# Travail et Emploi

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Ministère du Travail

Direction de l'animation de la recherche,
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N° **157** – 2019

## Polarization(s) in Labour Markets

# Éditorial

Le 19 juin 2018, la Direction de l'animation de la recherche, des études et des statistiques (DARES) du ministère du Travail et le Département de la recherche du Bureau international du travail (BIT) ont organisé une conférence internationale sur le thème « Polarisation(s) sur le marché du travail ». Le présent numéro de *Travail et Emploi* constitue un prolongement de cette journée puisqu'il rassemble des articles issus des contributions de plusieurs participant·es.

Si des numéros hors-série en anglais rassemblent, tous les deux ans, une sélection d'articles d'abord publiés en français dans la revue, il s'agit ici du premier numéro de *Travail et Emploi* composé d'articles publiés directement en anglais. Ce choix éditorial exceptionnel a été guidé notamment par la volonté de soumettre rapidement aux lecteurs et lectrices français·es les résultats de travaux économiques initialement rédigés en anglais, contribuant à un champ de recherche foisonnant autour de questions d'actualité, très débattues dans l'espace public, en France et bien au-delà, liées à la polarisation de l'emploi et du marché du travail.

L'année où *Travail et Emploi* fête ses 40 ans, l'équipe de la revue demeure très attachée à l'expression en français : c'est pourquoi ce numéro fera prochainement l'objet d'une publication en français.

Camille Peugny et Géraldine Rieucau (co-rédacteur/trice en chef)

# Introduction

# Polarization(s) in Labour Markets

*Bruno Ducoudré*[*], *Véronique Simonnet*[**]

Over the last two decades, researchers have paid a lot of attention to polarization in labour markets, that is to say the rise of high- and low-wage jobs relative to middle-wage jobs. The international conference on "Polarization(s) in Labour Markets", organised by the Directorate for Research, Studies and Statistics (DARES, French Ministry of Labour) and the International Labour Organization (ILO), took place in Paris on June 19, 2018. The conference attempted to provide answers to a new set of questions on this subject: are there structural causes, other than technological change and the emergence of information and communication technologies (ICT), for the development of polarization? What about the reallocation of jobs in Europe and the United States when labour market institutions (minimum wage, taxation, etc.) pursue different objectives? How have routine activities declined? Who are the employees most affected by this decline and what are the consequences for them? Finally, what roles do international trade and firms play in the development of polarization and its geography?

Following this conference, the Editorial Board of *Travail et Emploi* has proposed to some of the participants to write an original paper bringing together the results of several of their most recent works, already published or in the course of publication. This issue therefore highlights recent research in economics on the subject of job polarization. First, it places the polarization phenomenon in the set of changes that labour markets have undergone since the 1950s. It then discusses the firms' transformations and workers' professional transitions in connection with the development of new technologies and international trade. This issue aims to take stock of the remaining issues that call for future developments in research on polarization.

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## What is Polarization of the Labour Market?

At the beginning of the 2000s, researchers shed light on the phenomenon of polarization: the relative growth of wages and employment of high-wage occupations in the 1980s and 1990s and the relative growth of wages and employment of low-wage occupations compared to middle-wage occupations in the 1990s and the first decade of 2000 (Autor, Dorn, 2013; Autor *et al.*, 2006). This polarization is largely explained by the automation of routine tasks that disappear in favor of non-routine manual or cognitive tasks.

The study of the phenomenon originates from quantitative and case-study evidence that document a striking correlation between the adoption of computer-based technologies and the increased use of college-educated labour (this correlation is frequently interpreted as *skill biased technological change*). Autor *et al.* (2003) show that the rapid adoption of computer technologies, spurred by sharp real price decline, leads to changes in the tasks performed by workers and, ultimately, in the demand for human skills. Computer capital substitutes workers in performing cognitive and manual tasks that can be accomplished according to an explicit set of rules –called "routine tasks". Conversely, it complements workers in performing tasks that require flexibility, creativity, problem-solving skills, and complex communication activities– called "non-routine tasks." As the price of computer capital falls, these two mechanisms (substitution and complementarity) raise relative demand for workers who have a comparative advantage in non-routine tasks, typically the more educated workers.

But Autor *et al.* (2003) show that the changing composition of job tasks spurred by technological change affects almost all occupations and educational levels. It thus appears before the rise in the general level of education and accounts for 60% of the estimated relative demand growth favouring college labour between 1970 and 1998 in the United States. Their model predicts also that industries that are initially intensive in labour inputs will invest the most in computers and new technologies as their prices decline, thus triggering a considerable reduction in routine activities and an increase in non-routine activities. These industries would reduce labour demand for routine tasks, for which computer capital substitutes, and increase labour demand for non-routine tasks, which computer capital complements.

Goos and Manning (2007) further specify that routine tasks that require precision and can be performed by machines (such as some accounting tasks, for example), are not necessarily those requiring the lowest skill levels. Conversely, some non-routine manual tasks that essentially involve coordination (such as shelving, or tasks performed in service occupations involving assisting or caring for others) require very little qualification. As a result, automation leads to increased demand for well-paying skilled jobs that typically require non-routine cognitive skills and increased demand for low-skilled, low-wage jobs that typically require non-routine manual skills.[1] In contrast, there is less demand for "intermediate" jobs that require routine manual and cognitive skills. This process leads to job polarization and by extension to wages polarization. If the most skilled workers generally perform non-routine cognitive tasks and the least skilled workers perform manual non-routine tasks, employment polarization corresponds to an increase in jobs at both the top and the bottom of the wage distribution. The reduction of routine tasks, whether cognitive or manual, leads to a reduction in the share of jobs located in the middle of the distribution. One can thus observe polarization by looking at the evolution of employment per salary centile. By ranking and having a close look at the lowest paid occupations, the middle and the highest paid occupations, Goos *et al.* (2009, 2014) confirm the polarization of employment in all European countries over the period 1993-2010.

Finally, Autor and Dorn (2013) suggest that the fall in the price of new technologies that drives down the wage paid to routine tasks leads some low-skilled workers to switch to service occupations that are difficult to automate because "they rely heavily on dexterity, flexible interpersonal communication, and direct physical proximity" (p. 1590).[2] As in these sectors there is currently no substitutability between goods and services, the substitution of routine human tasks by machines in the production of goods can allow a growth of wages and employment in low-skilled service occupations.[3]

## Sources and Consequences of Polarization

The polarization of labour markets has raised a series of questions relating both to its origins, to the mechanisms at work and their consequences on occupational patterns and the wage distribution, to individual workers' occupational mobility patterns and wage trajectories and to the differentiated effects among social groups. In the first article of this issue of *Travail et Emploi*, **Alan Manning** addresses these questions, stating that polarization is a structural phenomenon prior to the diffusion of ICT. **Zsófia Bárány** and **Christian Siegel** demonstrate this point, explaining that the manufacturing share of employment began to decline as early as the 1960s, while services employment increased, and that wage differentials between services and manufacturing with equal skills increased. Since routine jobs are largely concentrated

1. Non-routine manual tasks need "eye-hand-foot" coordination. Non-routine cognitive tasks include "control, planning and direction" tasks, which correspond to managerial and interactive tasks, and/or the need for mathematical and formal reasoning. Routine tasks are identified by the possibility to set "limits, tolerances and standards" and by "finger dexterity" practice (Goos, Manning, 2007).

2. Such as services related to transportation, accommodation and food, personal care, building and grounds cleaning, housekeeping, delivery and security services.

3. This requires a strong elasticity of substitution between routine tasks and new technologies, on the one hand, and a low elasticity of substitution between goods and services, on the other hand. The decline in the price of new technologies then benefits the development of non-routine-manual-skills intensive services.

in manufacturing and located in the middle of the wage distribution, these reallocations have led to job polarization in the United States. This structural change has led to a reallocation of jobs between sectors and within sectors.

While the share of jobs requiring cognitive skills has grown across all sectors and the share of routine jobs has declined, half of the increase in manual employment has been due to the reallocation of employment between sectors –these employment reallocations evolving in accordance with the rate of diffusion of new technologies within the sectors and occupations. **Zsófia Bárány** and **Christian Siegel** show that the diffusion of new technologies within some occupations, and within some occupations in some sectors, is much faster than in any sector in general.

**Alan Manning** also points out the links between polarization and inequality, and the fact that structural changes in labour markets generate "winners" and "losers". Polarization does not manifest itself so much as a massive rise in wage inequalities between occupations –the supply of work by occupation is very elastic to relative wages between jobs– but rather as differentiated impacts among individuals and social groups. **Guido Matias Cortes** shows that in the United States, polarization has resulted in a decline in manufacturing skilled workers' jobs and middle-level administrative jobs. Thus, routine manual occupations have declined with the decrease in the proportion of men aged 20 to 50 without a diploma or with little education in the population, but even more so because of the decrease in men's probability of working in routine manual occupations. Two thirds of the decline in routine cognitive activities come from the decline in the probability of women aged 20 to 50 with high school diplomas or some post-secondary education of working in routine cognitive activities. Both these declines in the probability of working in routine activities have resulted in a slight increase in non-routine manual employment but above all in a strong growth in non-employment, which could partly explain the decline in men's employment rate observed in the United States during this period. Women have experienced fewer transitions to non-employment than men but have not switched to non-routine cognitive occupations either. **Guido Matias Cortes** also shows that the wage growth of men remaining in routine occupations is much lower than that of men who have switched from routine to non-routine occupations, even though those non-routine occupations are low-skilled manual jobs.

Polarization is a global phenomenon since it affects all countries, regardless of their income level, and since it grows in parallel with globalization, the two phenomena appearing to feed on one another. **Fredrik Heyman** and **Fredrik Sjöholm** highlight the links observed in Sweden between labour market polarization and the degree of firms' exposure to international competition. On the one hand, they show that multinational firms and exporting firms employ more highly-skilled workers than do local firms; on the other hand, global engagement impacts firm organization and the occupational structure of firms. Firms with a high initial level of routine jobs increase their share of high- and low-skilled jobs at the expense of routine, middle-skilled jobs. Technological change leading to a decline of routine jobs and to job polarization can improve firms' competitiveness and support the development of their international activities. Increased export shares skew the labour mix toward high-skilled occupations. Offshoring would help to increase both high-skilled and low-skilled occupations.

Finally, what is the overall impact of polarization on economies? Does it mean a rise or a fall in wages in the long term? **Alan Manning** provides answers by showing how technology can benefit workers on average over the long term, through a rise in average wages. This occurs when the capital stock varies in the long term, while the quantity of labour input available is limited, and the relative price of investment decreases in the long term. Under these conditions, productivity gains must benefit the compensation of employees as a whole, which would generate additional demand for goods and services that create jobs. This does not mean that there are only winners, since significant redistributive effects can occur simultaneously. With these results, Alan Manning invites us to think about the policies to implement so that gains from the diffusion of new technologies benefit the largest number as well as the instruments that can be mobilised: minimum wages, training policies, redistributive taxation.

This issue of *Travail et Emploi* does not claim to be exhaustive,[4] since it does not deal with the role of labour market institutions in the development of polarization. A minimum wage can thus influence the evolution of the occupational pattern, and offset wage inequalities if its level is high enough. Training systems for people working in occupations affected by automation are also ways to support their career transitions. The links (or lack of links) between labour markets polarization in high-income countries and offshoring in low-income countries have to be clarified, especially because polarization in labour markets in low-income countries is not clearly established. According to Maloney, Molina (2016), different reasons can explain this result. Let's give three of them: compared to developed countries, the share of routine occupations is often less important in developing countries since employment in the primary sector is still important; routine occupations in developing countries can partly benefit from offshoring; investment in new technologies may also be lower. The phenomenon of polarization also seems to have a spatial dimension, since it can impact the structure of employment and wages of local labour markets differently. Autor (2019) shows how technological changes have affected low-educated urban workers by reducing their advantage in working in metropolitan areas because routine occupations have been reduced in these areas. Finally, recent developments in artificial intelligence, and its potential to replace workers to perform some highly-skilled tasks (for example the diagnosis of certain diseases) raise the question of its complementarity or substitutability with high-skilled workers, which could deeply modify the process of polarization (Frank *et al.*, 2019). However, the effects of artificial intelligence development on productivity and employment may be slow to spread; both because the accumulation of capital stock based on this technology would take time to have macroeconomic effects, but also because its diffusion would require additional investments (Brynjolfsson *et al.*, 2017). All these questions open up fundamental research perspectives for the years to come.

4. See Delautre, Simonnet, 2018 for a more complete state of the works on polarization.

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# Polarization(s) in Labour Markets: Synthesis and Perspectives*

*Alan Manning***

Polarization is now well established and documented. The increase in the share of high-wage and low-wage jobs at the expense of "intermediate" jobs has led to a polarization of jobs in the US (Autor, 2010; Autor, Dorn, 2013; Autor *et al.*, 2006). One can largely explain this by the automation of routine tasks that then disappear in favour of non-routine manual or intellectual tasks. The automation of tasks has also contributed to polarization of employment in Europe (Goos *et al.*, 2009). Now there is a lot of concern in what the future holds for the world of work (e.g. Ford, 2015) and there are some important unanswered questions.

The first question is about whether polarization represents a fundamental change in the nature of technology and the way it affects the labour market, or whether it is a continuation of past trends. Technological change has caused huge changes on labour markets for decades, machines replacing what people could do. Does the appearance of information and computer technologies (ICT), artificial intelligence and robots make some difference compared to past trends? Is the pace of change faster than it used to be or not?

Another question is to know what polarization means for inequality, what it means for individuals. Evidence for polarization in employment shares is easy to find, but this is not the case for wage inequality since relative wage movements are small. This suggests the supply of labour to occupations is very elastic, and reallocation of labour can be achieved with small changes in flows of people into and out of occupations thanks to the fluidity across occupations. However, there are groups such as older workers for whom the impact of technology may be particularly bad. The question is then to know how individuals experience the process of polarization.

Polarization seems also to be related to globalisation, due to international reallocation of factors of production. An important question, not well-documented, is how globalisation affects polarization. Does the share of middle-skilled jobs increase in low and/or middle income countries or do these countries also experience polarization of their labour market?

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* This text is based on the transcription of the speech given by Alan Manning at the international conference on "Polarization(s) in Labour Markets", held in Paris on 19 June 2018.

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Most of the empirical studies on polarization tend to compare outcomes across occupations, sectors or firms that are more or less affected by the automation of tasks. Those studies cannot assess the aggregate effect of these changes. The question is then: how can we assess the overall impact of polarization on the labour market? I will present some theory suggesting that in a general equilibrium framework the long run effects of technology should be positive for wages of workers on average. In this framework, new technology cannot make all types of workers worse off. This is due to a perfectly elastic supply of labour of different types in different occupations, and labour being ultimately the fixed factor in the long run.

In this text, I will express the view that polarization is mostly a continuation of past changes rather than something radically new, that it has often not had big implications for inequality because of relatively easy mobility across occupations and that there are reasons why new technology, of any form, is likely to lead to higher wages for most workers. But, there are no grounds for complacency. There is no reason to think that a market economy will deliver the efficient level of growth and there needs to be an active state to ensure that all benefit from growth.

## Polarization: Change or Continuity?

Barany, Siegel (2018) argue that some aspects of polarization go back decades, before they attracted much attention from mainstream economists. The replacement of craft workers in manufacturing, which can be seen as machines replacing a stereotypical middling job, started long before the arrival of computers and ICT. On the other hand, the replacement of clerical workers, also a middling type of job, is more recent and more connected to ICT. If some elements of polarization are newer than the others, the driving force of polarization is routinisation or automation. Machines have been replacing labour in jobs that can be routinised. Those jobs have tended to be, in recent decades, in the middle of the job or the wage distribution, which has led to a job polarization. However, there's a lot of heterogeneity in these jobs and uncertainty about future evolution.

The replacement of workers by the machine has fed many fears, the most recent of which concern the impact of artificial intelligence and robots. In 2013, Frey and Osborne examined the extent to which jobs are subject to computerisation (Frey, Osborne, 2017). They estimated the probability of computerisation for a large number of occupations and, based on these estimates, predicted the expected impacts of future computerisation on US labour market outcomes. According to their estimates, about 47 percent of total US employment was at risk. These estimates of the probability of automation were over an unspecified number of years, though they suggested a decade or two.

It has been now six years since Frey and Osborne came up with their projections, about a quarter of the way through the two decades they talked about as a reasonable time horizon, and we can now have a look at what has happened in those five years. We reproduce in Table 1 the results of very simple occupations regressions from the *US Occupational Employment Survey* that provides data on employment and earnings for more than 700 occupations.

Table 1 – **Change in Employment, 2012-2017**

| **Dependent Variable** | **Change Log Employment** | **Change Log Employment** |
|---|---|---|
| Sample Period | 2012-2017 | 2012-2017 |
| | Unweighted | Weighted |
| Probability of Automation | –0.018<br>(0.004) | –0.015<br>(0.003) |
| $R^2$ | *0.016* | *0.015* |

*Source*: *US Occupational Employment Survey*, author's calculations.

