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Labour Market Polarization, Urbanization and Skill-Biased Consumption

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Abstract

We study changing patterns of labour market inequality in the US and Europe, with a particular focus on labour market polarization. We ask whether observed polarization patterns can be reconciled with skill-biased changes in consumption behaviour. We find that polarization has occurred to varying degrees in different places, but with greater polarization observed in more urban areas. We also uncover a skill-bias in service consumption expenditures that is consistent with these changes so that the demand for service jobs has risen by more, leading to greater job polarization, in places where consumers getting relatively richer from rises in inequality have increasingly demanded low wage services over time.

JEL Keywords: Labour market polarization; Urbanization; Skill-biased consumption.

JEL Classifications: J31; R11.

1. Introduction

Polarization of job growth across the skill distribution has been identified as an important feature of the way that labour markets of developed countries have changed in the past few decades. Increased polarization – with relatively fast job growth at the top and bottom end of the skill distribution, coupled with job falls in the middle - has been identified as a key aspect of rising labour market inequality. Empirical researchers have studied how this has interacted with technology and the tasks that workers perform in their jobs.[1] In particular, the notion that middle skill jobs have been disproportionately lost as the job distribution has hollowed out in the middle has received significant attention.

Most of the research literature in this area has concerned itself with whether one can identify the presence of labour market polarization. In doing so, a principal focus has been placed on identifying and documenting patterns and direction, rather than on studying magnitudes and possible variations. In fact hardly any research, at least to our knowledge, studies whether the extent of polarization varies and, if it does, what might be associated with differential patterns of polarization. A first exception to this is Autor and Dorn (2013) who make the observation that polarization differs across US commuting zones. A second is Lindley and Machin (2103) who show there to be differences in the extent of polarization across US states. It is also implicitly considered in the analysis of Goos, Manning and Salomons (2012) who present evidence from different European countries but their emphasis is very much on polarization being pervasive, in the sense of being present across the countries they study.

[1] See the review of Acemoglu and Autor (2010), and the series of US papers by Autor and colleagues (beginning with Autor, Levy and Murnane, 2003, and also Autor, Katz and Kearney, 2008, and Autor and Dorn, 2013). European papers showing job polarization in Europe include Goos and Manning (2007) for the UK, Spitz-Oener (2006) for Germany and Goos, Manning and Salomons (2009) for a number of countries.

Other than the focus on tasks in jobs, what has been less clear in the existing literature is the extent to why this polarization of the labour market has occurred. This is what we try to shed some light on by offering new evidence on in this paper, from both the United States and Europe. We study two dimensions of labour market polarization. The first is to examine spatial variations in the extent of polarization, with particular attention being placed on urbanization. There is good reason to do this as the urban economics literature makes it clear that cities have experienced skill sorting as more educated workers have differentially located there and thus inequality has risen faster in urban settings (see Combes et al., 2008, 2012).

The second is to consider whether one can garner evidence on an issue that has sometimes been discussed, but on which little hard evidence exists (with the exception of Autor and Dorn, 2013, and Mazzolari and Ragusa, 2013). This is the notion that, since some individuals and families have got richer as inequality has risen, they have increased their demand for low wage services and that is why job growth has risen at both the top and bottom of the skill distribution. One possibility is that consumption patterns, as well as earnings and income, could have a skill-bias associated with them. The spatial dimension is potentially important here as well, since one would think that spatial sorting to cities and high inequality has potential to generate a greater skill-bias in consumption and therefore a bigger demand for low wage service jobs. In their analysis of labour market (but not consumption) data, Autor and Dorn (2013) do not find a direct correlation between changes in service sector employment shares and college workers' wages and/or hours. We take a different tack in this paper, and study if there is any direct evidence of skill-bias in consumption patterns using actual consumer expenditure data.

To preview our main findings, we report evidence of spatial variations in labour market polarization. In particular, we consistently find that polarization is more pronounced in more urban places, and that these are the places where inequality has risen faster and more skill sorting has occurred. Moreover, we directly study patterns of changing urban consumer demand, asking whether one can detect any direct evidence of a skill-bias in consumption behaviour that is in line with the observed patterns of polarization. We find that consumer demand has shifted in a manner consistent with such a skill-bias as skilled households have increasingly demanded services produced by low wage workers as inequality has gone up over time.

The rest of the paper is structured as follows. In section 2 we use US and European microdata to document patterns of changing labour market polarization, and also study spatial variations in the extent of polarization. In section 3, we focus on urban non-urban differences in polarization. In Section 4, we study changing patterns of consumer demand in the US, with a particular focus on expenditures on services supplied by low wage workers, and ask whether one can find evidence of a skill-bias in consumer demand that is in line with the changed job structure in the labour market as polarization has taken place. Finally, section 5 offers some conclusions.

2. Patterns of Labour Market Polarization – Initial Descriptive Analysis

Labour Market Polarization in the US and Europe

The starting point of our analysis is the polarization of the labour market, as shown in Figure 1 for the United States for 320 consistently defined occupations from the 5 percent 1980 Census sample and the 1 percent samples from the 2009, 2010 and 2011 American Community Surveys (ACS). The chart reproduces the U-shaped pattern in job growth between 1980 and 2010 across the 1980 occupational skill distribution that has been documented before in Autor and Dorn (2013) and Autor, Katz and Kearney (2008).

The x-axis of Figure 1 orders 1980 occupations from lowest wage to highest wage then shows the growth in hours at each percentile of that initial skill distribution. The growth in hours is defined in relative terms so that a number above zero represents relative growth and a number below zero represents negative growth. A clear pattern of high hours growth at the top end emerges, together with a hollowing out of the middle, but also positive growth at the bottom end in low wage jobs.

This polarization of the labour market has become a central feature of the inequality literature, offering what is often referred to as a more nuanced refinement of the early literature that focussed on the impact of skill-biased technical change (see Acemoglu and Autor, 2010). Since Autor, Levy and Murnane (2003), the role of tasks dovetailing with technical change in shaping inequality has been stressed in this work. It has been argued that workers doing jobs involving routine tasks have been substituted by new technologies, whilst those performing non-routine tasks have been complemented so they have done better in relative terms in the labour market. Thus, there has been high job growth at the top end of the skill distribution where workers are more likely to do non-routine jobs, and a big hollowing out of the middling jobs involving routine tasks.

The nuance emerges because a lot of low wage jobs at the bottom end of the occupational distribution (the oft cited ones being cleaning and child care jobs) actually differentially involve non-routine tasks, so that there has also been an increase in these jobs as well. Hence the U-shape of the changing distribution of job growth that is shown in Figure 1.

Figure 2 shows a comparable polarization chart for fifteen European countries between 1994 and 2010. The Figure is based on European Labour Force Survey (ELFS) data and shows relative hours growth across an initial occupational wage distribution, this time defined in 1994, the first year when consistent data could be obtained. The wage ranking comes from the European Community Household Panel and is taken from the paper by Goos, Manning and Salomons (2009).

The U-shaped pattern of relative hours growth seen in the US labour market is also seen in Europe.[2] It is a little less pronounced at the bottom and top ends of the skill distribution in Figure 2 as compared to Figure 1, but (as in Goos, Manning and Salomons, 2009) a very clear pattern of job polarization seems to have characterised the European labour market as well.[3]

Spatial Patterns of Labour Market Polarization

Examining the spatial distribution of polarization reveals spatial heterogeneity in the extent of polarization. Figure 3 reconstructs a Figure from Lindley and Machin (2013) for hours growth (rather than job growth in their paper) in the US. The extent of polarization in the 48 contiguous US states was examined one at a time and then grouped into three sets of states described in the Figure as reflecting low, medium and high polarization.

In Figure 3 there is clearly a group of states characterized by significant job growth at both the bottom and top of the skill distribution with a very pronounced U-shape – this is the 'High polarization' chart in the south west quadrant of the panel of the Figure. But

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[2] Four of the fifteen countries whose data is used in Figure 2 only have usable consistently defined ELFS data for a start year later than 1994 (Austria 1995, Finland 1997, Sweden 1997 and Switzerland 1996). Appendix Figure A1 shows the same Figure for the eleven European countries where we have a start year of 1994. Very much the same polarization pattern is seen.

