are based on the data underlying the results in Acemoglu and Autor (2011, Table 6, p.1102); but with the original eleven industries collapsed into the two broad industries/sectors *manufacturing* and *service*. Here, *manufacturing* contains the industries "Mining and Quarrying", "Manufacturing", and "Construction", while *service* contain all other industries.

For the other subcategory of middle-wage jobs, routine cognitive jobs, the between-industry estimates in Tables A2 and A3 are generally more positive than in the main analysis in Tables 4 and 5. This suggests that shifts from manufacturing to service industries have, taken by themself, had a positive effect on the employment share of routine cognitive jobs. However, the between-estimates are still small in absolute magnitude and do not alter any main conclusions regarding the connection between structural change and shrinking employment shares in routine jobs as a whole.

For nonroutine manual jobs—the lowest-paid jobs—the results in Tables A2 and A3 suggest that shifts from manufacturing to service industries generally

account for the great majority of the positive between-industry components in Tables 4 and 5.

For nonroutine cognitive jobs and Sweden, the estimates in Table A2 suggest that shifts from manufacturing to service account for more than half of the positive estimate in Table 4. For the US, the contribution is smaller, with these shifts making up around a fourth to a third of the overall between-industry estimates in Table 5.

E. Additional Figures and Tables

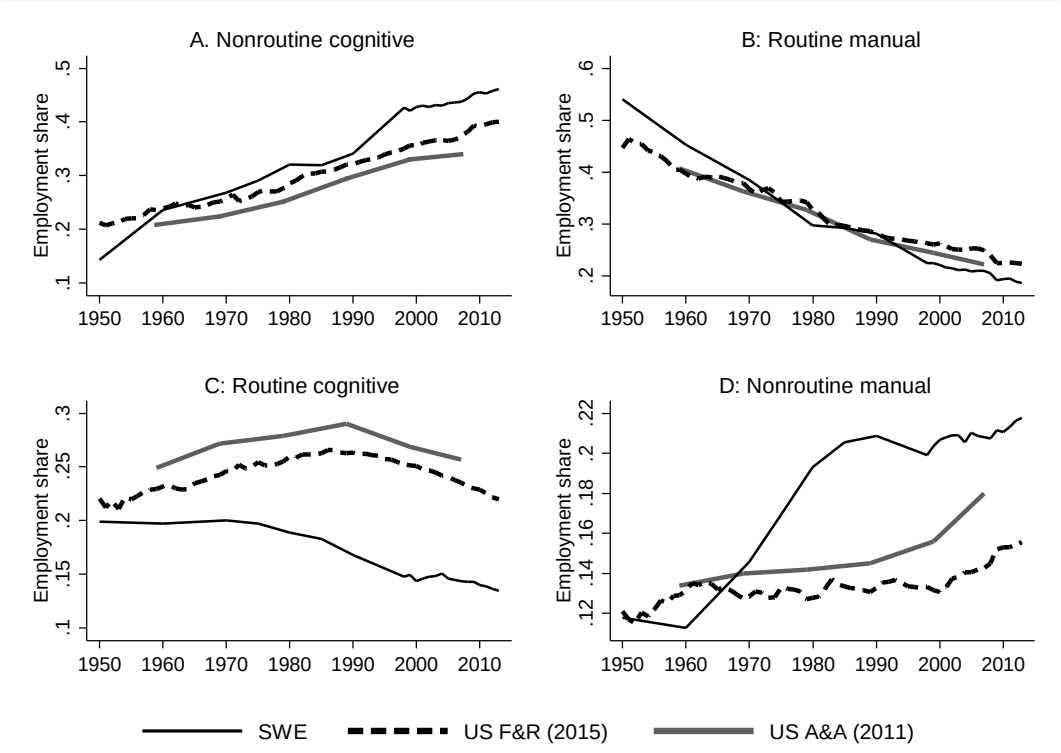

Fig A2. Shares of total nonagricultural employment in routine and nonroutine jobs, 1950–2013, Sweden compared to US estimates from Foote and Ryan (F&R) (2011) and Acemoglu and Autor (A&A) (2011)

Notes: Employment shares correspond to shares of total nonagricultural employment in each country. Time series for the US are from Foote and Ryan (2015, Figure 4, p.381) and Acemoglu and Autor (2011, Table 3a, p. 1069). Foote and Ryan (2015) contain annual estimates for the period 1950–2013. Acemoglu and Autor (2011) contain estimates for 1959, 1969, 1979,1989, 1999, and 2007.

Table A5. *Employment-share changes for Swedish 2-digit ISCO-88 occupations, ordered by 1970 median earnings*

Quartile	2-digit ISCO-88 occupation	Task	Share 1960	Δ share 1960–2013
4	22 Life science and health professionals	NrC	0.51	1.84
4	12 Corporate managers	NrC	2.38	2.06
4	21 Physical, mathematical and engineering science professionals	NrC	0.10	5.23
4	24 Other professionals	NrC	1.99	5.27
4	23 Teaching Professionals	NrC	2.86	2.30
4	31 Physical and engineering science associate professionals	NrC	7.52	-2.64
4	34 Other associate professionals	NrC	4.09	5.56
4	73 Precision, handicraft, craft printing and related trades workers	RM	1.44	-1.21
4	72 Metal, machinery and related trades workers	RM	2.88	-0.01
3	83 Drivers and mobile-plant operators	RM	6.02	-2.95
3	71 Extraction and building trades workers	RM	15.28	-9.72
3	81 Stationary-plant and related operators	RM	3.76	-2.46
3	93 Laborers in mining, construction, manufacturing and transport	RM	0.54	0.52
2	32 Life science and health associate professionals	NrC	1.06	2.16
2	13 Managers of small enterprises	NrC	3.03	-1.77
2	41 Office clerks	RC	12.08	-5.74
2	74 Other craft and related trades workers	RM	2.02	-1.79
1	82 Machine operators and assemblers	RM	13.41	-8.99
1	33 Teaching associate professionals	NrC	0.09	2.39
1	42 Customer service clerks	RC	2.01	0.01
1	52 Models, salespersons and demonstrators	RC	5.65	-0.55
1	51 Personal and protective services workers	NrM	8.29	8.23
1	91 Sales and services elementary occupations	NrM	2.99	2.27

Notes: The first column refers to the wage-quartile group in Figure 2. The second column contains the 2-digit ISCO-88 code for each occupation along with its official label. Occupations are ordered by their 1970 median annual earnings, with individuals employed in *Life science and health professionals* having the highest median earnings and individuals in *Sales and services elementary occupations* having the lowest median earnings. The column "Task" gives the job-task category for each occupation, where NrC is *nonroutine cognitive*, RM is *routine manual*, RC is *routine cognitive*, and NrM is *nonroutine manual*. The column "Share 1960" is the share of total nonagricultural employment in 1960, and the last column gives the change in this share from 1960 up to 2013.

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