With a very simple regression of the change in each occupation log-employment on their estimated probability of automation from 2012 to 2017 (the last data Frey and Osborne had when they made the projection was 2012), we get a significant and negative effect (Table 1). The jobs with a higher probability of automation according to their estimate do have a slower employment growth or even employment has fallen over the last five years. But the explanatory power of this variable is incredibly low (the r-squared is 0.016) and the effect is not really very big, implying a difference of 20 percentage points over a period of 10 years between one job with zero probability of automation and another with a probability of 1. For context, the actual changes at the 10th percentile is minus 22%, the 90th percentile is +53%. So, this is actually not predicting any Armageddon but it does seem to have some explanatory power for what happened after their projections. However, it remains possible that these results indicate only the beginning of the trend and that the phenomenon may accelerate. But if we take the 10 years prior to when Frey and Osborne made their prediction and see how well their estimated probability of automation predicts employment changes over that period, it actually turns out that is a much better predictor of employment change in the earlier years than it is in recent years (Table 2). It is not actually very surprising because the underlying task variables used to the routinisation measure are actually quite similar to those used to explain earlier technical change.

Another thing that may seem surprising is that if we look at the change in log-wages over the five-year period following the Frey and Osborne's prediction, there is basically no relationship. If there is any relationship, it actually goes in the opposite direction. Thus, the most automatable jobs have faster wage growth, which is rather surprising.

TABLE 2 – **Change in Employment and Wages, Different Sample Periods**

| **Dependent Variable** | **Change Log Employment** | **Change Log Employment** | **Change in Log Wages** |
|---|---|---|---|
| Sample Period | 2000-2011 | 2000-2004 | 2012-2017 |
| Probability of Automation | –0.036<br>(0.004) | –0.033<br>(0.006) | 0.003<br>(0.001) |
| $R^2$ | *0.069* | *0.026* | *0.067* |

*Source*: *US Occupational Employment Survey*, author's calculations.

This evidence suggests that polarization is more likely a continuation of existing trends than a radical break with the past.

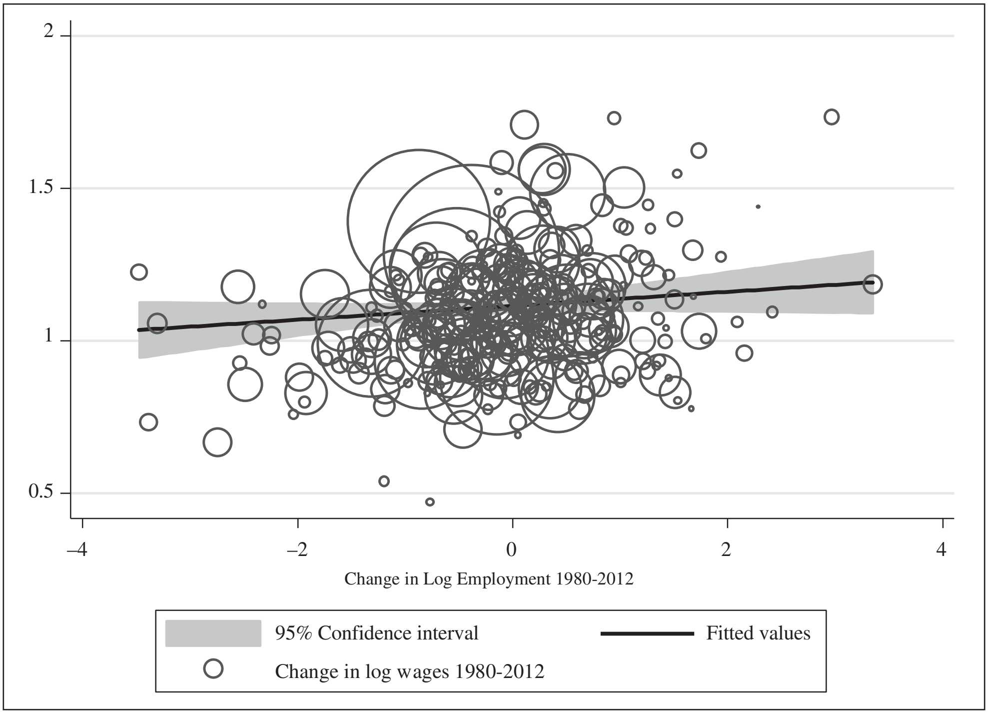
## Polarization and Inequality

A number of papers presented during the conference have mentioned that it is much easier to find evidence for polarization in changes in employment shares than in wage inequality itself. Some occupations can decline in size by 90, 95 percent; others grow by hundreds of percent. But movements in relative wages are much more muted than that, even if wages are measured correctly (BOZIO *et al.*, 2015). The wage of one occupation relative to another doesn't change by 90 percent or hundreds of percent. That just does not happen. An obvious explanation is that the supply of labour to occupations is very elastic. So when there is a demand shock in the form of a shift towards demanding certain occupations and not others, this shows up much more in the quantities, in the shares of employment, than it does in relative wages. Thus, it is wrong to think of the supply of labour to occupations as being inelastic. People can choose the occupations to go into, especially in the longer run. They tend not to go into occupations that are declining. So it is wrong to think that someone is fixed as a particular sort of worker in a very narrowly defined occupation, particularly in lower skilled occupations.

We can find some evidence of a positive but weak relationship between wage changes and employment changes over long periods of time. When we regress the change in log-wages in each occupation against the change in log-employment with the *US Occupational Employment Survey Data* from 1980 to 2012, we find a positive relationship between these two things (Figure 1). However, the coefficient is really tiny, 0.05, and not significantly different from zero. If we suppose that this relationship is estimating a supply curve of labour to different occupations, that suggests that shifts in demand are going to show up almost entirely in the quantity space. They are not going to show up in the wage space too. So the implication of polarization for wage inequalities is not that big.

What does polarization mean for individuals? Looking only at the aggregate measures of inequality doesn't necessarily tell us what happens to individuals. Examining how individuals experience this process is a very important issue to better

FIGURE 1 – **The Long-Run Relationship between Changes in Wages and Employment, US 1980-2012**




*Source*: *US Occupational Employment Survey*, author's calculations.

assess the consequences of polarization on inequalities. There are groups for whom we think that the impact of technology may be particularly bad. These tend to be older workers with specific skills that were once scarce or earned them good money, but now replaced by technology. Those are very clearly identifiable losers. In the past and now, one can give examples of those kinds of people (CORTES *et al.*, 2017). But it is important to understand that there is a lot of fluidity across occupations. In particular the gross flows of people into and out of occupations are much bigger than the net flow. We see people moving from declining occupations to growing occupations, people moving in the other direction. So we don't actually need very big changes in those flows in order to reallocate labour quite a lot. In the UK, for example, 20 percent of workers are changing their jobs every year. The biggest measures of the impact of automation say that might go up to 22 percent. This change is not really a dramatic change in the nature of the labour market and occupations may decline more by lower entry of labour market entrants than higher exit by older workers. In many cases, occupations decline primarily because people stop going into those occupations and, for the individuals already in those occupations, this is a gentle decline rather than anything more abrupt.

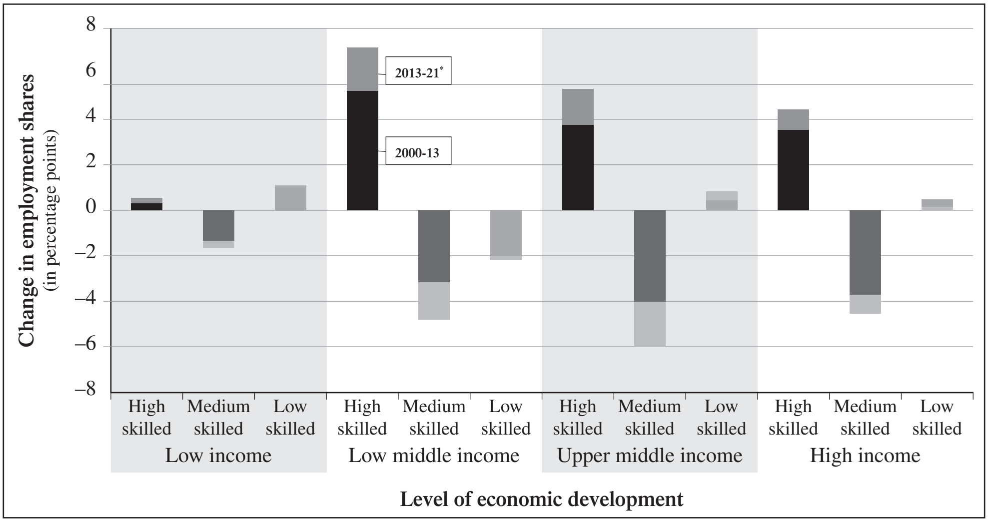
This evidence suggests that polarization may have relatively small implications for wage inequality but much larger implications for the structure of employment.

## Polarization: a Global Phenomenon

A number of papers talk about polarization and globalisation (see eg. Harrigan *et al.* [2016], Heyman [2016], Keller, Utar [2016], Malgouyres [2017]). The underlying question is: how much of the polarization as experienced in high-income countries is really the movement of some jobs to low and middle income countries? If this is happening, what one would expect to find on employment shares in those countries would be the mirror image of what is happening in the high-income countries. Middling jobs would become more important in low and middle-income countries, as they are shifted from countries like France or the UK to those countries. Twenty years ago, there were similar arguments about trade or technology. However, there are not many studies on the changing occupational structure of employment in countries other than high-income countries. So it is difficult to claim that this is what is happening.

On the contrary, some studies suggest polarization is happening in many countries. Figure 2 is taken from an International Labour Organization (ILO) briefing paper (ILO, 2018). It looks at what has been happening to job polarization around the world in countries with different levels of economic development. In all of them, the most negative is in medium-skilled jobs. Figures vary a bit according to whether they have got a lot of high skilled employment growth or low skilled employment growth. From a more general point of view, it looks like polarization is happening in every sort of country. This fact suggests that it is not just the relocation of some jobs from high-income countries to other countries. However, it is not sufficient as a proof, and we need more research on that point. This question should then be put forward on the research agenda.

Figure 2 – **Job Polarization around the Globe**




*Note*: Change in employment shares, in percentage points. * Forecasts after 2016.
*Source*: International Labour Organisation, ILO Trends Econometric Models, November 2016.

## General Equilibrium Assessments of Polarization

Finally, I will discuss polarization in a general equilibrium framework. Most of the empirical studies tend to compare outcomes across occupations, sectors or firms that are more or less affected by routinisation or globalisation. Those studies are incredibly useful, but by their nature they cannot say anything about what the aggregate effect of these changes is. The aggregate effect is often subsumed into some general time effect.

What do simple economic models predict about the consequence of new technology? Obviously, there is a very long history of fears about the impact of new technology. Let us put those fears into three groups going from the most extreme to the least extreme. The most extreme is: "new technology means the end of work, it is going to be awful for all workers". Then there is the intermediate one: "some workers might gain but it's generally going to be bad for workers and good for capitalists". And the mildest version is: "new technology might have some distributional consequences among workers, so some will gain, some will lose, but overall we don't really know whether it's going to be good or bad for them".

### Polarization from a Consumer's Perspective

Past predictions about the impact of new technology have always been wrong. Although there have often been groups of workers who have been losers, technology has been the source of the rise in living standards for everyone. Basically, in our societies today there is nobody who is worse off than the equivalent person would have been 200 years ago. That is almost entirely because of new technology. It is interesting to understand where people's past predictions went wrong. One reason is that they focused almost exclusively on a worker's perspective and exclusively on jobs where humans were going to be displaced by new technology. Those are the sort of losers who are often concentrated and visible. But these analyses often missed the gainers. One way of thinking about the gainers is to think about the impact of new technology not from the perspective of a worker but from the perspective of a consumer.

From a consumer's perspective the impact of new technology is the following. Firms are adopting new technology because it lowers costs. If the markets are reasonably competitive, lower costs lead to lower prices. From a consumer's perspective, one can buy everything he/she did before, and one has some income left over. What is he/she going to do with that leftover income? He/she is going to go out and spend it on all sorts of stuff. Doing so, he/she creates jobs for all sorts of people. Once we have that perspective in mind, we can talk about new technology raising the demand for labour. It is also important to understand that it is not just new types of jobs that are created. These are going to be jobs in areas where consumers want to spend their money which is pretty much everything, leading mostly to just more old jobs.

Much the same argument applies to the impact of China. China has made stuff cheaper, that is why there has been import penetration. That has given Western consumers more purchasing power. They have gone out and spent that money, and in doing so have created jobs. The worrying point in many current discussions of the impact of new technology is that they make exactly that same mistake of focusing on one narrow perspective and ignoring all the other effects. Nevertheless, it is hard to assess what those aggregate effects are going to be, and that is where general equilibrium models can be useful.

## Polarization in a General Equilibrium Framework

What follows is a very simple model coming from Caselli, Manning (2019). Consider a production function $F(L, K, \theta)$ in which output is produced by labour $L$, capital $K$ and technology $\theta$. Let us assume constant returns to scale, perfect competition, one type of labour, one capital good. Let us also assume that the labour supply is inelastic. So, any effect on the demand for labour must go into wages. If one relaxes that hypothesis it would go into employment as well. Consider this as a useful starting point.

Improvements in technology –higher $\theta$– means more output given input. It gives:

$$\frac{\partial F}{\partial \theta} > 0.$$

Nobody would disagree with that, but it is possible that new technology reduces the marginal product of labour:

$$\frac{\partial^2 F}{\partial L \partial \theta} < 0.$$

This situation is what people worry about. There is a lot of discussion about whether new technology is a substitute or complement for labour. Is it capital augmenting or labour augmenting? The reason people think that matters is that in a competitive market, workers will earn their marginal product so that:

$$W = \frac{\partial F(L, K, \theta)}{\partial L} > 0.$$

The impact of new technology on wages depends upon whether the marginal product goes up or down with new technology. With fixed capital we get the result that wage could fall with new technology:

$$\frac{\partial W}{\partial \theta} = \frac{\partial^2 F(L, K, \theta)}{\partial L \partial \theta}.$$

The problem with this argument is that it assumes that capital is fixed, and one cannot assume that capital is fixed. What happens if you assume that capital is variable? Assume there is a perfectly elastic supply of capital, which is perhaps reasonable as capital goods in the longer-run are all produced. There is no natural limit to the amount of capital in the same way as there is a natural limit to the number of workers. If the cost of capital is $P^K(r + \delta)$ made up with a relative price of capital goods $P^K$, the interest rate $r$ and the depreciation rate $\delta$, we know that profit maximization means the firm will employ capital up to the point where marginal product of capital is equal to the cost of capital:

$$\frac{\partial F(L,K,\theta)}{\partial K} = P^K(r+\delta).$$

What happens to wages when we improve new technology and supply of capital is elastic? Let us assume again constant returns to scale and perfect competition. Then payments to labour must be total output minus payments to capital:

$$WL = F(L,K,\theta) - P^K(r+\delta)\,K.$$

Differentiating that with respect to $\theta$, gives the results that are taking account of the endogeneity of capital in the long run. We get the following expression:

$$L\frac{\partial W}{\partial \theta} = \frac{\partial F(L,K,\theta)}{\partial \theta} + \left[\frac{\partial F(L,K,\theta)}{\partial K} - P^K(r+\delta)\right]\frac{\partial K}{\partial \theta} - \frac{\partial P^K(r+\delta)}{\partial \theta}K.$$

Looking at the first term, there is a positive effect which just comes from the fact that new technology leads to more output. Then there is the second effect which is about how capital changes. But that is multiplied by the difference between the marginal product of capital and the cost of capital. This difference is zero in the long run, so, that term just disappears. The third term is about how new technology alters the relative cost of capital relative to consumer goods. If the cost of capital goods relative to consumer goods does not rise, this term is positive. So, new technology of any form, whether it is a substitute or a complement to labour, whether it is labour augmenting or capital augmenting, does not matter. The prediction is that wages must go up. The intuition is that new technology leads to more output being produced, and there must be some gainers from it. It cannot be new capital that is being accumulated, because that is paid its marginal product. It just gets what it adds. It cannot also be old capital unless the relative price of capital goods rises.

If the relative price of capital goods does not rise, the only people left over to be gainers are workers. In the long-run labour is the fixed factor of production and all the gains from new technology have to go to the fixed factor. Everything else is produced. There is no particular reason that the rate of return on robots should be any higher than any other form of capital.

So, how can you get the opposite kind of result? There are a number of possibilities. Let us concentrate on imperfect competition. If new technology reduces competition, that can lead to falling wages. Similarly, if there is a rising cost of capital, which might be the case if investment is weak and the rate of return to capital rises, that can be to the disadvantage of workers. In this case, the problem is that the economy is under-investing in robots and new technology, and so the rate of return to investment is going up rather than that it is over-investing.