[3] See Goos and Manning (2007) for the UK, or Spitz-Oener (2006) for Germany for evidence on country-specific patterns of polarization.

there is also a set of states where there is no relative job growth at the bottom end coupled with job growth at the top end and far less evidence of a U-shape – this is the chart labelled ‘Low polarization’ in the north west quadrant of the Figure. Finally, there is the third group which lie in between, as shown in the chart labelled ‘Medium polarization’ in Figure 3.

Spatial heterogeneity also characterises the European polarization pattern. The Figure shows polarization charts for eight Northern, three Nordic and four Southern European countries. There are clear variations across these three groups. The ‘conventional’ U-shape emerges for the Northern group, but the patterns are different for the Nordic and Southern countries. It is notable that job growth amongst low wage occupations has been more modest in Southern Europe.

This initial descriptive analysis, despite still being pitched at a fairly high level of spatial aggregation (across US states, or across European countries), does seem to show that there are some places where polarization has been more pronounced and others where the feature of polarization driven by job growth at the bottom has been less evident. In the next two Sections of the paper we therefore go on to try and gain a better understanding of why.

3. Urbanization

The particular spatial variations in labour market polarization we chose to show in the previous section of the paper were across US states and across European countries. There are, however, good economic arguments to suppose that there may well be variations within these spatial units as well.

One important feature of the evolution of the economic development of modern economies has been the rise of cities in terms of their increased population shares and the agglomeration effects that can raise productivity (and wages) as stressed by urban economists (see Puga, 2010, or Rosenthal and Strange, 2004). Moreover, inequality is higher in more urban places as factors associated with rising inequality, like higher education levels of workers, have gone up by more (see, *inter alia*, Berry and Glaeser, 2005, Lindley and Machin, 2013, or Moretti, 2011).[4]

Thus in this Section, we look at whether polarization differs by urbanization. We show that it does, first looking at differences by the degree of urbanization in the US and Europe, then second considering big cities in both places. We then show that there are significant differences in the evolution of inequality and in the changing demand for high and low wage jobs that relate to the extent of urbanization.

Polarization Differences by Urbanization

Figure 5 shows polarization charts for urban, suburban and non-urban areas in the US and Figure 6 does the same for Europe. For the US urban is defined as living in the central city part of a metropolitan area and suburban living in the metropolitan area but outside the central city in the 1980 Census or 2009-2011 ACS.[5] For Europe, it comes from the degree of urbanization information collected in the ELFS.[6]

[4] Some other papers show strong connections between skills and the urban environment: see, for example, Bacolod et al. (2009) or Hendricks (2011).

[5] The US urban definition comes from a variable in the 1980 Census and the 209-2011 ACS where individuals are classified as 'not in a metro area', 'in a metro area, central city', and 'in a metro area, outside central city'.

[6] More precisely, the ELFS collects a degree of urbanization variable for local areas (very disaggregated at NUTS5 level, e.g. at ward level in the UK) within each country. Urban is defined as living in a densely populated urban area (population > 50,000; population density > 500 inhabitants per square km), Suburban is defined as living in an intermediate area (population > 50,000, population density > 100 inhabitants per square km), or adjacent to a densely populated area. Non-urban is thinly populated areas belonging to neither the Urban or Suburban definitions.

A striking, and broadly similar, pattern by urbanization emerges for the US and Europe. The U-shaped polarization pattern in both continents is confined to the urban and suburban areas, and the extent of polarization is larger in the former. In the non-urban areas, there is job growth at the top, but far less of an increase in job growth at the lower end of the skill distribution.

Big City Differences in Polarization

We push this further in Figure 7, by looking at big cities only. The Figure shows the extent of polarization in the four biggest US cities in 1980 (Chicago, Los Angeles, New York and Philadelphia) and for London, Madrid and Paris in our sample of European countries.

Figure 7 reveals that the big cities are very much characterised by the polarization of job growth over time. Both charts show a very clear U-shape, which is a little more pronounced in the big US cities as compared to the big European cities.

Correlates of Differential Polarization Across Places

These charts beg the question as to what has been going on in the urban areas characterized by more polarization. Table 1 shows some relevant aspects, breaking down changes over time in dimensions of labour market inequality and in the occupational structure of jobs across non-urban and urban areas, and for big cities alone.

The upper panel of Table 1 shows changes in education sorting as measured by the college share in hours and changes in the college/high school wage premium between 1980 and 2010 for the US and between 1994 and 2010 for Europe.[7] The change in the college hours share goes up by 0.088 in non-urban areas, by 0.164 in urban areas and by a huge 0.185 in the big cities between 1980 and 2010 in the US. Thus education sorting is

[7] The college/high school wage premium is composition adjusted by running separate regressions holding constant age, gender and race within the spatial units by year.

an urban phenomenon that seems to relate to rising polarization in the US. The same is the case in Europe, where the overall non-urban/urban gap is more muted, but more education sorting occurs in the big cities.

The college/high school wage differential also rises by more in more urban places. For the US, it goes up by 0.171 log points for non-urban areas, by 0.293 in urban areas and by a huge 0.348 in the big cities. In Europe, we do not have microdata on wages, education and the extent of urbanization over time to be able to carry out the same exercise, other than for some countries on a rather piecemeal basis.[8]

The lower panel of the Table focusses in on changes in the occupational structure of employment, showing changes in the hours shares of service sector occupations and in the hours shares of managers and professionals. In some ways, these pull together the particular occupation groups at a broader level than in the polarization Figures already analysed above. This is useful to see where (in terms of occupations) the demand for jobs is rising. The shares of service and manager/professional occupations show increases in both the US and Europe over time. However, both are more pronounced in the urban and/or big city areas reported upon in the Table.

The overall picture that follows from the Table is that places where polarization and inequality have risen by more in both Europe and the US are those characterised by more workers with higher education levels and who are more likely to be managers or professionals. At the same time, there are more people doing low wage service sector jobs in these urban areas. One way of looking at the extent to which the two are related is to ask whether there has been any evidence of a skill-bias in changing consumption patterns over time, and this is what we turn to in the next section of the paper.

[8] The ELFS does not contain wage data that we could study over time.

4. Skill-Biased Consumption

In this section we investigate whether it is possible to uncover evidence of a skill-bias in consumption that is in line with the increased polarization of work that has occurred over time. We consider data from the US Consumer Expenditure Survey (CEX) in 1980 and 2010 to study changes in the demand for service expenditures over time, and whether there is any evidence of a skill-bias in the observed temporal changes.[9]

The idea is to use consumption data to study the hypothesis that labour market polarization has resulted from high paid individuals getting even more high paid in relative terms over time (from higher wages and/or longer hours of work) and that being richer and working longer has resulted in shifts in consumption behaviour that could be a factor in generating the polarization of work patterns we have seen earlier. According to this hypothesis, it is the increased demand for low wage services that causes the rise in employment shares in the lower part of the skill distribution (see Autor and Dorn, 2013, Leonardi, 2013, and Mazzolari and Ragusa, 2013). We therefore look at changing consumption shares of low wage products and services.

Changes in Service Expenditures

The service categories we analyse from the CEX are those expenditures we classify as being supplied by low wage workers within the food away from home, personal care products and services and household operations: personal services categories of the CEX. The precise definitions of the detailed categories we select (along with Universal Classification Codes, or UCC) are given in Table A1 of the Data Appendix.

Table 2 describes the service consumption categories we consider and shows summary statistics on them in 1980 and 2010. The Table shows that, in 1980, mean annual

[9] For related work, but with a different focus, looking at variations in consumer demand for different sorts of workers or households see Diamond (2012) or Hanbury (2012).

service expenditure (in 2010 prices) was $2890. This rose by 25 percent to $3624 by 2010. This increase was quite a lot bigger than (almost double) the 13 percent rise in real total consumption, which is also shown in the Table. As a consequence, the share of these service expenditures in total expenditure rose from 5.4 to 6.0 percent between 1980 and 2010. The bigger than average rise occurs for both the eating out consumption group (which comprises around 2/3 of the service expenditure in both years) and for the personal care and household operations services. Expenditure on these groups goes up more rapidly than does average household expenditure, going up by 23 percent for food away from home, and by 31 percent for personal care and household operations.

Our principal interest is in whether it is possible to uncover evidence of a skill-bias connected to this rise in service expenditure. We thus define skill in terms of education or occupation and consider changes over time between college and non-college households and households with managers/professionals as compared to other occupations.[10] Table 3 shows changes in services and total expenditures, together with associated shares, between 1980 and 2010 for these groups.