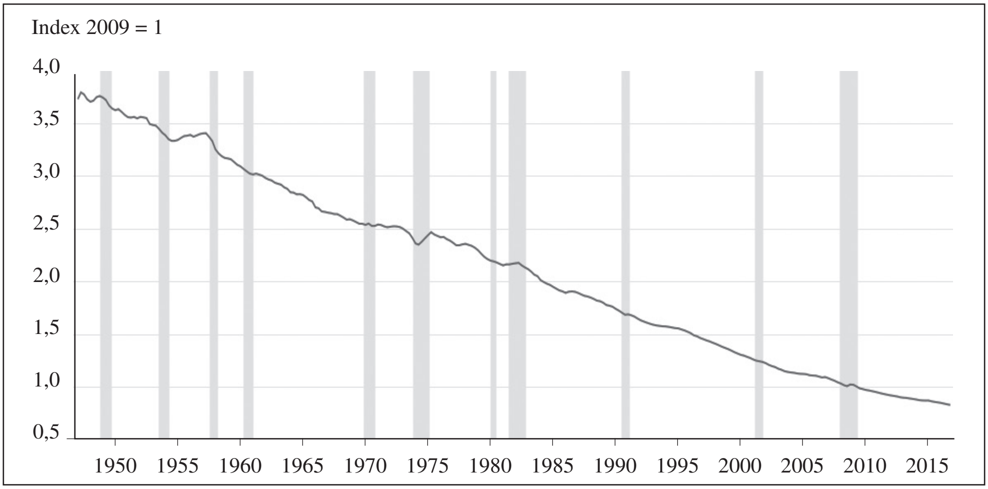
This framework may seem too simple. What about lots of types of goods and lots of types of workers? Let us try to be as general as possible. Assume any number of types of labour, although all in fixed supply, any number of types of goods –consumption, intermediate, investment goods. We also assume that new technology can affect production possibilities in any way whatsoever, in any sector, except that it must always weakly increase output. We assume there are constant returns to scale in all sectors and perfect competition.

Let us compare wages in steady state in two economies with different levels of technology. First, we show that it is impossible for new technology to make all types of workers worse off. One just cannot write down any model of that form which will make all workers worse off. But that might mean the gainers might be a tiny group –it might be one worker. What about the average worker? The second result is that if the price of investment goods relative to consumption goods falls, then new technology must raise the average wage of workers. Again, one cannot write it down any differently. It is the same intuition as before: someone is going to gain from new technology, new capital gets its marginal product, and if the relative price of investment goods is falling, old capital is losing out from this technological change, not gaining.

The only people left over are workers. It does not mean that the labour share of total income necessarily goes up. This is about real wages, not the share of income, and there might be severe distributional effects. But it is very clear that the relative price of investment goods has been falling for decades (Figure 3). There is no doubt about whether that condition holds or not.

A final result is that if the supply of labour of different types in different occupations is perfectly elastic, then workers of all types must gain from technological progress. Intuition then is that relative wages are fixed by that assumption. So, it is as if we would have only one type of worker. If there is one type of worker, that worker has

FIGURE 3 – **Relative Price of Investment Goods, US 1947-2016**




*Note*: Shaded areas indicate US recessions.
*Source*: DiCecio, Riccardo, Relative Price of Investment Goods [PIRIC], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PIRIC, accessed May 29, 2019. For further details, DI CECIO (2009).

to gain from new technology. I think that this is not a bad description of what happened in the past in the long-run, and what it suggests is that there are quite powerful forces causing new technology to transmit into higher wages. It also does not depend on the nature of new technology. It just depends on labour ultimately being the fixed factor, everything else being produced.

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This text has expressed the view that polarization is mostly a continuation of past changes rather than something radically new, that it has often not had big implications for inequality because of relatively easy mobility across occupations. And that there are reasons why new technology, of any form, is likely to lead to higher wages for most workers.

This paper may seem very complacent about what the implications of technological change are. However, we do need to have public intervention in order to deliver inclusive growth. There are two parts of inclusive growth. First, there is the growth part of it and that has proved particularly difficult for the last decade, but we do know that growth at the frontier is driven by increases in knowledge. We also know that knowledge is a public good: what someone knows does not stop others knowing the same thing. And we know that market economies do not deliver efficient levels of public goods. In this sense, there is no presumption at all, even on the most narrowly conventional economics that a "laisser faire" economy will deliver the efficient level of growth. Although there is some attention people pay to growth promoting policies, it is not perhaps as central as it should be given the importance of growth. The second part to worry about is the inclusive part of growth. We have a set of tools already to use, such as minimum wages, training and redistributing taxation (Lordan [2018], Keller, Utar [2016], Bozio *et al.* [2015]). We need to use them. And we do not need a new set of tools in order to deal with the challenges we face at the moment. We just have to be prepared to use the ones that we have got.

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# Job Polarization, Structural Transformation and Biased Technological Change*

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By reviewing our work in Bárány, Siegel (2018a, 2018b), this article emphasizes the link between job polarization and structural change. We summarize evidence that job polarization in the United States has started as early as the 1950s: middle-wage workers have been losing both in terms of employment and average wage growth compared to low- and high-wage workers. Furthermore, at least since the 1960s the same patterns for both employment and wages have been discernible in terms of three broad sectors: low-skilled services, manufacturing and high-skilled services, and these two phenomena are closely linked. Finally, we propose a model where technology evolves at the sector-occupation cell level that can capture the employment reallocation across sectors, occupations, and within sectors. We show that this framework can be used to assess what type of biased technological change is the driver of the observed reallocations. The data suggests that technological change has been biased not only across occupations or sectors, but also across sector-occupation cells.

Over the last several decades the labor markets in most developed countries have experienced substantial changes. Since the middle of the twentieth century there has been structural change, the movement of labor out of manufacturing and into the service sectors. One of the key explanations for structural transformation is differential productivity growth –or biased technological progress– across sectors, combined with complementarity between the goods and services produced by different sectors

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(Ngai, Pissarides [2007]).[1] At the level of occupations several papers have documented the polarization of labor markets in the United States and in several European countries since the 1980s: employment has shifted out of middle-earning routine jobs to low-earning manual and high-earning abstract jobs. The main explanation for this phenomenon is the routinization hypothesis, which assumes that information and computer technologies (ICT) substitute for middle-skill, routine occupations, while they complement high-skill, abstract occupations; in other words technological progress that is biased across occupations (Autor *et al.* [2003], Autor *et al.* [2006], Autor, Dorn (2013), Goos *et al.* [2014]). Both literatures –on structural change and polarization– study the impact of differential productivity growth. One focuses on the productivity across sectors and its interaction with the demand for goods and services, while the other focuses on the productivity of tasks or occupations, and its impact on the relative demand for these occupations. In this paper we review our previous work which suggests that these two phenomena are connected and should not be studied in isolation, especially in order to understand the driving forces behind the reallocation of labor across sectors and occupations.

In Bárány, Siegel (2018a) we show that polarization started much earlier than previously thought, and that it is closely linked to the structural transformation of the economy. This on its own suggests that there might be a common driving force behind structural transformation and polarization. In Bárány, Siegel (2018b) we go further; we demonstrate that there is an even tighter connection between the sectoral and occupational reallocation of employment, and we explicitly study the technological changes underlying both.

In Bárány, Siegel (2018a) we document first that in the US, occupational polarization both in terms of wages and employment has started in the 1950s, much earlier than suggested by previous literature. Second, we show that a similar polarization pattern is present for broadly defined sectors of the economy, low-skilled services, manufacturing, and high-skilled services. Moreover, we show that a significant part of the occupational employment share changes is driven by shifts of employment across sectors, and that sectoral effects also explain a large part of occupational wage changes. These findings suggest that the decline in routine employment is strongly connected to the decline in manufacturing employment. We propose a model to show that differences in productivity growth across sectors lead to the polarization of wages and employment at the sectoral level, which in turn implies polarization in occupational outcomes.

In Bárány, Siegel (2018b) we look at the data from a different perspective: we study employment patterns across sector-occupation cells in the economy. We document some trends in occupation and sector employment that have not received much attention in the literature. First, the manufacturing sector has the highest share of routine workers;

1. Some papers emphasize changes in the supply of an input which is used at different intensity across sectors (Caselli, Coleman [2001], Acemoglu, Guerrieri [2008]). Other papers study the role of non-homothetic preferences, where changes in aggregate income induce a reallocation of employment across sectors (Kongsamut *et al.* [2001], Boppart [2014]).

by far most of the decline in routine employment has occurred in manufacturing, and conversely almost all of the contraction in manufacturing employment has occurred through a reduction in routine employment. Second, the high-skilled service sector has the highest share of abstract workers; most of the expansion in abstract employment has happened in the high-skilled service sector, and most of the increase in high-skilled service employment has been due to an expansion in abstract employment. These patterns reveal that the sectoral and the occupational reallocation of employment are closely linked. Furthermore, the overlap of occupations and sectors implies that it is hard to identify the technological changes which underlie the observed labor market patterns. To overcome this issue, we specify a flexible model of the production side of the economy in which technological change can be biased towards workers in specific sector-occupation cells. We use key equations of this model together with data from the *US Census* and from the U.S. Bureau of Economic Analysis (BEA) to draw conclusions about the bias in productivity changes across sector-occupation cells.

This approach departs from the recent literature connecting the phenomena of structural change and polarization across occupations in that we do not *a priori* restrict the nature of technological change. Goos *et al.* (2014) suggest that differential occupation intensity across sectors and differential occupational productivity growth can lead to employment reallocation across sectors. Duernecker, Herrendorf (2016) show in a two-sector two-occupation model that unbalanced occupational productivity growth by itself provides dynamics consistent with structural change and with the trends in occupational employment, both overall and within sectors. Lee, Shin (2017) allow for occupation-specific productivity growth and find that their calibrated model can quantitatively account for polarization as well as for structural change, and in an extension find a limited role for sector-specific technological change. Aum *et al.* (2018) analyze the role of routinization (differential productivity growth of occupations) and computerization across industries as well as industry-specific Total Factor Productivity (TFP) differences in the recent productivity slowdown, and find in their model with homogeneous labor that sectoral TFP differences have a rather small effect.

The close link in the data between the sectoral and occupational reallocation of labor explains why models which allow for productivity growth differences only at the sectoral or only at the occupational level can go a long way in accounting for the reallocations across both dimensions. However, such restricted models load all differences in technological change on one type of factor, therefore not allowing to identify whether these differences arise indeed at the level of sectors or of occupations. We view our framework as an important and useful first step in identifying the true bias in technological change. In this article we explain how certain aspects of the data can be used to draw qualitative conclusions, whereas in Bárány, Siegel (2018b) we use a richer methodology to quantify the bias in technology across sector-occupation cells and to decompose it further into common components. To summarize our results, we find that technological change has been biased in more nuanced ways, not just across occupations or sectors, but across sector-occupation cells.

# A Historical Perspective on Polarization

In Bárány, Siegel (2018a) we use data from the *US Census* between 1950 and 2000 and the 2007 *American Community Survey (ACS)* to study the patterns of employment and wages both across occupations and across sectors. In the following three subsections we summarize the main empirical results we established there. Our main findings are the following: (1) occupational polarization both in terms of wages and employment started as early as 1950 in the US, (2) wage and employment polarization is also visible in terms of broadly defined industries, (3) a large part of polarization in terms of occupations is driven by changes at the level of industries. In the last subsection we go further and document the changes in employment at the sector-occupation cell level where we see a strong overlap between the evolution of occupational and sectoral employment trends.

## Occupational Polarization

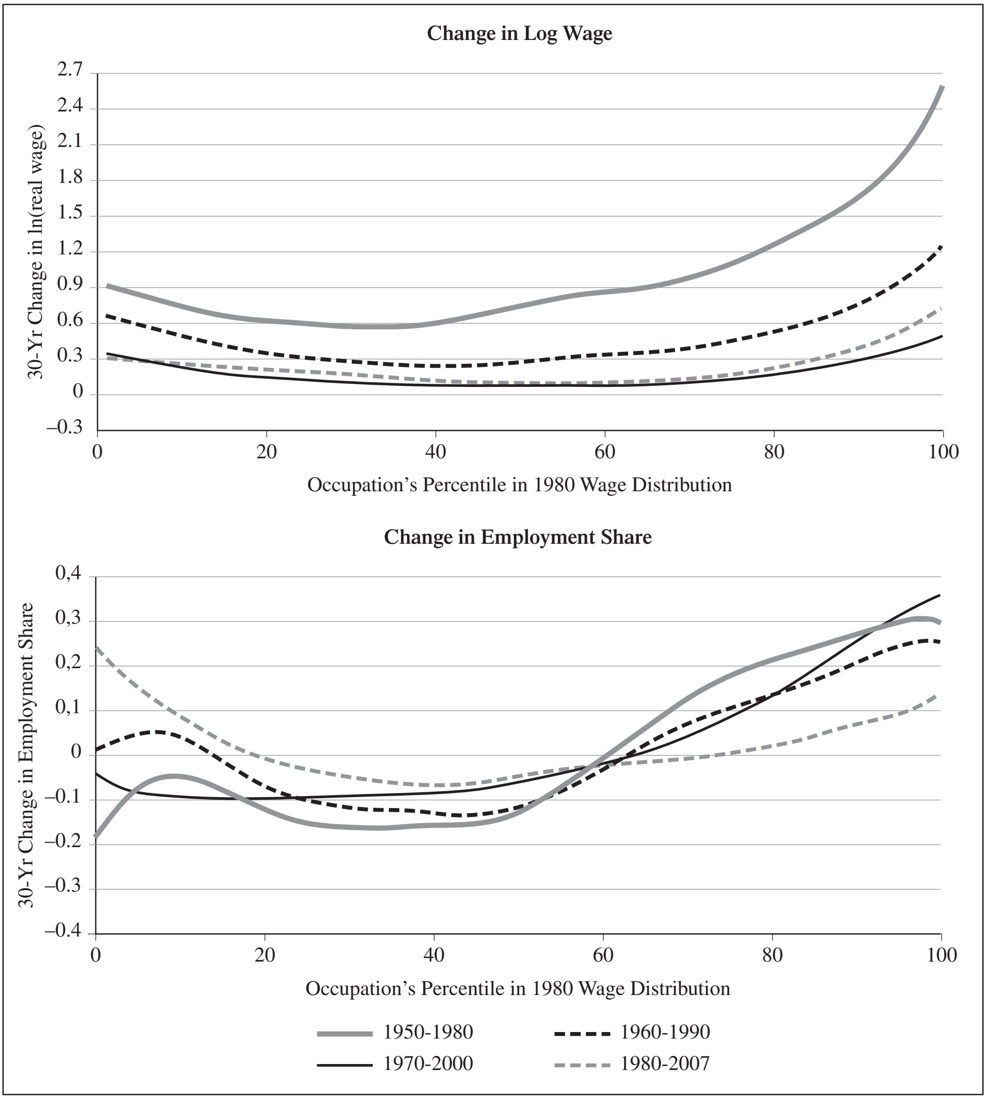
Figure 1 plots the smoothed changes in log real wages and employment shares for occupational percentiles, with occupations ranked according to their 1980 mean hourly wage, following the methodology used in Autor *et al.* (2006), Acemoglu, Autor (2011), and Autor, Dorn (2013) (Box 1). Departing from the literature, we do not restrict attention to recent years but show the changes starting from 1950 for different 30-year periods. The top panel shows that there has been (real) wage polarization throughout, as occupations towards the middle of the wage distribution have gained less than occupations at both extremes. The bottom panel shows that also in terms of their shares in hours worked, middle earning occupations have been tending to do worse than both low- and high-earning occupations. Though the pattern is less striking than for wages, polarization of employment has occurred since the 1950s.

Box 1

**Ranking Occupations by Skill Level**

Figure 1 –as is standard in the literature, e.g. Autor *et al.* (2006), Acemoglu, Autor (2011) and Autor, Dorn (2013)– shows smoothed changes in log real wages or in employment shares by percentiles of the occupational wage distribution, where occupations are ranked by their "skill level", which is approximated by the average wage of workers in the given occupation in a base year. These occupations are then put into 100 bins on the horizontal axis, each representing 1 percent of employment. For such a comparison over time a balanced set of occupational codes are needed. In Bárány, Siegel (2018a) we construct the finest possible set of occupational codes that is balanced over 1950 to 2007, extending the work of Meyer, Osborne (2005) and Dorn (2009).

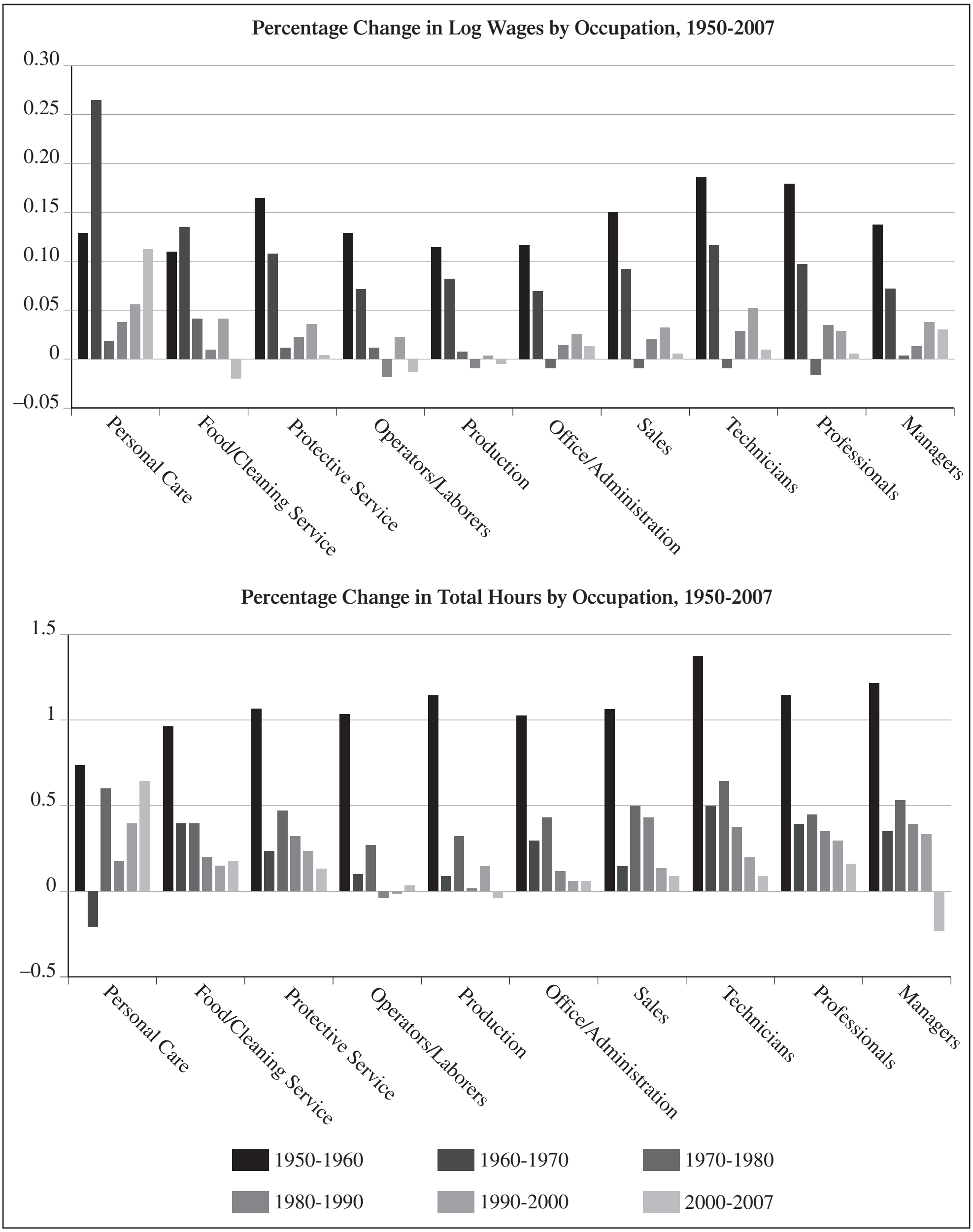
FIGURE 1 – **Smoothed Changes in Wages and Employment**




*Note*: Balanced occupation categories (183 of them) have been defined by the authors based on MEYER, OSBORNE (2005), DORN (2009) and AUTOR (2013). The horizontal axis contains occupational skill percentiles based on their 1980 mean wages. In the top panel the vertical axis shows for each occupational skill percentile the 30-year change in log hourly real wages, whereas in the bottom panel it shows the 30-year change in employment shares (calculated as hours supplied).
*Source*: BÁRÁNY, SIEGEL (2018a). The data is taken from IPUMS *US Census* data for 1950, 1960, 1970, 1980, 1990, 2000 and the *American Community Survey* (ACS) for 2007. The sample excludes agricultural occupations/industries and observations with missing wage data.

To get a sense of which occupations are driving these changes and whether there are any significant differences across decades, in Figure 2 we show the decade-by-decade change in total hours worked and mean log wages for 10 coarser occupational categories. The categories we use follow ACEMOGLU, AUTOR (2011), and are ranked according to the occupations' mean wages, from lowest earners on the left to highest earners on the right. Between 1950 and 1960 a clear pattern cannot be discerned, whereas from 1960 onwards, it is clear that both total hours worked and mean log wages have grown faster at both extremes than for occupations in the middle.

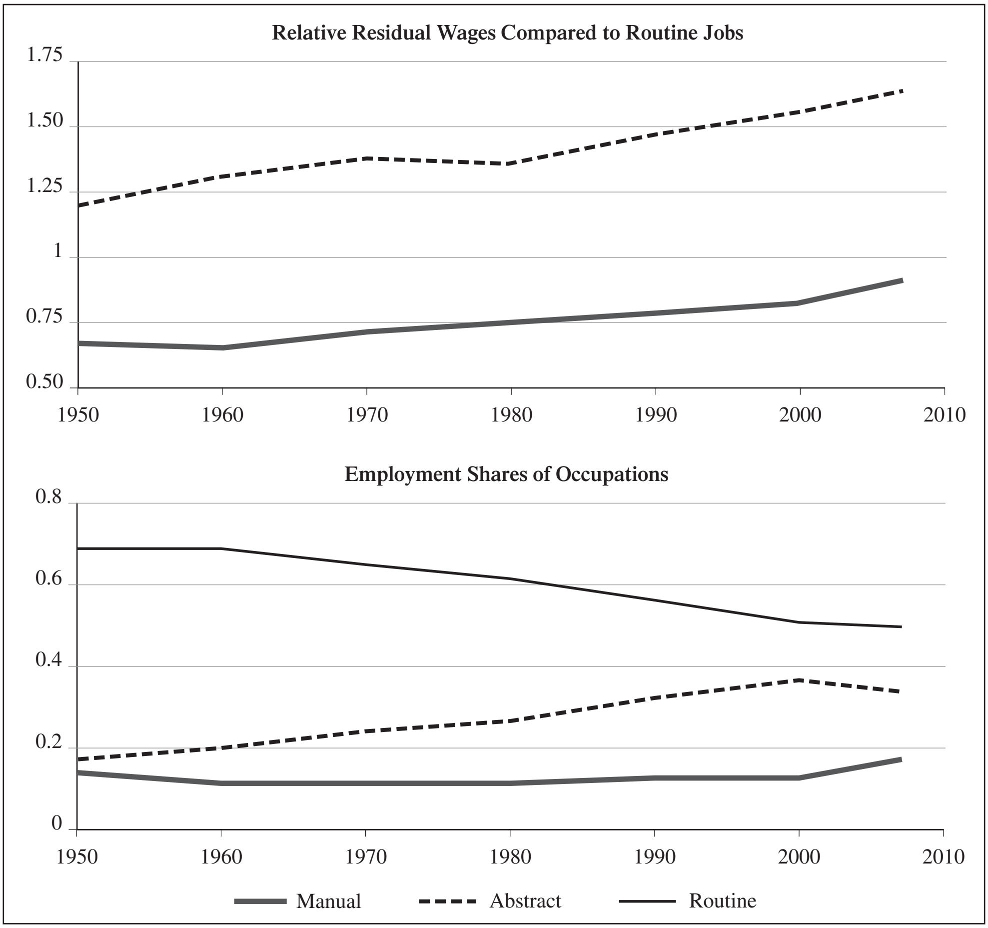
FIGURE 2 – **Polarization in Broad Occupational Categories**




*Source*: Bárány, Siegel (2018a). The data used is the same as in Figure 1.

Finally, following Acemoglu, Autor (2011), we classify occupations into manual, routine and abstract categories.[2] Figure 3 plots their paths of relative wages and of employment shares. The top panel shows the path of occupational premia. These premia are the exponents of the coefficients on occupation dummies, obtained from a regression of log wages controlling for gender, race, a polynomial in potential experience, as well as occupation dummies. Obtaining the occupation premia from these regressions allows us to disregard changes in wage differences across occupations which are potentially caused by age, gender, or racial composition differences. It is worth to note that, as expected, the manual premium is less than the routine, while

Figure 3 – **Polarization for Broad Occupations**




*Source*: Bárány, Siegel (2018a). Occupational wage premia and employment shares (in terms of hours) are calculated from the same data as in Figure 1.

2. See Box 2 for details of which 1-digit occupational codes are in each category.

the abstract premium is the largest. However, over time, the advantage of routine jobs over manual jobs has been falling, and the advantage of abstract jobs over routine jobs has been rising. The bottom panel shows that the employment share of routine occupations has been falling, of abstract occupations has been increasing since the 1950s, while that of manual occupations, following a slight compression until 1960, has been steadily increasing. Thus, the middle earning group, the routine workers, has lost both in terms of relative average wages and in terms of the employment share to the benefit of manual and abstract workers.

All these figures constitute evidence that at the occupational level there has been employment and wage polarization in the US since at least the 1960s.

## Sectoral Polarization

Similar patterns can be discerned when considering the economy in terms of three broad sectors, low-skilled services, manufacturing, and high-skilled services (Box 2). As common in the structural change literature our manufacturing category includes mining and construction (e.g. as in Herrendorf *et al.* [2013]), whereas we split services in two (e.g. as in Buera, Kaboski [2012], Duarte, Restuccia [2017], Duernecker *et al.* [2017]). Classification of economic activities into broad sectors for the purpose of a model should be such that industries within sectors are very good substitutes, while they are complements across sectors. Since the service sector as a whole includes very different types of services, by splitting it in two, we improve the analysis with regards to this criterion.

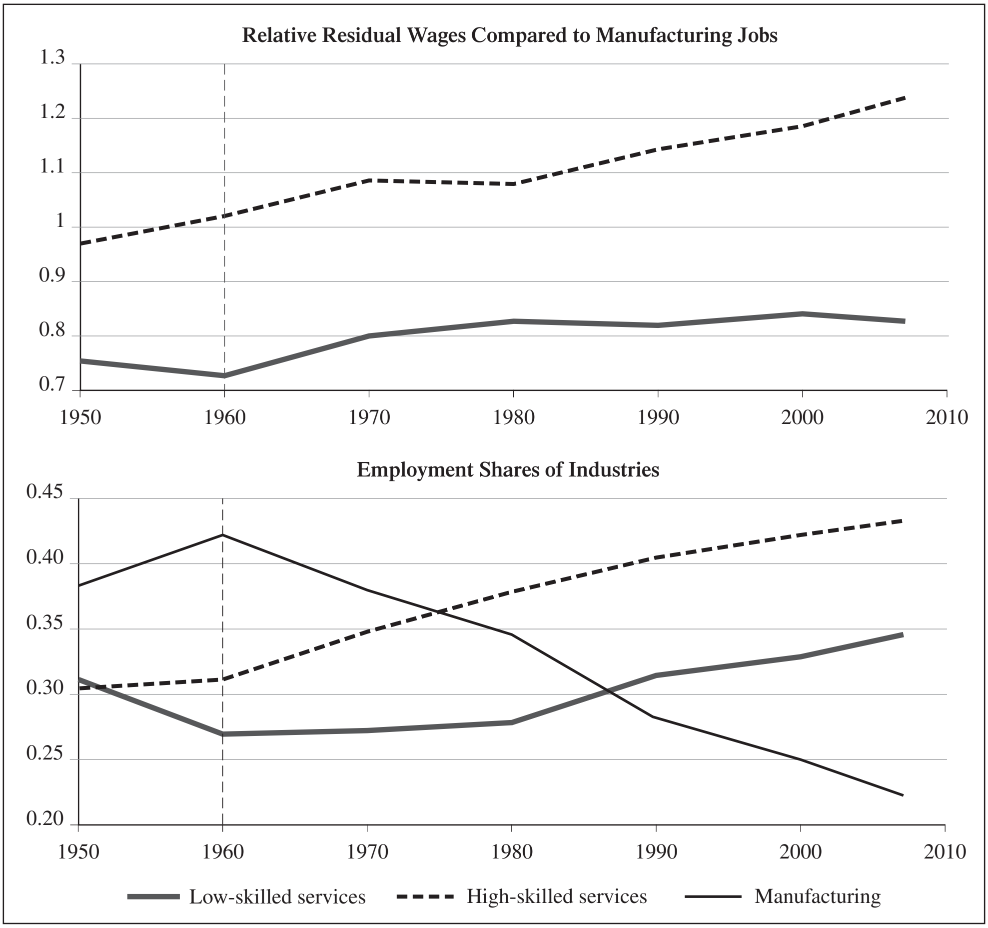
Box 2

**Classification of Industries and Occupations**

Industries are classified into our three categories as follows: low-skilled services are personal services, entertainment, low-skilled transport, low-skilled business and repair services, retail trade, and wholesale trade; manufacturing also includes mining and construction; high-skilled services are professional and related services, finance, insurance and real estate, communications, high-skilled business services, utilities, high-skilled transport, and public administration. In terms of occupations, manual workers are those working in: housekeeping, cleaning, protective service, food preparation and service, building, grounds cleaning, maintenance, personal appearance, recreation and hospitality, child care workers, personal care, service, healthcare support. Routine occupations are construction trades, extractive, machine operators, assemblers, inspectors, mechanics and repairers, precision production, transportation and material moving occupations, sales, administrative support. Finally abstract occupations comprise managers, management related, professional specialty, technicians and related support workers.

Figure 4 plots for these three sectors how wage premia and shares of hours worked have evolved over time. Similarly to the occupational premia, these sector premia are calculated from a Mincerian log wage regression as the exponents of the coefficients on sector dummies, where we also control for gender, race, and a polynomial in potential experience. By construction, these sector premia do not contain changes in wage differences across sectors which are potentially caused by age, gender, or racial composition differences. As the top panel of the figure shows, workers in low-skilled services typically earn less and workers in high-skilled services earn more per hour than those in the manufacturing sector. Moreover, it reveals that there has been a

FIGURE 4 – **Polarization for Broad Industries**




*Note*: The top panel shows relative wages: the high-skilled service and the low-skilled service premium compared to manufacturing (and their 95% confidence intervals), implied by the regression of log wages on gender, race, a polynomial in potential experience, and sector dummies. The bottom panel shows employment shares, calculated in terms of hours worked. The dashed vertical line represents 1960, from when on manufacturing employment has been contracting.

*Source*: BÁRÁNY, SIEGEL (2018a). The data used is the same as in Figure 1. Each worker is classified into one of three sectors based on their industry code (for details of the industry classification see Box 2).

pattern of wage polarization in terms of sectors, as the wage premia in low- and in high-skilled services have been increasing since the 1960s relative to manufacturing. The bottom panel of the figure shows the evolution of employment shares across sectors. Manufacturing employment has been falling since the 1960s, while employment in both low- and high-skilled services has been increasing. Putting it differently, there has been employment polarization at the sectoral level as the employment share of the middle-earning sector has declined relative to both the low- and high-end sectors.

## Quantifying the Impact of Sectoral Changes on Occupations

A standard shift-share decomposition can be used to quantify the contribution of sectoral employment share changes to each occupation's employment share changes. We denote by $\Delta E_{ot} = E_{ot} - E_{o0}$ the change in the employment share of occupation *o* between year 0 and *t*, which can be decomposed as:

$$E_{ot} = \sum_i \lambda_{oi} \Delta E_{it} + \sum_i \Delta\lambda_{oit} E_i,$$

where $\lambda_{oit} = L_{iot} / L_{it}$ is the share of occupation *o* employment within industry *i* employment at time *t*, $E_{it} = L_{it} / L_t$ is the employment share of industry *i* in the economy at time *t*, we denote the change between period 0 and *t* with Δ, and with the variables without a time subscript we denote the average of the variable between period 0 and period *t*. The first term captures the between-industry changes, this is the change in the employment share of occupation *o* due to changes in the industrial composition, while the changes due to within-sector reallocations are represented by the second term.

Table 1 shows the results from this decomposition for the three broad occupational categories. We conduct this decomposition for either our 3 broad occupations and 3 broad sectors, or for 10 broad occupations and 11 broad sectors. No matter the time frame or the number of industrial/occupational categories we consider, we find that a significant part of each occupation's employment share change has been driven by between-industry forces. Between 1960 and 2007 around a half of the change in the manual employment share, about a third of routine, and around a quarter of abstract employment share change has been driven by changes in the industrial composition of the economy.

In a similar fashion we decompose relative occupational wage changes into a component that is due to industry effects and one that is due to occupation effects. We start from the relative average wage of a given occupation compared to routine wages:

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

where $L_{iot} / L_{ot}$ denotes the fraction of workers of occupation *o* in industry *i* in period *t*, $w_{it} / w_{rt}$ denotes the ratio of the average wage in industry *i* relative to the average wage of routine occupations in period *t*, and $w_{iot} / w_{it}$ denotes the wage

TABLE 1 – **Decomposition of Changes in Occupational Employment Shares**

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

*Note*: For each occupational category, the first row presents the total change, the second the between-industry component, and the third the within-industry component over the period 1950 or 1960 to 2007. The first two columns use 3 occupations and 3 sectors, the last two use 10 occupations and 11 industries. The 10 occupations are the same as in Figure 2, while the 11 industries are: 1 personal services, entertainment and low-skilled business and service repairs, 2 low-skilled transport, 3 retail trade, 4 wholesale trade, 5 extractive industries, 6 construction, 7 manufacturing, 8 professional and related services and high-skilled business services, 9 finance, insurance, and real estate, 10 high-skilled transport and public utilities (including communications), 11 public administration.
*Source*: BÁRÁNY, SIEGEL (2018a). Same data as in Figure 1.

premium of occupation *o* in industry *i* in period *t*. We implement the three-way decomposition as follows. The *occupation effect* is the change in the occupational wage premium within each industry relative to the industry average ($w_{iot} / w_{it}$). The *industry effect* is made of two parts: first, workers within an occupation move across industries which have different wages ($L_{iot} / L_{ot}$), and the second part comes from changes in each industry's average wage compared to routine wages ($w_{it} / w_{rt}$). Table 2 shows the

TABLE 2 – **Decomposition of Changes in Relative Occupational Wages**

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

*Note*: For each occupational category, the first row presents the total change, the second the industry component, and the third the occupation component over the period 1950 or 1960 to 2007. The first two columns use 3 occupations and 3 sectors, columns three and four 10 occupations and 11 industries.
*Source*: BÁRÁNY, SIEGEL (2018a). Same data as in Figure 1.