The upper panel of the Table shows the breakdown by college status. In 1980, overall the college group spent 1.36 times as much as the non-college group and they spent 1.50 times as much on service expenditures. By 2010, these ratios respectively rose to 1.58 and to 2.02. Thus the increase in the share of expenditures on services went up considerably faster for the college group, going up from 0.059 to 0.065, as compared to a very small rise from 0.050 to 0.052 for the non-college households.

As a first piece of descriptive evidence, this seems in line with the notion of a skill-bias in service expenditures over time by education. What about by occupation? The

[10] A college or manager/professional household is defined as one with the reference group adult or (in the case of couples) their spouse (or both) being a college graduate or in a managerial or professional job.

bottom panel of the Table also reveals patterns in line with a skill-bias, as the rise in expenditure on the service categories we consider is faster for managers and professionals than for households in other occupations. The education and occupation splits are quite similar. Therefore for of the rest of our analysis so as to keep the presentation manageable we mostly consider only the education based results. These are probably more appropriate and better for examining the skill-bias hypothesis, though we do report some occupation results for the key results we highlight below.

Estimates of Engel Curves

We next report whether this descriptive finding of a skill-biased shift over time in expenditures of services supplied by low wage workers holds up when we estimate Engel curves that are potentially different for more and less skilled households. To do so, we estimate Engel curves using conventional approaches derived from the consumer demand literature (see Deaton, 1986, Deaton and Muellbauer, 1980, or Lewbel, 2008).

We begin with an Engel curve that relates expenditure on a particular good or service i, C^i, to total consumption, C (= $\sum_{i=1}^{N} C^i$ for i = 1,2……N groups of expenditures), holding prices fixed, so that $C^i = g(C, Z)$ where Z is a set of other characteristics of the consumer (like age and household composition). This model can be empirically operationalised in various ways, but one straightforward and convenient approach is to specify a budget share equation which relates the share of C^i to total consumption expenditure (in logs) and the Z's. For household j in year t, this can be expressed as:

$$S^i_{jt} = \alpha^i + \beta^i \log(C_{jt}) + \delta^i Z_{jt} + \theta^i T_t + u^i_{jt} \qquad (1)$$

where $S^i = C^i/C$, T is a time period effect and u is an error term. Because the dependent variable is a share, then in the full demand system with N expenditure categories we have adding up conditions for the parameter estimates across the N consumption groups so that $\sum_{i=1}^{N}\alpha^i=0$, $\sum_{i=1}^{N}\beta^i=0$ and $\sum_{i=1}^{N}\theta^i=0$.

In equation (1) the estimate of β reveals how the share of spending on a particular consumption category i varies as total expenditure increases. The elasticity of expenditure on i with respect to total expenditure is $\eta^i = \partial \log C^i/\partial \log C = 1 + (\beta^i/S^i)$ which denotes that i is a luxury for values of η^i greater than unity and a necessity for those less than unity (and above zero).

Our main interest from the Engel curves is in the estimated parameter θ^i on the time effect T and in our analysis we have estimated (1) separately for high/low skill households in 1980 and 2010. In this setting, the specific test of skill-bias we adopt considers whether service expenditures change over time differentially by skill. For high skill households H and low skill households L in years 1980 and 2010, this corresponds to a high skill/low skill difference in the estimated time effect, conditional upon the variables entered into the Engel curve. This can be defined as $\Phi = (\theta^{i,\ H,\ 2010} - \theta^{i,\ L,\ 2010})$, where the 1980 parameters $\theta^{i,\ H,1980}$ and $\theta^{i,\ L,1980}$ are normalized to zero in the usual way through the inclusion of a 2010 dummy variable in the high and low skill estimating equations.

Whilst we consider estimates from the full demand system below, our main interest is in the low wage service budget shares and so we start by looking only at results from the service expenditure share equation. Table 4 reports estimates of Engel curves by education for service expenditure shares for data pooled across 1980 and 2010. Two sets of estimates are presented, ordinary least squares estimates for graduate and non-graduate households in specifications (1) and (2), and instrumental variable estimates for the two samples in specifications (3) and (4). In the latter, because of possible concerns of measurement error in the total consumption data from the CEX interviews, we instrument

Log(Real Expenditure) using Log(Real Income) at household level.[11] The instrument predicts very well, as the F-tests in the notes to the Table testify.

It turns out that the two sets of estimates tell much the same story, both with respect to the nature of the estimated Engel curves and with respect to whether one uncovers differential changes over time by skill.[12] On the first of these, all four specifications in the Table show positive estimated coefficients on the Log(Real Expenditure) variable. Thus service expenditures seem to be a luxury in relative terms as shown by the elasticities above unity in the Table. The estimated elasticities are very similar for graduate and non-graduate households.

In terms of our main interest, the estimated coefficients on the 2010 year dummy variable are significant and positive for the graduate households, and suggest an increase in the service expenditure share of 0.008 to 0.009 depending on specification. Relative to the 1980 mean of 0.054 reported in Table 2 above, this corresponds to a 15 to 17 percent increase in the budget share of low wage services in graduate households that occurred between 1980 and 2010, holding constant household expenditure and composition.

In the non-graduate households, the estimated coefficient on the 2010 year dummy variable is small in magnitude (at 0.001 for specifications (1) and (3)) and insignificantly different from zero. Considering the skill-bias dimension, graduate/non-graduate differences in the estimated time coefficient are also reported. These are statistically significant at 0.008 for both least squares and instrumental variable specifications. According to these estimates, it thus seems that there has been a skill-bias in service

[11] See Bee, Meyer and Sullivan (2013) or Crossley and Winter (2013) for in-depth discussion of measurement concerns and of the relative merits of both the interview and diary samples of the CEX.

[12] The reported results to date are for working households because we anted to use education and occupation based measures of skill in a comparable manner. For the graduate split, we can study non-employed households as well. However, as the results in Table A2 of the Appendix makes clear, this has little impact on the nature of the findings.

consumption that, when put together with the trends in education sorting and rising inequality in urban areas, has potential to explain the bigger rise in the demand for service jobs in those places.

Variations by Population Size

Earlier we showed that labour market polarization increased by more in urban settings and in big cities, and also that they were characterised by more education sorting, rising wage differentials by education and by increased shares of manager and service jobs. It therefore seems natural to explore whether the skill-bias in service expenditure we have uncovered is more marked in bigger cities.

The CEX contains a population size variable and so Table 4 reports on what happens to the graduate/non-graduate time effect differences when we estimate the models of Table 4 separately for bigger cities (population > 1.2 million) and smaller ones (population ≤ 1.2 million). The Table also shows results broken down by occupation.

The estimates in the Table show the evidence of skill-bias from our formulation is concentrated in the bigger cities. In fact the estimates are only statistically significant for households residing in cities with populations of over 1.2 million. These correspond to about 60 percent of households in the overall sample we study. The finding holds for both education and occupation breakdowns of households by skill. Thus the skill-bias associated with changing service expenditures is a feature of urban settings with higher populations. This, of course, is precisely where our earlier analysis showed that patterns of labour market polarization changes have been more marked.

Estimates From the Full Demand System

The adding up properties of the demand system specified in terms of budget shares, given in equation (1) above, means that a skill-biased increase in service consumption has to be matched by a relative fall in other consumption categories. In the full system it is possible that various shares could rise and fall over time.

Table 6 shows system estimates for ten consumption categories, where to ensure adding up, the service consumption categories that are our main focus have been netted out of the aggregate group in which they would normally appear (e.g. the food away from home services we consider are subtracted from total food). [13] The estimates show that, along with the increased relative consumption of low wage services by graduate households as compared to non-graduate households, graduates have also increased their relative consumption of food and of personal insurance. To balance the system, they have reduced their relative spending (or alternatively non-graduate households have increased their relative spending) on apparel, transport and entertainment.

These patterns are broadly similar across the population size cutoff (with some minor variations). Probably the most notable difference in this regard is our main finding, namely that evidence of skill-bias in low wage service expenditures is only present in the bigger cities. The other main difference is a relative reduction in transport expenditure for graduate vis-à-vis non-graduate households that is only present in the bigger cities as well – interestingly, that points to more spending on transport among the lower skill households, something that is probably not unrelated to the labour markets of larger cities. The other significant positive/negative graduate/non-graduate differences (food, personal insurance, apparel, entertainment) do not display much variation by population size.

[13] These are estimates of Equation (1) using seemingly unrelated regression which allows errors to be correlated for the same households across different budget share equations. The results for Managers and Professionals verses Other Occupations are broadly supportive of those presented in Table 6 and are available from the authors on request.

5. Concluding Comments

In this paper, we study changing patterns of labour market inequality, placing a particular focus on the increased polarization of the labour market that has characterised the labour markets of a number of countries in the recent past. We study spatial variations in this and ask whether the observed polarization patterns are consistent with skill-biased changes in consumption behaviour.

From an analysis of US and European microdata, we find that polarization has occurred to varying degrees in different places, in particular with more polarization occurring in more urban areas. We also uncover a skill-bias in service consumption expenditures that is consistent with these changes so that the demand for low wage service jobs has risen by more, leading to the polarization of jobs, in places (bigger cities) where consumers getting richer from the rise in inequality have increasingly demanded low wage services over time.

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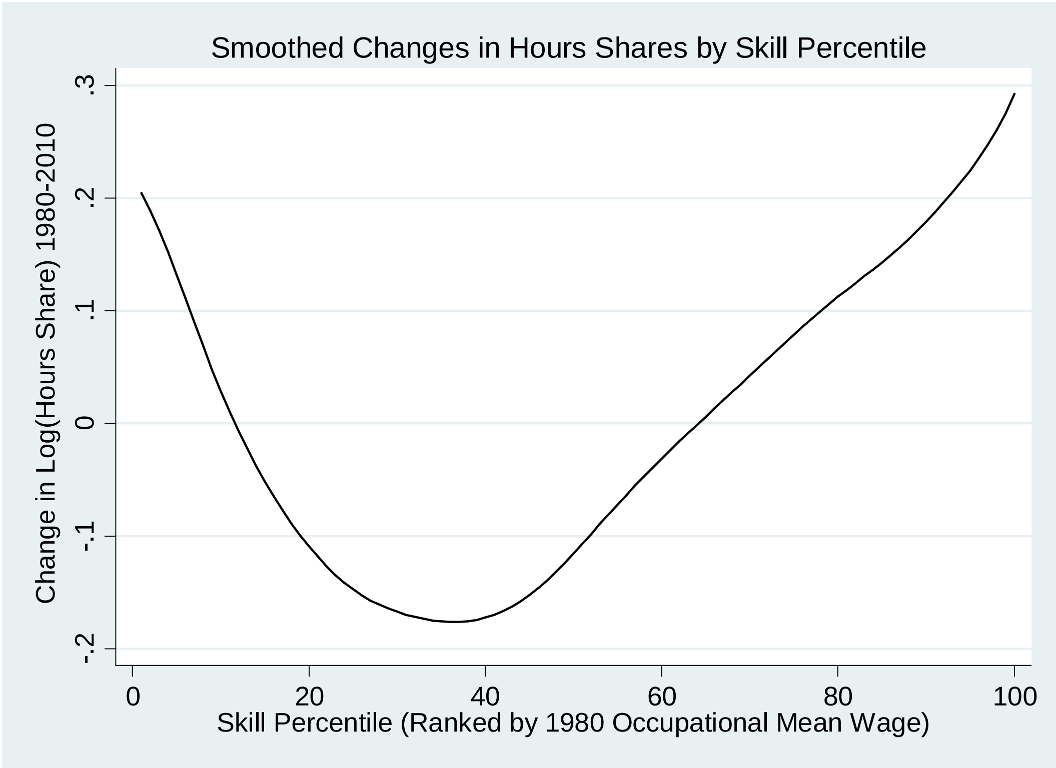
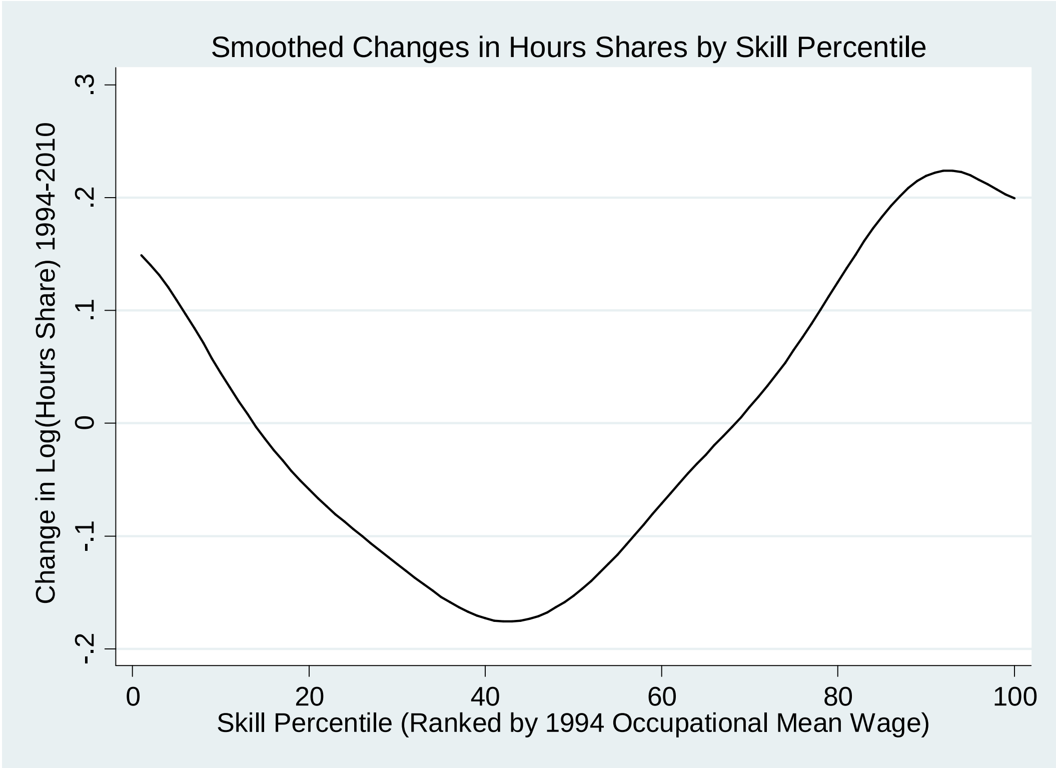
Figure 1:
Labour Market Polarization, United States, 1980-2010