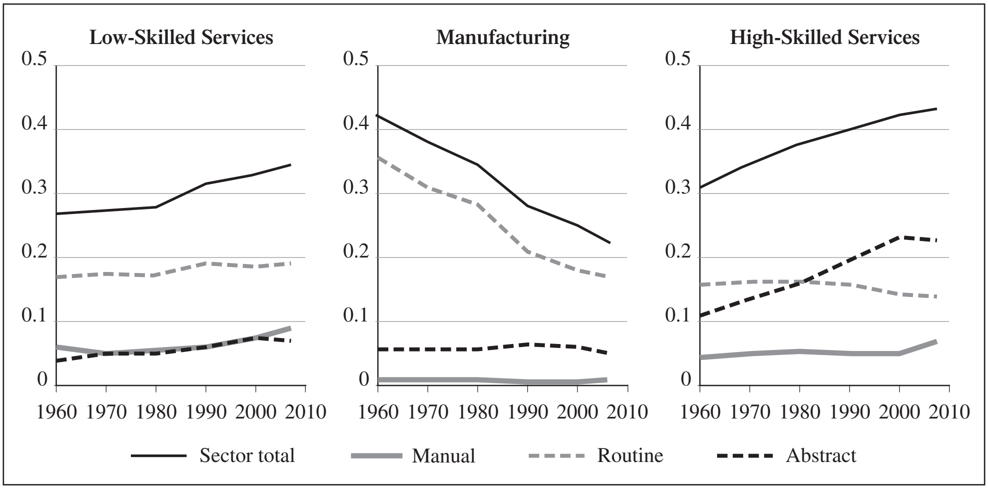
results of this decomposition. It is apparent in this table that both manual and abstract occupations have been gaining in terms of wages relative to routine occupations. Furthermore, this table shows that more than half of occupational wage changes can be due to industry effects: due to either the reallocation of manual or abstract workers to industries with higher wages, or by faster wage growth in those industries where manual or abstract workers are employed more intensively.

## Overlap between Occupational and Sectoral Employment

While the shift between sectors *per se* has implications for occupational outcomes, it is informative to consider the evolution of employment at the level of sector-occupation cells since there are several distinct patterns. For the three broad sectors and the three occupational categories defined above, Figure 5 plots the evolution of sector-occupation employment shares in the U.S. between 1960-2007. The dark lines show the employment share of each sector (manufacturing, low- and high-skilled services), which is then broken down into manual, routine, and abstract occupations. The economy's structural transformation is apparent in the pronounced decline in the manufacturing sector's employment and the rise in (particularly high-skilled) service sector employment. Occupational employment polarization is manifested in the fall of the share of routine occupations.

However, looking at occupations and sectors more carefully, two additional facts are apparent. First, the manufacturing sector has the highest share of routine labor. Second, by far most of the decline in routine employment has occurred in manufacturing,

FIGURE 5 – **Sector-Occupation Employment Shares**




*Note*: Each worker is classified into one of three sectors based on their industry code and one of three occupations based on their occupation code (for details of the industry and the occupation classification see Box 2), employment shares in the entire economy are calculated in terms of hours.
*Source*: The data used is the same as in Figure 1.

whereas in the two service sectors it has declined only slightly. Similarly, almost all of the increase in the employment share of abstract occupations has taken place in the high-skilled service sector, and most of the increase in manual employment up to 2000 has occurred in low-skilled services. It is these patterns that imply that different economic models can explain both the sectoral and the occupational reallocations to a large degree through either sector- or occupation-specific technological change alone. However, as many models tend to *a priori* restrict attention to one form of technological bias, for instance only across sectors (as in Bárány, Siegel [2018a]) or only across occupations (e.g. as in Goos *et al.* [2014] or Duernecker, Herrendorf [2016]), they do not address the nature of the bias in technological change, despite the fact that they replicate many aspects of the data.

In Bárány, Siegel (2018b) we take a different approach and propose a flexible setup that allows for productivity changes that are neutral (economy-wide), specific to firms in particular industries (producing particular products), specific to workers in certain occupations (linked to their task content), or specific to occupation-sector cells. In the next section we outline key features of this model and explain how certain aspects of the data inform us about how productivity has changed differentially across sectors and occupations. One important aspect is that we focus on employment reallocations not only between sectors and occupations, but also between occupations within sectors. Inspecting Figure 5 closely reveals for instance that routine employment has declined not only overall, but also as a share within each sector. In the next section we show that observing the changes in occupational wages, within-sector shares of employment and of income, and sectoral prices, allows us to infer what type of biased technological change has been occurring.

## Technological Biases

To understand what type of technological change might be driving these phenomena, we formulate a model of the production side of the economy. There are two key assumptions in our framework. The first is that we explicitly assume that workers in different occupations are not perfect substitutes, and thus the factors of production are the labor supplied in various occupations. This formulation is based on the observation that there are significant differences in wages across occupations, and that workers in different occupations perform different tasks. Second, we allow for different sectors to value these types of workers differently in production. In the following we outline the key features of the model and draw some conclusions about the likely biases in technological change based on the data we have summarized in the previous section. In Bárány, Siegel (2018b) we go much further by providing a framework that can be used to quantify and decompose factor-augmenting technological change into neutral, sector, occupation, and idiosyncratic components.

## Assumptions: The Production Side of the Economy

The three sectors in the economy respectively produce in perfect competition low-skilled services (*L*), manufacturing (*M*), and high-skilled services (*H*). Labor is the only input in production, but differentiated in terms of occupations. Each sector $J \in \{L, M, H\}$ employs all three types of occupations (*m,r, a*: manual, routine and abstract), with the following Constant Elasticity of Substitution (CES) production function:

$$Y_J = \left[ \left(\alpha_{mJ} l_{mJ}\right)^{\frac{\eta-1}{\eta}} + \left(\alpha_{rJ} l_{rJ}\right)^{\frac{\eta-1}{\eta}} + \left(\alpha_{aJ} l_{aJ}\right)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{1}$$

where $\eta \in [0,\infty)$ is the elasticity of substitution between the different types of labor, $l_{oJ}$ is occupation *o* labor used in sector *J*, and $\alpha_{oJ} > 0$ is a *sector-occupation* specific labor augmenting technology term for occupation $o \in \{m,r,a\}$ in sector *J*. In this formulation, $\alpha_{oJ}$ in the initial year reflects the initial productivity as well as the intensity at which sector *J* uses occupation *o*, whereas any subsequent change over time reflects sector-occupation specific technological change. The assumption that the productivity depends on both the sector and the occupation of the worker renders this production function very flexible, as it does not impose any restrictions on the nature of technological change. In particular, it does not require taking a stance on whether technological change is specific to sectors or occupations.

Firms in all sectors take prices and wages as given and maximize profits by choosing occupation $o \in \{m, r, a\}$ employment such that:

$$\frac{\partial \pi_J}{\partial l_{oJ}} = \frac{\partial \left( p_J Y_J - \sum_i w_i l_{iJ} \right)}{\partial l_{oJ}} = p_J Y_J^{\frac{1}{\eta}} \alpha_{oJ}^{\frac{\eta-1}{\eta}} l_{oJ}^{\frac{-1}{\eta}} - w_o = 0\,. \tag{2}$$

We combine these first order conditions for different occupations. Optimal relative occupational employment within sectors satisfies:

$$\frac{l_{mJ}}{l_{rJ}} = \left(\frac{w_r}{w_m}\right)^{\eta} \left(\frac{\alpha_{mJ}}{\alpha_{rJ}}\right)^{\eta-1}, \tag{3}$$

$$\frac{l_{aJ}}{l_{rJ}} = \left(\frac{w_r}{w_a}\right)^{\eta} \left(\frac{\alpha_{aJ}}{\alpha_{rJ}}\right)^{\eta-1}. \tag{4}$$

These expressions show how optimal relative labor demand depends on the relative wages and on the relative productivity of different occupations. *Ceteris paribus*, all sectors optimally use more manual labor relative to routine labor if the relative routine wage, $w_r / w_m$, is higher. Additionally, if in sector *J* the term $(\alpha_{mJ} / \alpha_{rJ})^{\eta-1}$ is larger then it is optimal to use relatively more manual labor in that sector. It is important to note that an improvement in the relative productivity of for example manual compared to routine workers, *i.e.* an increase in $\alpha_{mJ} / \alpha_{rJ}$, would lead to a different impact on the optimal relative labor use depending on whether η is larger or smaller than 1. If $\eta > 1$, then the different occupations are good substitutes, so the improvement in the relative productivity of manual workers would lead to an increased relative demand for manual workers. If, on the other hand $\eta < 1$ and the different workers are complements, then an improvement in relative technology would lead to a reduction in relative demand. So for example *routinization* in sector *J*, *i.e.* the replacement of routine workers by certain technologies, would be captured by an increase in $(\alpha_{mJ} / \alpha_{rJ})^{\eta-1}$ and in $(\alpha_{aJ} / \alpha_{rJ})^{\eta-1}$.

Using optimal manual and abstract labor as a function of routine labor from (3) and (4) and substituting these into (2) for routine labor, we can express sector *J* prices as:

$$p_J = \left[ \frac{\alpha_{mJ}^{\eta-1}}{w_m^{\eta-1}} + \frac{\alpha_{rJ}^{\eta-1}}{w_r^{\eta-1}} + \frac{\alpha_{aJ}^{\eta-1}}{w_a^{\eta-1}} \right]^{\frac{1}{1-\eta}}. \tag{5}$$

## Inferring Technological Biases

The assumptions we have made about the economy's production side constitute a framework which, given η, the elasticity of substitution between the different types of occupational labor within sectors, can be used to draw conclusions from the data about the sector-occupation specific labor augmenting technologies, the αs. While there is no consensus on the exact value of $\eta$, the literature agrees that occupations tend to be complements, and therefore this elasticity of substitution has to be less than 1. Goos *et al.* (2014) estimate, while Duernecker, Herrendorf (2016), Lee, Shin (2017) and Aum *et al.* (2018) calibrate the elasticity of substitution to be between 0.5 and 0.9. For this reason in what follows we assume that $\eta < 1$, that is that the different occupational labor inputs are complements in production.

Multiplying the optimality conditions (3) and (4) with $w_m / w_r$ and $w_a / w_r$ respectively and re-arranging the equations, we get the following expressions:

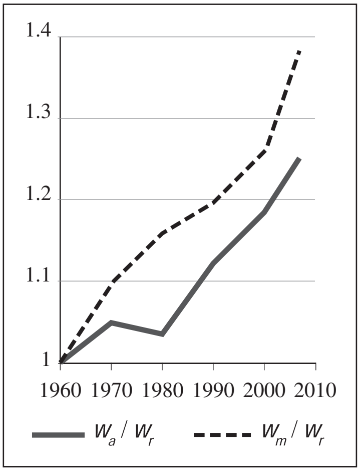
$$\frac{\alpha_{mJ}}{\alpha_{rJ}} = \frac{w_m}{w_r} \left( \frac{\theta_{mJ}}{\theta_{rJ}} \right)^{\frac{1}{\eta-1}}, \tag{6}$$

$$\frac{\alpha_{aJ}}{\alpha_{rJ}} = \frac{w_a}{w_r} \left( \frac{\theta_{aJ}}{\theta_{rJ}} \right)^{\frac{1}{\eta-1}}, \tag{7}$$

where $\theta_{oJ} = (w_o l_{oJ}) / (p_J Y_J)$ denotes the share of income in sector *J* going to workers in occupation *o*. Note that we assume that there is perfect competition, the production function is constant returns to scale, and that the only factors of production are the different types of occupational labor, which implies that profits are zero and $\sum_o \theta_{oJ} = 1$. From these equations, given data on relative occupational wages and on occupational income shares within sectors we can infer the evolution of relative occupational productivities within a sector.

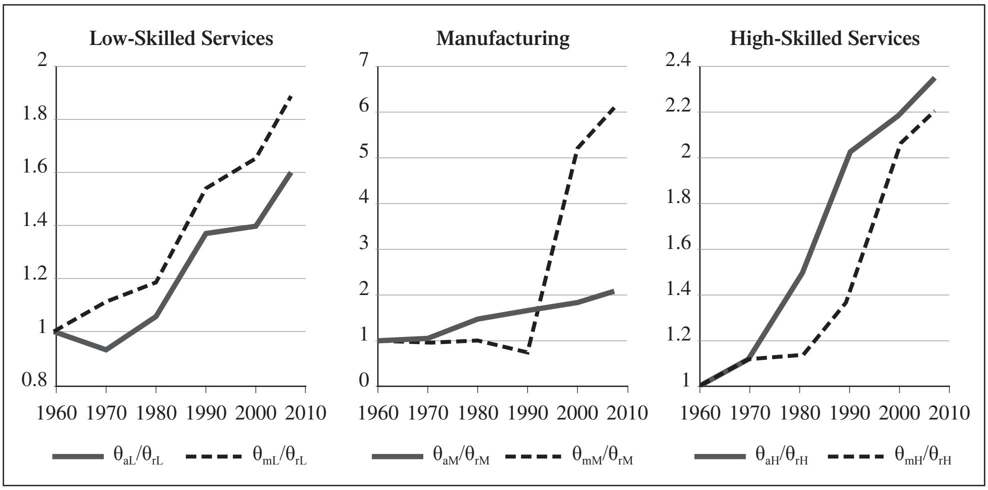
We are primarily interested in the change in relative sector-occupation productivities within sectors over time. For this reason, in Figure 6 we plot the evolution of relative wages of different occupations relative to their 1960 values. Wages in both abstract and manual occupations have increased relative to routine occupations. Overall the gain in relative wages has been around 25 percent in abstract occupations and around 38 percent in manual occupations. In Figure 7 we show the evolution of relative occupational income shares in all three sectors between 1960 and 2007, relative to their 1960 values. The income share of both abstract and manual workers has increased relative to routine ones in all three sectors albeit at a different rate. Abstract workers' income share has increased the most in high-skilled services (almost 2.5 fold), in manufacturing it has more than doubled, while in low-skilled services it has increased by 50 percent. Manual workers' income share has increased the most in manufacturing (six fold); in high-skilled services it has more than doubled, whereas in low-skilled services it has increased but less than doubled.

FIGURE 6 – **Change in Relative Occupational Wages**




*Note*: Each worker is classified into one of three occupations based on their occupation code (for details of the occupation classification see Box 2).
*Source*: The data is taken from IPUMS *US Census Data* for 1960, 1970, 1980, 1990, 2000 and the *American Community Survey (ACS)* for 2007.

FIGURE 7 – **Change in Relative Occupational Income by Sector**




*Note*: Each worker is classified into one of three sectors based on their industry code and one of three occupations based on their occupation code (for details of the industry and the occupation classification see Box 2).
*Source*: The data used is the same as in Figure 6.

It is important to note that for values of the elasticity of substitution below 1, the change in relative wages and the change in income shares imply changes of opposite sign in relative productivities. The changes in relative income shares are much larger than the changes in relative wages. The lower is $\eta$ the smaller is the change implied by the change in income shares, but even for relatively low values of $\eta$ it dominates the implied change coming from wages. We can therefore conclude that the productivity of routine workers had to increase in all sectors relative to both manual and abstract workers. This is a pattern common across sectors, and it is in line with the routinization hypothesis. The relative productivity of routine workers has increased, and since different occupations are complements in production in all sectors, this implies a lower relative demand for routine workers in all sectors. At the same time, the magnitude of change in relative income shares is markedly different across sectors, which points to the presence of sector-occupation specific changes in productivity.