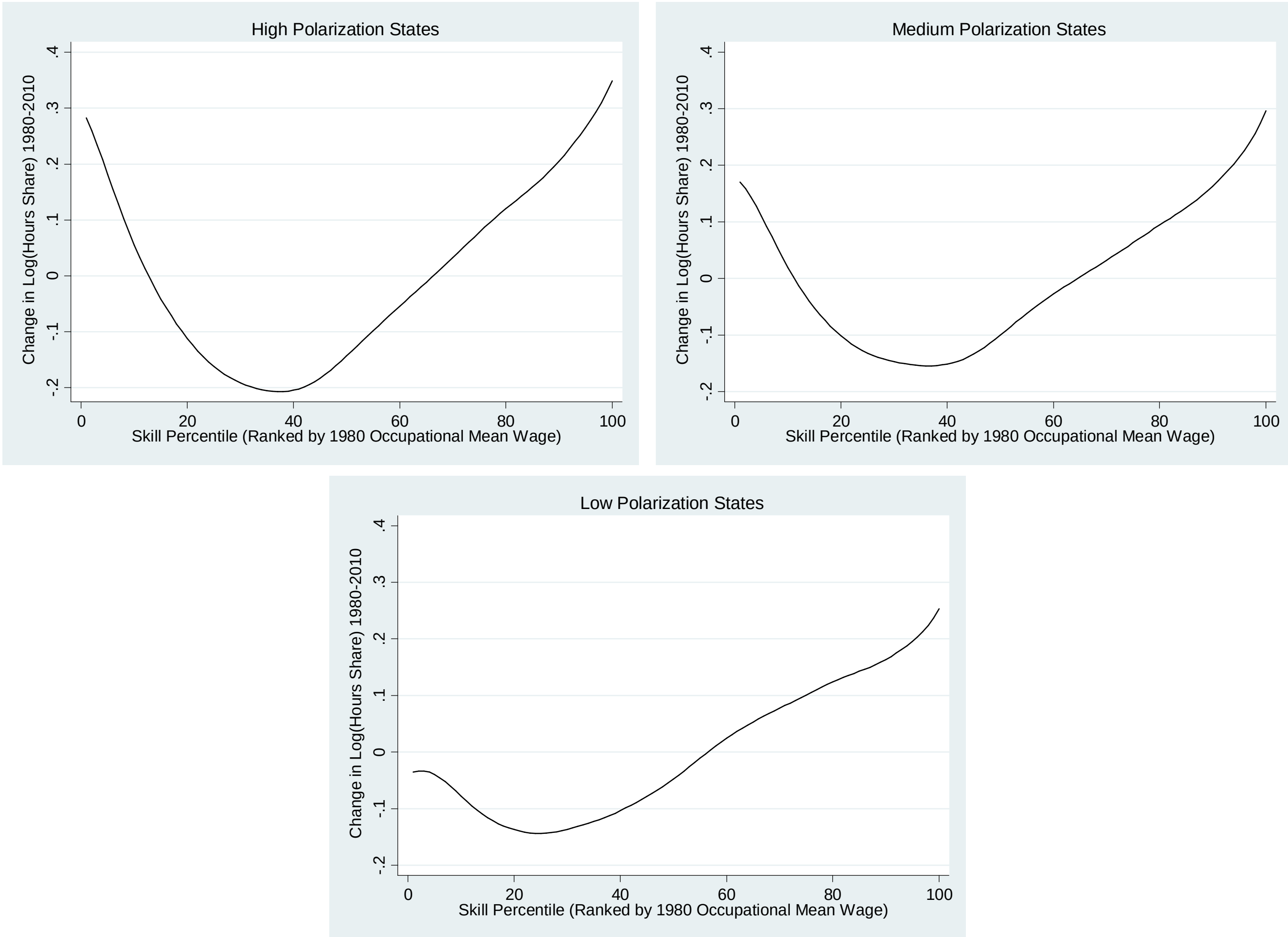
Notes: Based on 320 consistently defined non-farm occupations from the 1980 Census and the pooled 2009 to 2011 American Community Surveys. Skill percentiles are based on the hours weighted 1980 mean occupational log(hourly wage).

Figure 2:
Labour Market Polarization, Fifteen European Countries, 1994-2010



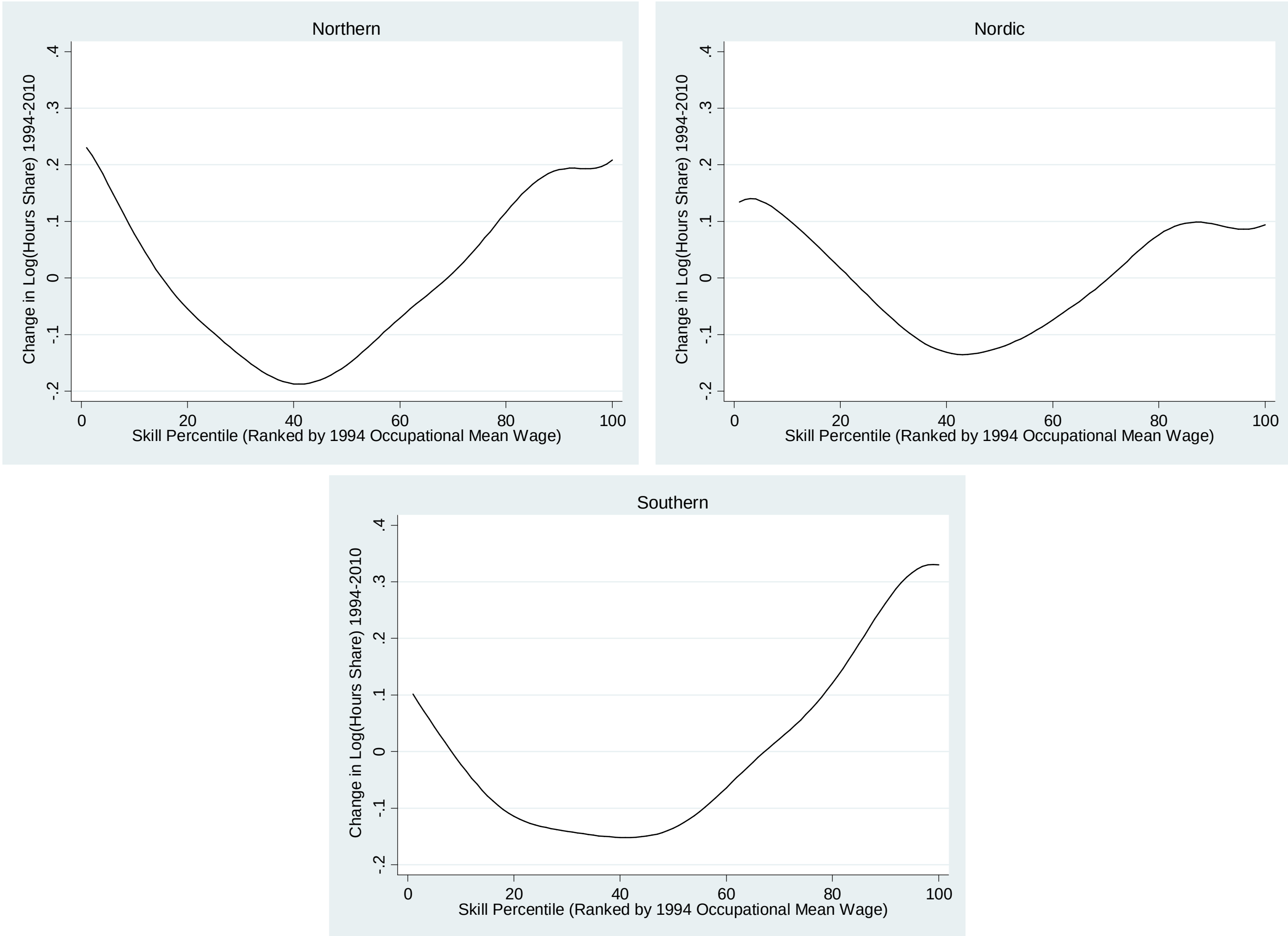
Notes: Based on 21 consistently defined non-farm occupations from the European Labour Force Survey in 1994 and 2010 for countries with data in those years. Skill percentiles are based on the hours weighted 1994 mean occupational log(hourly wage), where the wage rank is taken from Goos, Manning and Salomons (2009) (derived from the European Community Household Panel Survey). The fifteen countries are: Austria, Belgium, Denmark, Finland, France, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

Figure 3: Labour Market Polarization, Variations Across Groups of US States, 1980-2010



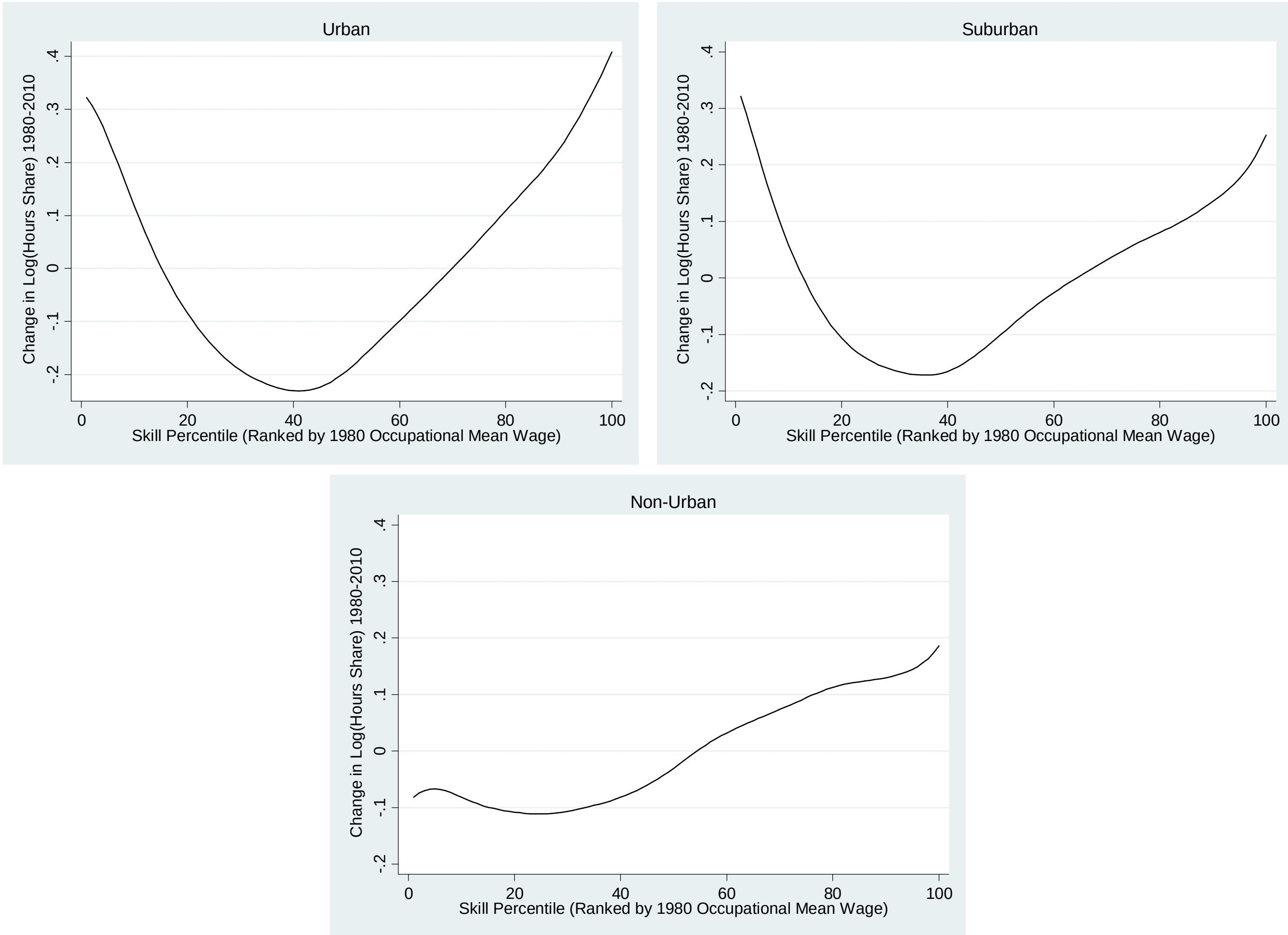
Notes: The states are grouped as follows – 18 high polarization, Arkansas, California, Colorado, Connecticut, Delaware, Illinois, Indiana, Maryland, Massachusetts, Michigan, New Hampshire, New Jersey, New York, North Carolina, Oregon, Rhode Island, South Carolina, Virginia; 24 medium polarization, Arizona, Florida, Georgia, Idaho, Iowa, Kansas, Kentucky, Louisiana, Maine, Minnesota Missouri, Montana, Nebraska, New Mexico, Ohio, Oklahoma, Pennsylvania, Tennessee, Texas, Utah, Vermont, Washington, West Virginia, Wisconsin; 6 low polarization, Alabama, Mississippi, Nevada, North Dakota, South Dakota, Wyoming.

Figure 4: Labour Market Polarization, Variations Across Groups of European Countries, 1994-2010



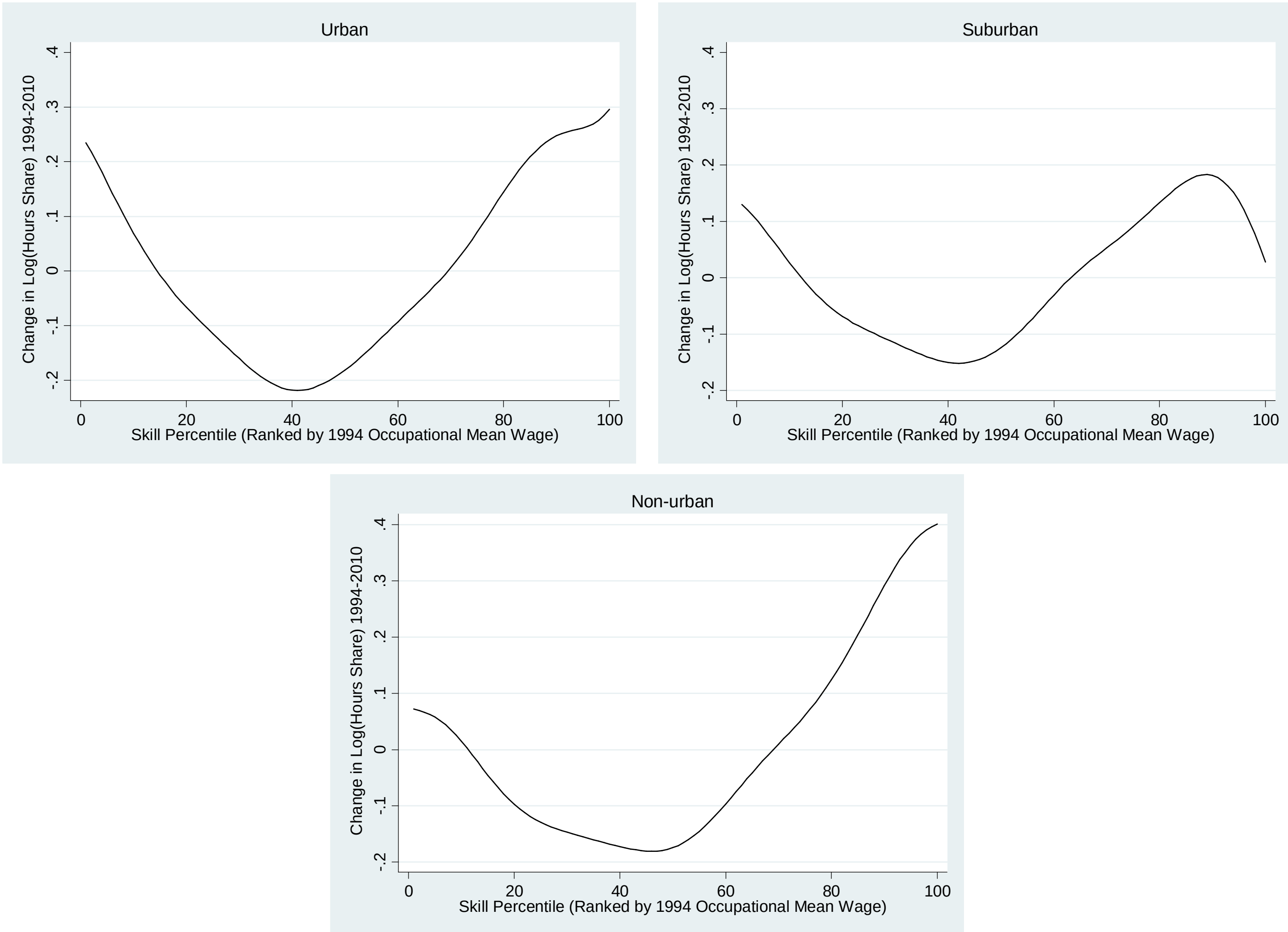
Notes: The countries are grouped as follows – 8 Northern (Austria, Belgium, France, Ireland, Luxembourg, the Netherlands, Switzerland, United Kingdom); 3 Nordic (Denmark, Finland, Sweden); 4 Southern (Greece, Italy, Portugal, Spain).

Figure 5: Labour Market Polarization and Urbanization, United States



Notes: Urban is defined as living a metropolitan area, central city; Suburban is defined as living a metropolitan area, central city; Non-urban is defined as not living in a metropolitan area.

Figure 6: Labour Market Polarization and Urbanization, Europe



Notes: Urban is defined as living in a densely populated urban area (population > 50,000; population density > 500 inhabitants per square km); Suburban is defined as living in an intermediate area (population > 50,000, population density > 100 inhabitants per square km) or adjacent to a densely populated area; Non-urban is thinly populated areas belonging to neither the Urban or Suburban definitions.