Next we analyze the evolution of relative productivities across sectors. This is informed by the movement of relative sectoral prices. Using relative occupational productivities within sectors (equations [6] and [7]) and given that $\sum_o \theta_{oJ} = 1$, we can express sectoral prices (5) in terms of observables as:

$$p_J = \frac{w_r}{\alpha_{rJ}}\left[\left(\frac{\alpha_{mJ}}{\alpha_{rJ}}\frac{w_r}{w_m}\right)^{\eta-1} + 1 + \left(\frac{\alpha_{aJ}}{\alpha_{rJ}}\frac{w_r}{w_a}\right)^{\eta-1}\right]^{\frac{1}{1-\eta}} = \frac{w_r}{\alpha_{rJ}}\left[\frac{\theta_{mJ}}{\theta_{rJ}} + 1 + \frac{\theta_{aJ}}{\theta_{rJ}}\right]^{\frac{1}{1-\eta}} = \frac{w_r}{\alpha_{rJ}}\left[\frac{1}{\theta_{rJ}}\right]^{\frac{1}{1-\eta}}.$$

Computing relative prices across sectors, we can express relative sector-occupation productivities as:

$$\frac{\alpha_{rM}}{\alpha_{rL}} = \frac{p_L}{p_M}\left(\frac{\theta_{rM}}{\theta_{rL}}\right)^{\frac{1}{\eta-1}}, \tag{8}$$

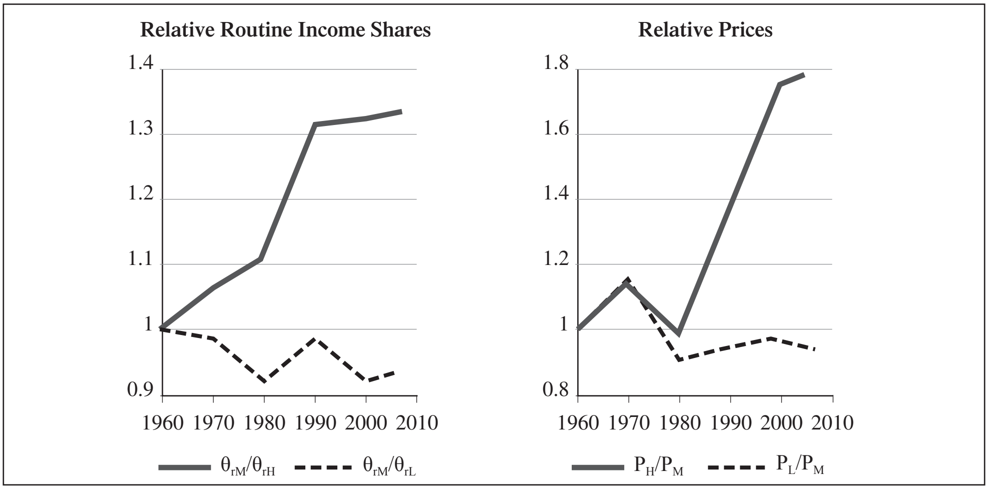
$$\frac{\alpha_{rM}}{\alpha_{rH}} = \frac{p_H}{p_M}\left(\frac{\theta_{rM}}{\theta_{rH}}\right)^{\frac{1}{\eta-1}}. \tag{9}$$

These two equations show that the evolution of relative sector-occupation productivities across sectors can be inferred from changes in relative sectoral prices and in the cross-sector ratio of routine workers' income shares.

Figure 8 shows how these two objects have evolved over time, compared to their 1960 values. The relative income share of routine workers in manufacturing has increased by more than 30 percent relative to high-skilled services, while relative to low-skilled services it has fallen, by just under 10 percent. Both relative prices have fluctuated a bit, but while overall there has been no significant change in the relative price of low-skilled services compared to manufacturing (but it has decreased slightly), the relative price of high-skilled services has increased by almost 80 percent.

The trends in relative prices imply that routine workers' technology improved at a faster rate in manufacturing than in high-skilled service, and at a slightly lower rate than

FIGURE 8 – **Change in Relative Routine Income and Prices across Sectors**




*Note*: Each worker is classified into one of three sectors based on their industry code and one of three occupations based on their occupation code (for details of the industry and the occupation classification see Box 2).
*Source*: The data is taken from IPUMS *US Census Data* for 1960, 1970, 1980, 1990, 2000 and the *American Community Survey (ACS)* for 2007 and the BEA.

in low-skilled services. The changes in the relative income share of routine workers, however, point in the opposite direction. Nonetheless, unless the two just happen to offset each other, this analysis highlights that routine workers' productivity changed not in the same way across sectors. For the range of the elasticity of substitution considered in the literature, i.e. $\eta \in (0.5,0.9)$, stronger conclusions can be drawn. Given the documented data, the implied change coming from income shares dominates, implying that routine workers' productivity in manufacturing grew faster than in low-skilled services, but it grew slower than in high-skilled services.

More generally, interpreting the patterns in the data through the lens of our model suggests that technological change has been biased across sector-occupation cells –a pure bias across occupations or sectors alone is not enough to explain the data. It is of course conceivable that there are common patterns in the cell technologies, such as common occupation or sector factors, but these are not the sole drivers.

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In this article we have reviewed our work in BÁRÁNY, SIEGEL (2018a, b) on the nexus of job polarization and structural transformation as drivers of the observed changes in labor market outcomes both at the sectoral and at the occupational level, stressing the importance of biased technological change. While sectoral reallocations, which might be caused by productivity growth differences across sectors, imply changes in employment shares and in wages across occupations that are qualitatively in line with certain aspects of the data, they cannot speak to the observed within-sector changes of occupational employment shares. This suggests that technological change must have been biased in more complex ways. However, explanations of technological change affecting workers according to their occupations differentially, such as ICT technologies adversely affecting workers in routine jobs, fall short of explaining all aspects of the data as well.

We show an occupation-bias in technology alone is not consistent with the joint observed changes in sectoral prices, occupational wages, and occupation-sector employment shares. Analyzing the data through our framework instead suggests that the productivity of routine workers relative to abstract or manual workers has changed differentially across the three sectors we consider. This leaves the possibility that technological change is entirely specific to the sector-occupation cell, or that it is biased across sectors and across occupations.

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# The Individual-Level Patterns Underlying the Decline of Routine Jobs*

*Guido Matias Cortes***

This article reviews the findings from Cortes (2016) and Cortes, Jaimovich, and Siu (2017), which explore the micro-level patterns associated with the decline in middle-wage routine employment in the United States. I show that male workers who remain in routine jobs experience significantly slower long-run wage growth than those who switch to other occupations, even when compared to those who transition to lower-skill non-routine manual jobs. I also show that changes in the employment patterns of men with low levels of education and women with intermediate levels of education account for the majority of the decline in routine employment. Individuals with these demographic characteristics used to predominantly work in routine jobs. In more recent years, they have become increasingly likely to be out of work.

Over recent decades, many developed countries have experienced marked declines in the fraction of the population employed in middle-skill occupations (e.g. Dustmann *et al.*, 2009; Goos *et al.*, 2009; Acemoglu, Autor, 2011; Goos *et al*, 2014; Jaimovich, Siu, 2012; Albertini *et al.*, 2017; Goos *et al.*, 2019). This has been linked to the declining employment in occupations that are intensive in routine tasks, *i.e.*, occupations that focus on a relatively narrow set of job tasks that can be performed by following a well-defined set of instructions and procedures. The key insight, first put forward by Autor *et al.* (2003), is that recent technological changes have resulted in the creation of machines, computers, and other forms of capital that are particularly effective at performing tasks that are routine in nature. This new capital therefore acts as a substitute for workers in occupations that feature a high content of routine tasks. As shown by Goos and Manning (2007) and the subsequent literature, these routine occupations tend to be in the middle of the wage distribution. Although there is a large

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and growing literature documenting overall patterns of labor market polarization, relatively little is known about the individual-level patterns underlying these changes. The question of who has been impacted by the decline of routine employment, and how those affected have adjusted to these changes, is not only of academic interest, but is also essential in order to design appropriate public policy responses to the observed labor market changes.

In this article I review the findings from two papers that analyze the individual-level patterns underlying the decline in routine employment in the U.S. The first, Cortes (2016), uses longitudinal data to track male workers who are initially employed in routine occupations, and explores their subsequent occupational mobility patterns and the associated short and long-term wage changes that they experience. The second, Cortes, Jaimovich, and Siu (2017) takes a broader view, analyzing which demographic groups account for the majority of the decline in routine employment, and how they have adjusted in terms of their employment outcomes.[1]

When focusing on male workers who are initially employed in routine occupations, and tracking their occupational mobility patterns over time, I find strong evidence of selection on ability among those who switch occupations. Specifically, routine workers with low ability (that is, those with relatively low wages compared to other routine workers) are more likely to switch to non-routine manual jobs, while those with high ability are more likely to switch to non-routine cognitive jobs. Interestingly, I find that workers who switch to other jobs –regardless of the direction in which they switch– experience significantly faster wage growth over long-run horizons compared to those who stay in routine jobs.[2]

While these results focus on individuals who were already employed in routine jobs, it is clear that many individuals who used to find employment in these types of jobs are no longer able to do so. Using cross-sectional data for the entire working-age population in the U.S. between 1979 and 2014, I show that changes among a relatively small subset of demographic groups can account for the vast majority of the decline in per capita routine employment. Specifically, the decline in routine manual employment is primarily attributable to changes among young and prime-aged men with low levels of education, while the majority of the decline in routine cognitive employment is accounted for by changes in the employment patterns of young and prime-aged women with intermediate levels of education. In addition to becoming much less likely to work in routine jobs, individuals from these groups have experienced sharp increases in the

1. While I focus here on heterogeneity across individuals, other papers in the literature have explored heterogeneity across other dimensions, such as local labor markets (e.g. Autor, Dorn, 2013; Dauth, 2014; Autor *et al.*, 2015) or firms (e.g Pekkala Kerr *et al.*, 2016; Böckerman *et al.*, 2019; Cortes, Salvatori, 2019; Harrigan *et al.*, 2016; Heyman, 2016).

2. A separate and rich strand of the literature studies occupational mobility and its implications for individuals' human capital and wages, but without considering the link with the aggregate changes in employment shares for different occupations. Some examples from this literature include Moscarini, Thomsson (2007); Kambourov, Manovskii (2008); Poletaev, Robinson (2008); Kambourov, Manovskii (2009); Gathmann, Schönberg (2010); Sullivan (2010); Groes *et al.* (2015); Cortes, Gallipoli (2018).

propensity to be out of employment (either unemployed or out of the labor force), and in the propensity to work in non-routine manual occupations. Interestingly, the changes experienced by this relatively small subset of demographic groups account not only for much of the decline in routine employment, but also for a substantial fraction of the increase in non-employment and in non-routine manual employment observed in the U.S. over recent decades.

## Grouping Occupations: Task-Based Approach

I begin by providing a brief overview of the way in which occupations can be grouped following the task-based approach. The literature, starting with Autor *et al.* (2003), has highlighted the usefulness of classifying occupations according to their task content. Researchers have generally focused on two dimensions of tasks: "cognitive" versus "manual," and "routine" versus "non-routine." The distinction between cognitive and manual occupations is based on the extent of mental versus physical activity. The distinction between routine and non-routine is based on whether the tasks involved can be summarized as a set of specific activities accomplished by following well-defined instructions. If this is the case, the occupation is considered routine. If instead the job requires flexibility, creativity, problem-solving, or human interaction, the occupation is non-routine.

Acemoglu and Autor (2011) discuss how occupations can be readily grouped into task categories based on their broad occupational classification. Specifically, the four major task groups can be delineated as follows:

– Non-Routine Cognitive (NRC): professional, technical, management, business and financial occupations.
– Routine Cognitive (RC): clerical, administrative support, sales workers.
– Routine Manual (RM): craftsmen, foremen, operatives, installation, maintenance and repair occupations, production and transportation occupations, laborers.
– Non-Routine Manual (NRM): service workers.

Table 1 provides examples of specific occupations included in each category, based on the mapping used in Section 3 of this paper, which combines routine cognitive and routine manual occupations into a single routine category.[3] Table 2 illustrates the differences across the three occupation groups using data for male household heads from the *Panel Study of Income Dynamics (PSID)*. The first clear pattern that emerges is that routine jobs are middle-wage jobs: in all three sub-periods, mean real wages are highest in non-routine cognitive occupations and lowest in non-routine manual ones. It is also clear that non-routine cognitive jobs are the most skill-intensive: in all three sub-periods, they have a substantially higher share of college educated workers as compared to the other two occupational groups.

3. See Cortes *et al.* (2014) for details on the exact mapping.

Table 1 – **Occupation Code Groupings**

| Task Label | Occcupations Included | 3-digit Census Codes 1970-COC | 3-digit Census Codes 2000-COC |
|---|---|---|---|
| Non-Routine Cognitive | Professional, technical and kindred workers | 001-195 | |
| | Professional and related occupations | | 100-354 |
| | Managers, officials and proprietors, except farm | 201-245 | |
| | Management, business and financial occupations | | 001-095 |
| | Managers of retail and non-retail sales workers | | 470-471 |
| Routine | Sales workers, except managers | 260-285 | 472-496 |
| | Clerical and kindred workers | 301-395 | |
| | Office and administrative support occupations | | 500-593 |
| | Craftsmen, foremen and kindred workers | 401-575 | |
| | Operatives, except transport | 601-695 | |
| | Laborers, except farm | 740-785 | |
| | Construction and extraction occupations | | 620-694 |
| | Installation, maintenance and repair occupations | | 700-762 |
| | Production occupations | | 770-896 |
| | Transport equipment operatives | 701-715 | |
| | Transportation and material moving occupations | | 900-975 |
| Non-Routine Manual | Service workers | 901-984 | 360-465 |
| Not classified | Members of armed forces | 600 | 984 |
| | Farmers, farm managers, farm laborers, farm foremen | 801-824 | |
| | Farming, fishing and forestry occupations | | 600-613 |

*Note*: COC= Census Occupation Codes. Details on the 3-digit codes are available from IPUMS (King *et al.*, 2010): https://usa.ipums.org/usa/volii/97occup.shtml for the 1970 codes and https://usa.ipums.org/usa/volii/occ2000.shtml for the 2000 codes (accessed 21 May 2019).
*Source*: Cortes (2016) Online Appendix.

Table 2 – **Descriptive Statistics**

| | Non-Routine Cognitive | | | Routine | | | Non-Routine Manual | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1976-1986 | 1987-1996 | 1997-2007 | 1976-1986 | 1987-1996 | 1997-2007 | 1976-1986 | 1987-1996 | 1997-2007 |
| Employment Share | 0.40 | 0.44 | 0.42 | 0.54 | 0.50 | 0.49 | 0.06 | 0.06 | 0.09 |
| Average Wages | 10.47 | 11.82 | 13.78 | 7.07 | 6.78 | 7.30 | 5.65 | 5.82 | 6.27 |
| **Fractions within the occupation group:** | | | | | | | | | |
| High School Dropout | 0.03 | 0.01 | 0.01 | 0.22 | 0.14 | 0.10 | 0.13 | 0.10 | 0.08 |
| High School Graduate | 0.15 | 0.15 | 0.16 | 0.49 | 0.54 | 0.52 | 0.42 | 0.44 | 0.42 |
| Some College | 0.19 | 0.22 | 0.24 | 0.22 | 0.23 | 0.26 | 0.33 | 0.33 | 0.34 |
| College | 0.63 | 0.62 | 0.59 | 0.08 | 0.09 | 0.12 | 0.12 | 0.13 | 0.16 |
| **Task measures:** | | | | | | | | | |
| Non-Routine Cognitive | 6.08 | 6.01 | 5.95 | 1.81 | 1.82 | 1.88 | 1.31 | 1.32 | 1.21 |
| Routine | 3.17 | 2.99 | 2.95 | 4.81 | 4.70 | 4.46 | 2.35 | 2.30 | 2.31 |
| Non-Routine Manual | 0.72 | 0.76 | 0.78 | 1.89 | 1.86 | 1.82 | 2.47 | 2.32 | 2.31 |

*Note*: Sample includes male household heads aged 16 to 64 employed in non-agricultural, non-military jobs, who are part of the *PSID*'s core sample and have non-missing wage data. Average wages are in constant 1979 dollars. The task measures are from the *Dictionary of Occupational Titles (DOT)* 4th Edition, published in 1977 (National Academy of Science, Committee on Occupational Classification and Analysis, 1977, 1981). *DOT* task measures are aggregated to 1970 Census Occupation Codes (COC), rescaled to have a (potential) range from zero to 10, and attached to the occupation codes observed in the data at the individual level. The average task measures for the post-1997 period are for 1997-2001, as task measures at the 1970-COC level cannot be attached to *PSID* data from 2003 onwards (when occupations are coded in 2000 Census codes).
*Source*: Cortes (2016).

The bottom three lines of Table 2 illustrate the task content measures that justify the name that has been given to each category. These task measures are obtained from the *Dictionary of Occupational Titles* (National Academy of Science, Committee on Occupational Classification and Analysis, 1977, 1981), which records a large amount of information about the tasks that are important for successful job performance in different occupations. Following Autor, Levy, and Murnane (2003), non-routine cognitive tasks are measured as the mean score for the importance of "mathematics" and "direction, control and planning". Routine tasks are captured by the mean importance of "dealing with set limits, tolerances and standards" and "finger dexterity", while non-routine manual tasks are measured based on the importance of "eye-hand-foot coordination". The table clearly shows that the occupations that we have categorized as non-routine cognitive are most intensive in these tasks; middle-wage routine occupations are most intensive in routine tasks; and non-routine manual occupations are most intensive in non-routine manual tasks. Similar task content patterns can be obtained from the O*Net dataset, which is the successor to the *Dictionary of Occupational Titles* (Acemoglu, Autor, 2011).

## Tracking Individuals over Time: Where Do Male Routine Workers Go?

This section presents results based on data from the *Panel Study of Income Dynamics (PSID)*. The *PSID* is a longitudinal dataset which has tracked a sample of individuals and their offspring since 1977. This dataset makes it possible to analyze individual workers' occupational mobility patterns and wage trajectories over different time horizons.[4] The analysis in Cortes (2016), which is discussed in this section, focuses on male household heads in the *PSID*, aged between 16 and 64, employed in non-agricultural, non-military jobs, and observed between 1977 and 2005. Before discussing the empirical results, the next sub-section outlines a theoretical framework that helps organize our thoughts about the predicted effects of routine-biased technical change (RBTC) on wage changes and occupational switches at the individual level.

### Theoretical Framework: Impacts of Technological Change on Employed Workers

Consider an economy with a continuum of workers who differ in terms of their skill levels. Workers may sort into one of three occupations: non-routine manual, routine and non-routine cognitive. Each individual worker's wage will depend both

4. The *PSID* is primarily sponsored by the National Science Foundation, the National Institute of Aging, and the National Institute of Child Health and Human Development and is conducted by the University of Michigan. *PSID* data is publicly available at http://PSIDonline.isr.umich.edu/ (accessed 21 May 2019). More details on the data are provided in Cortes (2016).

on their skill level, and on the task that they perform. Workers of higher skill levels are assumed to be particularly productive at more complex non-routine cognitive tasks.

In such a model, workers will sort into occupations as illustrated in Panel A of Figure 1.[5] The lines in the Figure represent potential wages in each occupation. The assumption that workers of higher skill levels are particularly productive at non-routine cognitive tasks is reflected in the fact that the potential wage curve is steepest in that occupation, and flattest for the non-routine manual occupation. The equilibrium of the model features two endogenously determined skill thresholds, such that the least skilled workers find it optimal to select into the non-routine manual occupation; the middle-skilled workers into the routine occupation; and the most skilled workers into the non-routine cognitive occupation. In equilibrium, average real wages are lowest among non-routine manual workers, and highest among non-routine cognitive workers, which is consistent with the data.

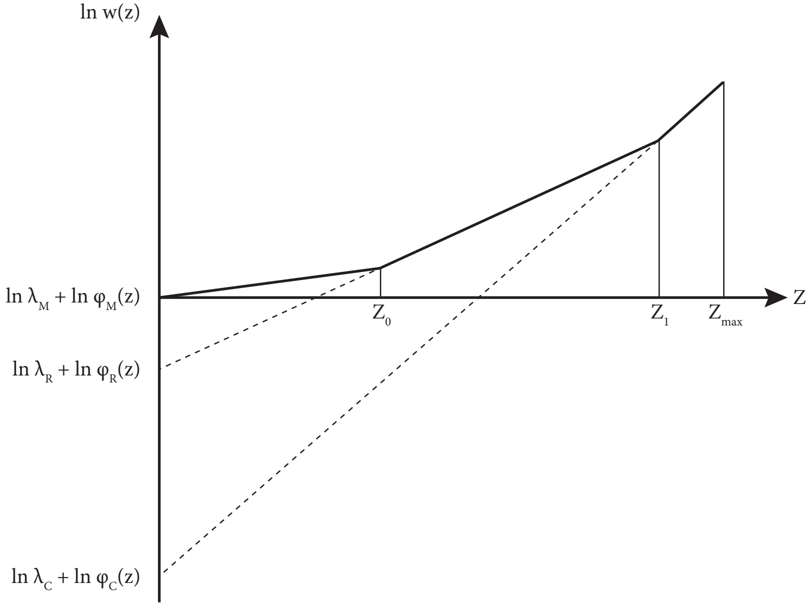
RBTC is modeled as an exogenous shock which decreases the relative demand for labor performing routine tasks and increases the relative demand for labor performing non-routine cognitive tasks. The predicted effects of RBTC are illustrated in Panel B of Figure 1. The shock shifts down the potential wage curve for the routine occupation and shifts up the potential wage curve for the non-routine cognitive occupation. In the new equilibrium, the ability thresholds shift, such that employment in both types of non-routine occupations expands, while employment in the routine occupation contracts. As the skill cutoff between routine and non-routine cognitive tasks falls, the highest ability routine workers will be the ones who find it optimal to switch to non-routine cognitive jobs (due to comparative advantage). Meanwhile, the increase in the skill cutoff between non-routine manual and routine tasks implies that it is the lowest ability routine workers who find it optimal to switch to non-routine manual tasks. Workers switching out of routine jobs must do at least as well in terms of wage growth as those who stay, as they could have chosen to stay in the routine occupation but find it optimal not to do so.

To summarize, the model provides the following predictions for the impact of RBTC: (i) workers at the bottom of the ability distribution within routine occupations switch to non-routine manual jobs, workers at the top of the ability distribution within routine occupations switch to non-routine cognitive jobs, (ii) workers staying in routine jobs experience a fall in real wages relative to those staying in other jobs, and workers staying in non-routine cognitive jobs experience an increase in real wages relative to those staying in other jobs, and (iii) workers who switch from routine to non-routine jobs (either cognitive or manual) experience an increase in real wages relative to those who stay in the routine occupation.

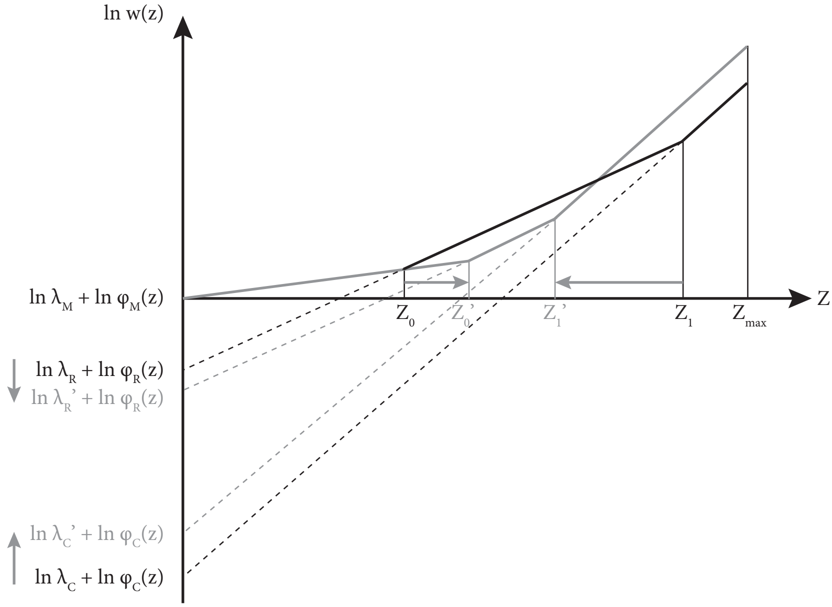
5. See also Gibbons *et al.* (2005) for a framework with the same type of sorting mechanism.

FIGURE 1 – **Equilibrium Relationship between Skills, Occupational Choices and Wages, and Effects of Routine-Biased Technical Change**

**Panel A: Model Equilibrium**




**Panel B: Effects of Routine-Biased Technical Change**



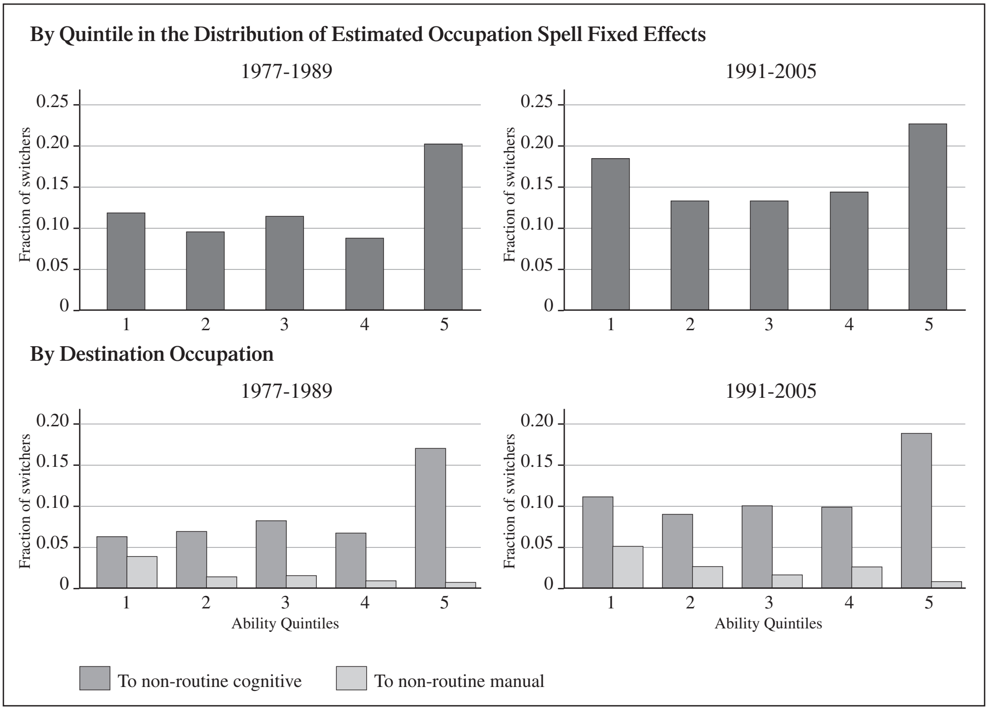

*Source*: CORTES (2016).

## Empirical Evidence: Occupational Mobility Patterns

In CORTES (2016), I estimate a series of wage regressions in order to obtain individual-specific occupation spell fixed effects which allow me to rank workers according to their position within the wage distribution in their occupation, after controlling for a number of observable characteristics. I interpret their relative position in the estimated occupation spell distribution as a proxy for their relative ability, and use these estimates to rank workers into ability quintiles within their occupation. I then determine the probability that an individual will switch out of a routine job, according to their position in this distribution.

Figure 2 plots the probability of switching occupations by ability quintile for two different periods: 1977-1989 and 1991-2005. The fraction of switchers is calculated over two year windows; that is, each bar indicates the fraction of workers from ability quintile $q$ who switch out of routine occupations between period $t$ and period $t+2$. Only odd years are used to generate the graph. These restrictions are imposed in order to ensure comparability with the period from 1997 onwards, when the *PSID* became bi-annual. The fraction of switchers is calculated over the total number of workers from each quintile who have valid occupation reports in years $t$ and $t+2$.

FIGURE 2 – **Exit Probabilities by Ability Quintile, Routine Workers**

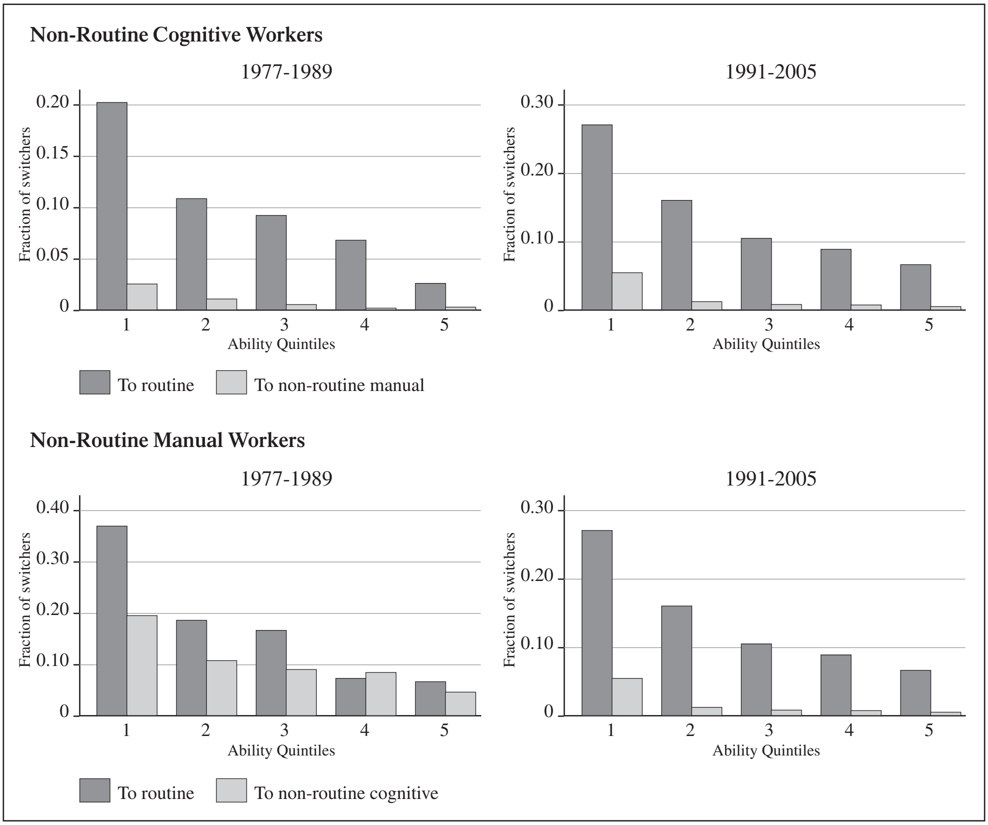



*Note*: Sample includes male workers in routine occupations, and plots their probability of switching out of this type of occupation between years $t$ and $t+2$, according to their ability quintile.
*Source*: Data from *PSID*, see CORTES (2016).

The figure shows that the highest ability workers are more likely to switch out of routine jobs compared to lower ability workers in both sub-periods. This difference is statistically significant. After 1991, the probability of switching increases for workers of all ability levels, but the increase is particularly strong for lower ability workers. This leads to a U-shaped pattern in the probability of switching after 1991.

In the bottom panels of Figure 2, I analyze the direction of the switches occurring at each quintile of the ability distribution. Switchers from all quintiles are more likely to go to non-routine cognitive jobs than to non-routine manual ones. This would be expected even if the direction of switch were random, as the non-routine cognitive occupation is much larger in terms of employment than the non-routine manual one. However, there is a clear pattern of selection according to ability quintiles. Consistent with the prediction of the model, the probability of switching to non-routine manual jobs is decreasing in ability, while the probability of switching to non-routine cognitive

FIGURE 3 – **Direction of Switch by Ability Quintile, Non-Routine Workers**




*Note*: Sample includes male workers in non-routine occupations, and plots their probability of switching out of this type of occupation between years $t$ and $t + 2$, according to their ability quintile.
*Source*: Data from *PSID*, see CORTES (2016).

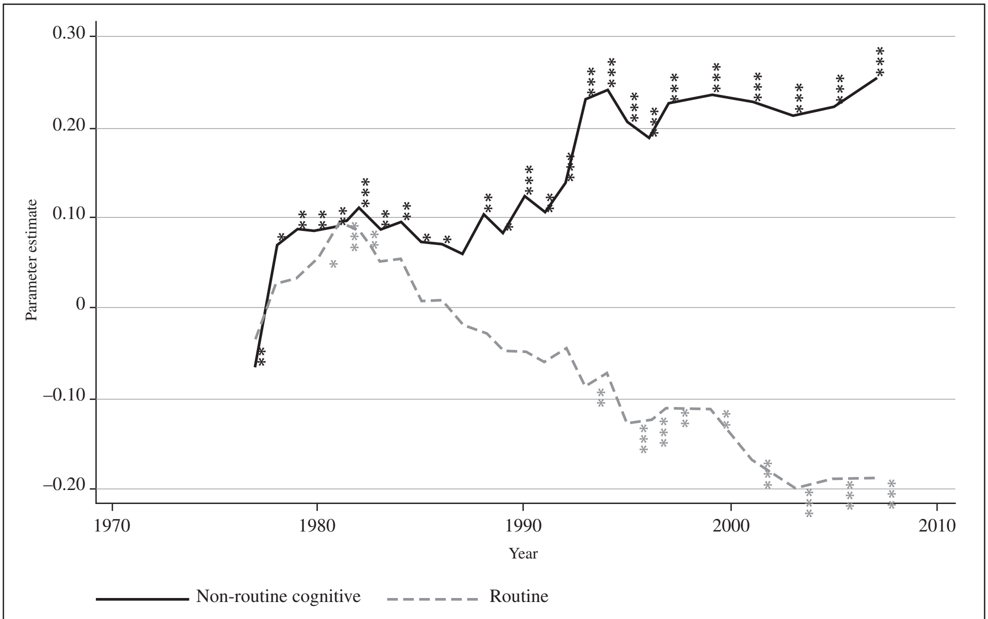
jobs is increasing in ability.[6] The differences in switching probabilities across quintiles are statistically significant during both sub-periods.

These results for routine workers can be contrasted with the switching patterns for workers in non-routine occupations. These are presented in Figure 3. Among non-routine workers we do not observe the U-shaped mobility pattern that is observed for routine workers; instead it is only the low ability workers who are disproportionately likely to switch occupations.

## Empirical Evidence: Wage Changes

Next, I analyze the wage outcomes for different workers. I consider first the wage changes for workers who do not switch occupations. These are particularly relevant, as they capture changes in the return to an occupation (*i.e.* the occupation wage premium) that are purged of compositional changes occurring within the occupation. In general, average wages within an occupation may change due to the fact that workers with certain characteristics leave an occupation while other workers enter the occupation. By focusing only on continuing workers, one can obtain a composition-adjusted estimate of the change in the return to a particular occupation.[7]

FIGURE 4 – **Estimated Changes in Occupational Returns**




*Note*: Estimated coefficients on composition-adjusted occupation-year fixed effects. Stars denote the level at which the estimated coefficients are significantly different from zero (* = 10%, ** = 5%, *** = 1%).
*Source*: Data from *PSID*, see CORTES (2016).