Figure 7:
Labour Market Polarization and Urbanization, Big Cities, United States and Europe

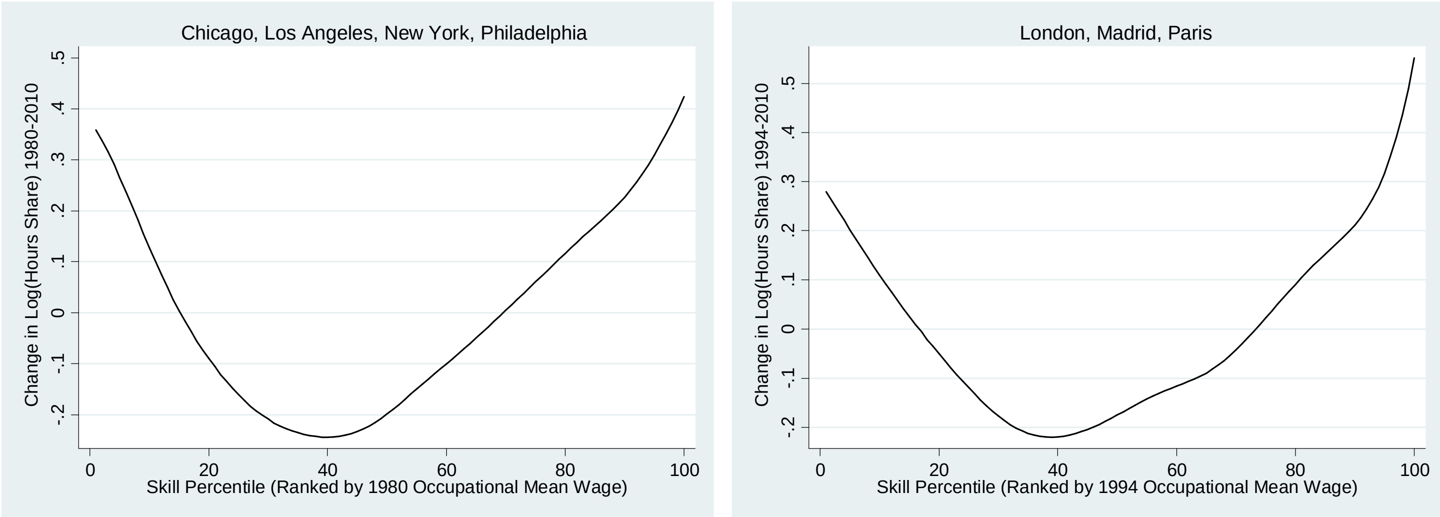


Table 1:
Factors Associated With Labour Market Polarization, Differences by Urbanization

	United States, 1980-2010				Europe, 1994-2010			
	Non-Urban	Suburban	Urban	Big Cities	Non-Urban	Suburban	Urban	Big Cities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Changes in Labour Market Inequality								
Change in College Hours Share	0.088	0.163	0.166	0.185	0.105	0.120	0.152	0.175
Change in Composition Adjusted College/High School Log(Wage) Differential	0.171	0.271	0.340	0.348	-[a]	-[a]	-[a]	-[a]
B. Changes in Occupation Hours Shares								
Change in Service Share	0.022	0.029	0.040	0.062	0.030	0.030	0.041	0.024
Change in Service Share (Excluding Child and Personal Care Workers)	0.023	0.027	0.023	0.060	0.002	0.019	0.026	0.014
Change in Manager and Professional Share	0.097	0.124	0.123	0.123	0.082	0.085	0.081	0.123

Notes: Changes based on 1980 Census and 2009-2011 ACS data are from 1980 to 2010 for the US. Changes based on the 1994 and 2010 ELFS for Europe. [a] denotes that we absence of suitable data we cannot calculate the Log(Wage) Differential for Europe.

Table 2:
Service Expenditure Categories

	1980	2010	Percent Change
Food away from home – Dining out and alcoholic beverages in restaurants	1912	2346	23
Personal care products and services and Household operations: Personal services – Personal care for men and women, child care, housekeeping, gardening, babysitting, other care, miscellaneous household services	977	1277	31
Total services expenditure	2890	3624	25
Total expenditure	53163	60266	13
Share of services in total expenditure	0.054	0.060	
Number of households	1417	2079	

Notes: Sample of urban working households aged 18-65 (aged 18-65 for both in couples) with education and occupation data from the 1980 and 2010 Consumer Expenditure Surveys. Annual consumption expenditures reported in 2010 dollars. Weighted using CEX weights. Precise definitions and more detail on the categories are given in Table A1 of the Appendix.

Table 3:
Changes in Service Expenditures by Skill, 1980-2010

	1980			2010		
	College Graduates		Non-Graduates	College Graduates		Non-Graduates
Total Expenditure	66675		49140	74981		47449
Graduate Ratio		1.36			1.58	
Service Expenditure	3880		2594	4961		2459
Graduate Ratio		1.50			2.02	
Share Service/Total	0.059		0.050	0.065		0.052
	Managers and Professionals		All Other Occupations	Managers and Professionals		All Other Occupations
Total Expenditure	64407		46685	72073		45765
Occupation Ratio		1.38			1.57	
Service Expenditure	3643		2455	4533		2507
Occupation Ratio		1.48			1.81	
Share Service/Total	0.056		0.050	0.061		0.053

Notes: Sample of urban working households aged 18-65 (aged 18-65 for both in couples) with education and occupation data from the 1980 and 2010 Consumer Expenditure Surveys. Annual consumption expenditures reported in 2010 dollars. Weighted using CEX weights. Sample sizes (number of households) are: 1980 College Graduates – 337; 1980 Non-Graduates – 1080; 2010 College Graduates – 971; 2010 Non-Graduates – 1108; 1980 Managers and Professionals – 533; All Other Occupations – 884; 2010 Managers and Professionals – 1134; 2010 All Other Occupations – 945.

Table 4:
Estimates of Engel Curves by Skill For Service Expenditures

	Engel Curve Estimates By Education					
	Ordinary Least Squares			Instrumental Variables		
	Graduates	Non-Graduates	Graduate/Non-Graduate Difference	Graduates	Non-Graduates	Graduate/Non-Graduate Difference
	(1)	(2)	(2) – (1)	(3)	(4)	(4) – (3)
Year = 2010	0.008* (0.003)	0.001 (0.002)	0.008* (0.003)	0.009* (0.003)	0.001 (0.002)	0.008* (0.003)
Log(Real Expenditure)	0.011* (0.003)	0.014* (0.002)	-0.003 (0.003)	0.008* (0.006)	0.016* (0.004)	0.002 (0.007)
Age and Household Composition Controls	Yes	Yes		Yes	Yes	
Elasticity, η	1.147* (0.037)	1.182* (0.025)	-0.034 (0.043)	1.242* (0.077)	1.208* (0.053)	0.035 (0.090)
Sample Size	1308	2188		1308	2188	

Notes: Sample of working households. Age and household composition controls are age, whether a couple and family size. Weighted using CEX weights. Standard errors in parentheses. * (**) denotes statistically significant at the 5 (10) percent level. In (3) and (4) Log(Real Income) is used as the instrumental variable for Log(Real Expenditure). F-Tests from the first stages are respectively: F(1,1301) = 395.11, P-value = 0.000 for (3); and F(1,2181) = 632.10, P-value = 0.000 for (4).

Table 5:
Variations by City Population

	Estimates of Differences in Year = 2010 Coefficients				
	Graduate/Non-Graduate Difference		Managers and Professionals/All Other Occupations Difference		Sample Size
	OLS	IV	OLS	IV	
All	0.008* (0.003)	0.008* (0.003)	0.002 (0.003)	0.001 (0.003)	3489
Population Size > 1.2 million	0.013* (0.004)	0.015* (0.005)	0.009* (0.004)	0.009* (0.004)	2081
Population Size ≤ 1.2 million	-0.002 (0.005)	-0.004 (0.005)	-0.007 (0.004)	-0.009* (0.004)	1408

Notes: As for Table 4. The All sample size is slightly smaller than the 3496 of Table 3 owing to missing values on the population size variable. * (**) denotes statistically significant at the 5 (10) percent level.

Table 6: Estimates From the Full Demand System

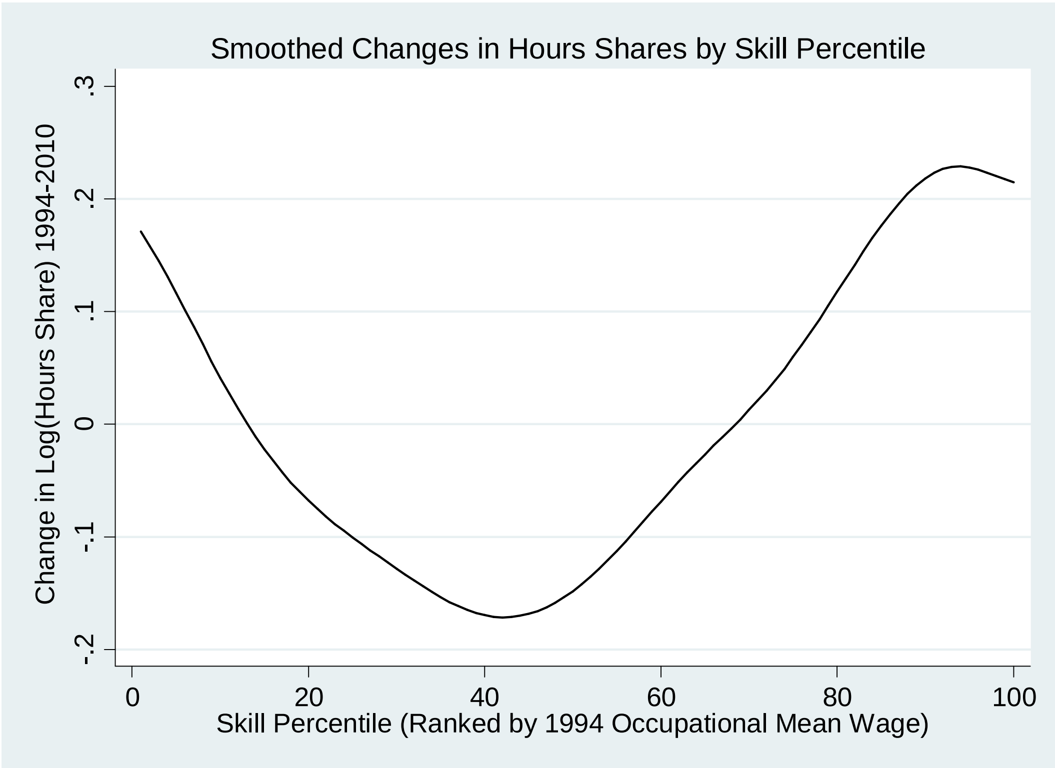
Engel Curve Estimates By Education,
Estimates of Differences by Skill in Year = 2010 Coefficients

	Ordinary Least Squares			Instrumental Variables		
	All	Population Size > 1.2 million	Population Size ≤ 1.2 million	All	Population Size > 1.2 million	Population Size ≤ 1.2 million
Services	0.008* (0.003)	0.013* (0.004)	-0.002 (0.005)	0.008* (0.003)	0.013* (0.004)	-0.002 (0.005)
Food (excluding Services)	0.020* (0.004)	0.022* (0.005)	0.020* (0.006)	0.020* (0.004)	0.023* (0.005)	0.020* (0.007)
Housing (excluding Services)	-0.013 (0.008)	-0.010 (0.011)	-0.018 (0.012)	-0.013 (0.008)	-0.010 (0.011)	-0.018 (0.012)
Apparel	-0.004** (0.002)	-0.002 (0.003)	-0.006** (0.003)	-0.004** (0.002)	-0.002 (0.003)	-0.006** (0.003)
Transport	-0.021* (0.008)	-0.045* (0.011)	0.004 (0.014)	-0.021* (0.008)	-0.044* (0.010)	0.004 (0.014)
Entertainment	-0.008* (0.003)	-0.007** (0.004)	-0.011* (0.005)	-0.008* (0.003)	-0.007** (0.004)	-0.011* (0.005)
Education and Health	-0.003 (0.004)	-0.002 (0.006)	-0.006 (0.007)	-0.003 (0.005)	-0.002 (0.006)	-0.006 (0.007)
Alcohol and Tobacco (excluding Services)	0.001 (0.002)	0.005* (0.002)	-0.003 (0.003)	0.001 (0.002)	0.005* (0.002)	-0.003 (0.003)
Personal Insurance	0.019* (0.003)	0.025* (0.007)	0.017* (0.008)	0.019* (0.005)	0.022* (0.007)	0.016* (0.008)
Miscellaneous Expenditures (excluding Services)	0.001 (0.003)	-0.002 (0.004)	0.006 (0.006)	0.001 (0.003)	-0.002 (0.004)	0.006 (0.005)
Age and Household Composition Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample Size	3489	2081	1408	3489	2081	1408

Notes: Same specification and samples as used in Table 4. Full demand system estimated by seemingly unrelated regression. Weighted using CEX weights. Standard errors in parentheses. * (**) denotes statistically significant at the 5 (10) percent level.

Appendix

Figure A1:
Labour Market Polarization, Eleven European Countries, 1994-2010



Notes: Based on 21 consistently defined non-farm occupations from the European Labour Force Survey in 1994 and 2010 for countries with data in those years. Skill percentiles are based on the hours weighted 1994 mean occupational log(hourly wage), where the wage rank is taken from Goos, Manning and Salomons (2009) (derived from the European Community Household Panel Survey). The eleven countries are those with usable consistently defined ELFS data from a start year of 1994 and are: Belgium, Denmark, France, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain and the United Kingdom.

Table A1: Service Expenditures in Food Away From Home, Personal Care Products and Services and Household Operations: Personal Services

1980			2010		
UCC	Codebook Description	Share of Service Consumption	UCC	Codebook Description	Share of Service Consumption
Food Away From Home					
790410	Dining out at restaurants etc. (excluding alcoholic beverages)	0.575	790410	Dining out at restaurants, cafeterias, drive-ins, etc. (excluding alcoholic beverages)	0.616
790420	Alcoholic beverages at restaurants etc	0.087	790420	Alcoholic beverages at restaurants, cafeterias, drive-ins, etc	0.032
Personal Care Products and Services And Household Operations: Personal Services					
650110	Personal care services for females, including haircuts	0.097	650310	Personal care services for males and females, including haircuts	0.098
650210	Personal care services for males, including haircuts	0.065			
670310	Day care expenses including tuition	0.056	670310	Other expenses for day care centers and nursery schools, including tuition	0.132
340210	Babysitting or other home care for children	0.062	340211	Babysitting or other child care in your own home	0.034
			340212	Babysitting or other child care in someone else's home	0.012
340310	Housekeeping service	0.027	340310	Housekeeping service, incl. management fees for maid service in condos	0.036
340410	Gardening and lawn care services.	0.022	340410	Gardening and lawn care services, incl. management fees for lawn care in coops and condos	0.029
340420	Water softening service	0.001	340420	Water softening service	0.001
340520	Non-clothing household laundry or dry cleaning – not coin-operated	0.002	340520	Non-clothing household laundry or dry cleaning – not coin-operated	0.001
340903	Miscellaneous home	0.002	340903	Miscellaneous home services and small repair jobs not already specified	0.005
340906	Care for invalids, convalescents, handicapped or elderly persons in the CU	0.003	340906	Care for invalids, convalescents, handicapped or elderly persons in the CU	0.005

Notes: UCC denotes Universal Classification Codes. Based on 1417 households in 1980 and 2079 households in 2010. Shares weighted using CEX weights.

Table A2: Estimates of Engel Curves For Service Expenditures for All Households

	Engel Curve Estimates By Education					
	Ordinary Least Squares			Instrumental Variables		
	Graduates	Non-Graduates	Graduate/Non-Graduate Difference	Graduates	Non-Graduates	Graduate/Non-Graduate Difference
	(1)	(2)	(2) – (1)	(3)	(4)	(4) – (3)
Year = 2010	0.006*	0.000	0.006*	0.007*	0.001*	0.006*
	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)
Log(Real Expenditure)	0.011*	0.015*	-0.004	0.014*	0.017*	-0.004
	(0.003)	(0.001)	(0.003)	(0.006)	(0.003)	(0.006)
Age and Household Composition Controls	Yes	Yes		Yes	Yes	
Elasticity, η	1.139*	1.199*	-0.060	1.183*	1.237*	-0.054
	(0.034)	(0.021)	(0.038)	(0.077)	(0.041)	(0.081)
Sample Size	1413	2801		1413	2801	

Notes: Sample of all households. Age and household composition controls are age, whether a couple and family size. Weighted using CEX weights. Standard errors in parentheses. * (**) denotes statistically significant at the 5 (10) percent level.