6. See GROES *et al.* (2015) for evidence of related patterns using administrative data from Denmark.
7. For related exercises, see BÖHM (2017) and GOTTSCHALK *et al.* (2015).

Figure 4 plots the estimates of the composition-adjusted changes in occupational returns, relative to the non-routine manual occupation. From the early 1980s onwards, the estimated return to routine occupations has a clear downward trend. Meanwhile, the corresponding return for non-routine cognitive occupations shows an upward trend, particularly from the 1990s onwards. This is consistent with the predictions of the model. Note that all of the coefficients for the later periods are significantly different from zero. The magnitude of the fall in the occupation wage premium for routine jobs is substantial. The fall from its peak in the early 1980s until the mid-2000s is similar in magnitude to the estimated rise in the college wage premium over that period.

Next, I study the wage changes for routine workers who follow different switching patterns. Table 3 presents the results of a number of wage regressions where the sample is restricted to routine workers only (both stayers and switchers). The dependent variable is the wage change, and the regressors are dummies for the direction of occupational switching (either to non-routine cognitive or to non-routine manual). Staying in routine jobs is the omitted category. The estimated coefficients reflect the differential wage growth for each type of switcher, relative to the stayers. Column (1) defines switchers and stayers based on individuals' occupational codes in years $t$ and $t + 1$, while the remaining columns are based on the codes in years $t$ and $t + 2$.

The results show that wage growth is significantly lower over horizons up to two years for workers who switch to non-routine manual jobs. When considering longer horizons (10 years), however, the differential becomes positive and significant. For example, when using fitted model wages, workers switching from a routine job in year $t$ to a non-routine manual job in year $t + 2$ experience a wage change that is 14% lower than that experienced by stayers in routine jobs. By year $t + 10$ however, the wage change for these workers is 5% above that of stayers. This result is not driven by changes in the composition of the workers included in the different regressions, as discussed in detail in Cortes (2016).

Over all time horizons, those who switch to non-routine cognitive jobs experience significantly faster wage growth than stayers. Fitted model wages grow 12% faster over a two-year period for switchers to non-routine cognitive occupations, relative to those who stay in routine jobs. The figure is similar (14%) over a 10 year horizon.

The findings presented so far on the wage growth of workers switching out of routine jobs are consistent with the predictions of the model. However, one potential concern is the possibility that occupational switching may simply reflect career progression. It might be the case that, regardless of the type of transition made, workers who switch occupations experience faster wage growth than stayers in the long run. To rule out this concern, in Cortes (2016) I replicate the analysis from Table 3 for the sample of non-routine workers and show that there is no evidence that switching occupations is generally beneficial. In fact, switchers out of non-routine cognitive occupations suffer wage losses over all time horizons considered, regardless of the direction of switch.

Table 3 – **Wage Changes for Routine Workers, According to Direction of Switch**

***Panel A: Dependent Variable is Change in Log Real Wages***

| | Change in Log Real Wages between Year *t* and Year: | | | | | |
|---|---|---|---|---|---|---|
| | *t* + 1 | *t* + 2 | *t* + 4 | *t* + 10 | *t* + 2 | *t* + 2 |
| Period | 1976-1997 | 1976-2007 | 1976-2007 | 1976-2007 | 1977-1991 | 1991-2007 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| To non-routine cognitive | 0.034<br>(0.008)*** | 0.059<br>(0.008)*** | 0.085<br>(0.010)*** | 0.163<br>(0.019)*** | 0.022<br>(0.016) | 0.088<br>(0.012)*** |
| To non-routine manual | –0.112<br>(0.023)*** | –0.143<br>(0.023)*** | –0.035<br>(0.026) | 0.115<br>(0.046)** | –0.134<br>(0.039)*** | –0.123<br>(0.033)*** |
| Constant | 0.037<br>(0.007)*** | 0.066<br>(0.009)*** | 0.016<br>(0.011) | –0.002<br>(0.018) | 0.026<br>(0.009)*** | 0.041<br>(0.010)*** |
| Observations | 15800 | 18341 | 14278 | 7568 | 4754 | 6701 |
| Number of Individuals | 2655 | 3253 | 2701 | 1735 | 1609 | 2234 |
| $R^2$ | 0.013 | 0.028 | 0.033 | 0.061 | 0.019 | 0.025 |

***Panel B: Dependent Variable is Change in Fitted Model Wages (in Logs)***

| | Change in Fitted Model Wages between Year *t* and Year: | | | | | |
|---|---|---|---|---|---|---|
| | *t* + 1 | *t* + 2 | *t* + 4 | *t* + 10 | *t* + 2 | *t* + 2 |
| Period | 1976-1997 | 1976-2007 | 1976-2007 | 1976-2007 | 1976-1991 | 1991-2007 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| To non-routine cognitive | 0.086<br>(0.010)*** | 0.122<br>(0.009)*** | 0.098<br>(0.008)*** | 0.139<br>(0.011)*** | 0.051<br>(0.014)*** | 0.184<br>(0.012)*** |
| To non-routine manual | –0.152<br>(0.023)*** | –0.139<br>(0.021)*** | –0.030<br>(0.019) | 0.054<br>(0.027)** | –0.151<br>(0.037)*** | –0.115<br>(0.028)*** |
| Constant | –0.038<br>(0.002)*** | 0.026<br>(0.003)*** | 0.049<br>(0.004)*** | –0.014<br>(0.008)* | 0.067<br>(0.003)*** | –0.034<br>(0.004)*** |
| Observations | 15800 | 18341 | 14278 | 7568 | 4754 | 6701 |
| Number of Individuals | 2655 | 3253 | 2701 | 1735 | 1609 | 2234 |
| $R^2$ | 0.168 | 0.174 | 0.147 | 0.09 | 0.179 | 0.221 |

***Panel C: Fraction of Routine Workers in Each of the Switching Categories (%)***

| | Fraction of Routine Workers in Year *t* Switching to Non-Routine Jobs in Year: | | | | | |
|---|---|---|---|---|---|---|
| | *t* + 1 | *t* + 2 | *t* + 2 | *t* + 2 | *t* + 2 | *t* + 2 |
| Period | 1976-1997 | 1976-2007 | 1976-2007 | 1976-2007 | 1977-1991 | 1991-2007 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| To non-routine cognitive | 8.07 | 10.95 | 11.26 | 11.47 | 9.82 | 13.10 |
| To non-routine manual | 1.51 | 2.18 | 1.92 | 1.88 | 1.83 | 2.75 |

*Note*: Workers who stay in routine occupations are the omitted category. All regressions include year dummies. The wage changes are taken over the time horizons indicated above each column (in years). For column (1), occupation transitions between years *t* and *t* + 1 are considered. For column (2) onwards, occupation transitions between years *t* and *t* + 2 are considered (even though the wage change may be taken over a longer horizon). Columns (5) and (6) use odd years only. Observations with log real hourly wages below 0.1 ($1.1 1979 dollars) or above 4 ($54.6 1979 dollars) are excluded. Standard errors are clustered at the individual level.
* Statistically different from zero at the 10% level.
** Statistically different from zero at the 5% level.
*** Statistically different from zero at the 1% level.
*Source*: Cortes (2016). Panel A uses changes in real wages, while Panel B uses changes in fitted model wages (changes over time in the estimated occupation spell fixed effects for each individual). For reference purposes, Panel C reports the percentage of routine workers classified into each of the switching categories.

To summarize, the results show that (conditional on remaining employed), it is workers who remain in routine jobs who are most hardly hit in terms of their long-run wage growth. Workers who transition out of routine occupations, regardless of the direction of switch, experience faster long-run wage growth than those who stay.

## Tracking Demographic Groups: Which Groups Drive the Decline in Routine Employment?

The analysis in the previous section focuses only on employed workers. However, it is clear that many workers who might have been able to find employment in routine jobs in the past are no longer able to do so. In this section, I discuss the findings from Cortes, Jaimovich, and Siu (2017), where we use nationally representative data from the *Monthly Current Population Survey (CPS)* –the main source of U.S. labor market statistics– in order to determine which demographic groups are most impacted by the decline of routine employment.[8]

### Changes in Routine Employment: Demographic Composition *vs* Propensities

We begin our analysis by determining the importance of aggregate changes in the demographic composition of the population in accounting for the decline in *per capita* routine employment. We classify individuals into 24 groups based on their age (three groups: 20-29, 30-49, 50-64, which we refer to as the young, prime-aged, and old respectively), education (four groups: less than high school, high school graduates, some college, and college graduates), and gender. The change in the fraction of the population in state *j* between period 0 and period 1 can be decomposed as follows:

$$\bar{\pi}_t^j = \sum_g w_{gt}\pi_{gt}^j, \tag{1}$$

where $w_{gt}$ is the fraction of individuals of demographic group *g* at time *t*, and $\pi_{gt}^j$ is the fraction of individuals of demographic group *g* in state *j* at time *t*. We consider five labor market states: employment in one of the four occupation groups (non-routine cognitive, routine cognitive, routine manual, or non-routine manual), and non-employment (which includes unemployment and labor force non-participation).

The change in the fraction of the population in state *j* can be decomposed as follows:

$$\bar{\pi}_1^j - \bar{\pi}_0^j = \sum_g w_{g1}\pi_{g1}^j - \sum_g w_{g0}\pi_{g0}^j = \sum_g \Delta w_{g1}\pi_{g0}^j + \sum_g w_{g0}\Delta\pi_{g1}^j + \sum_g \Delta w_{g1}\Delta\pi_{g1}^j. \tag{2}$$

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8. The *CPS* data is made available through IPUMS (Flood *et al.*, 2015). As above, we focus on the civilian, non-institutionalized population aged 20 to 64 years old, excluding those employed in agriculture and resource occupations. In Cortes *et al.* (2014), we exploit the limited longitudinal dimension of the *CPS* in order to construct worker flows into and out of routine employment, and we analyze the relative importance of changes in the different flows in accounting for the decline in routine employment.

The first term is the *composition effect*, which captures the portion that is driven by changes in the population shares of different demographic groups. The second component is the *propensity effect,* which captures the portion that is driven by changes in the fraction of individuals from group $g$ that are in state $j$. The third term is an *interaction effect.*

The results of this decomposition are presented in Table 4. In Panel A we focus on the period that features a strong decline in *per capita* employment in Routine Manual (RM) occupations: 1979–2014. In Panel B we focus on the period that features a strong decline in *per capita* employment in Routine Cognitive (RC) occupations: 1989-2014. The observed fraction of the population in each of the five labor market states is displayed in Columns (1) and (2), with the total change displayed in Column (3).

TABLE 4 – **Decompositions Based on Age-Education-Gender Groups**

| | | | **Difference** | | | |
|---|---|---|---|---|---|---|
| | **Pre** | **Post** | **Total** | **Composition** | **Propensity** | **Interaction** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| ***Panel A: 1979-2014*** | | | | | | |
| *Number of Observations* | *976,672* | *922,931* | | | | |
| NRC (%) | 21.5 | 28.2 | +6.7 | +9.7 | −2.9 | −0.0 |
| RC (%) | 17.3 | 16.1 | −1.2 | +0.6 | −2.0 | +0.3 |
| RM (%) | 23.2 | 15.1 | −8.1 | −5.2 | −5.7 | +2.7 |
| NRM (%) | 8.4 | 12.3 | +3.9 | −1.9 | +6.6 | −0.8 |
| Not Working (%) | 29.6 | 28.3 | −1.3 | −3.1 | +4.0 | −2.2 |
| ***Panel B: 1989-2014*** | | | | | | |
| *Number of Observations* | *977,282* | *922,931* | | | | |
| NRC (%) | 24.7 | 28.2 | +3.5 | +6.3 | −2.7 | −0.1 |
| RC (%) | 19.6 | 16.1 | −3.5 | +0.3 | −3.9 | +0.2 |
| RM (%) | 21.0 | 15.1 | −5.9 | −3.5 | −4.0 | +1.6 |
| NRM (%) | 9.6 | 12.3 | +2.7 | −1.7 | +4.7 | −0.3 |
| Not Working (%) | 25.2 | 28.3 | +3.1 | −1.4 | +5.9 | −1.3 |

*Note*: NRC stands for Non-Routine Cognitive, RC for Routine Cognitive, RM for Routine Manual, and NRM for Non-Routine Manual. Column (1) shows the composition for the initial period (1979 in Panel A; 1989 in Panel B); Column (2) shows the composition for the final period (2014 in both Panels). Column (3) shows the total change for the entire period, which is decomposed into the fraction attributable to changes in the composition of demographic groups in the population (Column (4)), changes in the propensity to enter the different categories conditional on demographic characteristics (Column (5)), and the interaction of the two (Column (6)).
*Source*: CORTES, JAIMOVICH, and SIU (2017). Composition of the population across different occupational groups and not working, based on individuals aged 20-64 from the monthly *Current Population Survey*, excluding those employed in agriculture and resource occupations.

Panel A shows a decline in *per capita* Routine Manual (RM) employment of 8.1 percentage points between 1979 and 2014. Although part of it is due to composition change (mainly related to the reduction in the share of the population with at most high school education), a greater proportion is driven by changes in propensities. Meanwhile, the decline in *per capita* Routine Cognitive (RC) employment in Panel B is entirely driven by the propensity effect. In fact, demographic change would have predicted an *increase* in the fraction of the population employed in routine cognitive occupations.

## Which Demographic Groups Account for the Decline in Routine Employment?

In order to determine *which* demographic groups account for the decline in per capita routine employment, we compute the change induced by each group $g$, $w_{g1}\pi_{g1}^{j} - w_{g0}\pi_{g0}^{j}$ from Equation (2), as a fraction of the total change.

The results for routine manual employment are presented in Panel A of Table 5. Five groups account for 94% of the fall in routine manual employment: male high school dropouts of all ages and male high school graduates under the age of 50.

TABLE 5 – **Fraction of change accounted for by each demographic group**

***Panel A: Routine Manual Employment, 1979-2014***

| | Males | | | Females | | |
|---|---|---|---|---|---|---|
| | 20-29 | 30-49 | 50-64 | 20-29 | 30-49 | 50-64 |
| Less Than High School | **10.26** | **19.60** | **18.66** | 3.60 | 8.41 | 5.60 |
| High School Diploma | **30.86** | **14.88** | –4.03 | 7.39 | 6.62 | 0.30 |
| | | *All Ages* | | | *All Ages* | |
| Some College | | –13.55 | | | –2.88 | |
| At Least College | | –4.41 | | | –1.33 | |

***Panel B: Routine Cognitive Employment Propensity, 1989-2014***

| | Males | | | Females | | |
|---|---|---|---|---|---|---|
| | 20-29 | 30-49 | 50-64 | 20-29 | 30-49 | 50-64 |
| High School Diploma | –2.35 | 3.16 | 3.13 | **14.80** | **24.13** | 3.54 |
| Some College | 2.15 | 5.43 | 2.38 | **12.27** | **10.62** | 1.50 |
| | | *All Ages* | | | *All Ages* | |
| Less Than High School | | 0.65 | | | 3.37 | |
| At Least College | | 8.75 | | | 6.46 | |

*Note*: Panel A presents the fraction of the total change in the population share of Routine Manual (RM) employment that can be attributed to the changes experienced by each demographic group (by age, education and gender). Panel B presents the fraction of the total change in the propensity to work in a Routine Cognitive (RC) occupation that can be attributed to each demographic group. The analysis is based on individuals aged 20-64 from the monthly *Current Population Survey*, excluding those employed in agriculture and resource occupations. The changes accounting for the majority of the total change are highlighted in bold.
*Source*: CORTES, JAIMOVICH, and SIU (2017).

Panel B performs a similar analysis with regards to the change in routine cognitive employment between 1989 and 2014. Given that the decline in routine cognitive employment is entirely driven by the propensity effect, we focus only on the groups that are most important in accounting for the changes in this component. The table shows that the groups accounting for the bulk of the decline in routine cognitive propensity are young and prime-aged females with either high school diplomas or some post-secondary education. These groups account for 62% of the propensity effect.

In Table 6 we document the change in the population share and the change in routine employment propensities for each of these key groups. Panel A focuses on the groups of men with low levels of education that are important in accounting for the decline in routine manual employment. These groups are shrinking in terms of their share of the population (*i.e.*, $w_g$ is falling). While they represented nearly a quarter of the U.S.

population in 1979, they represent less than 15% in 2014. Individuals from these key groups have also experienced dramatic reductions in the propensity to work in routine manual jobs (*i.e.*, $\pi_g$ is falling as well). For example, the fraction has fallen by about 25 percentage points for low-educated young men; while more than 60% of such individuals worked in a routine manual occupation in 1979, this is closer to one-third in 2014.

TABLE 6 – **Key Demographic Groups**

***Panel A: Routine Manual***

| | **Population Share (%)** | | | **Fraction in RM (%)** | | |
|---|---|---|---|---|---|---|
| | 1979 | 2014 | Change | 1979 | 2014 | Change |
| *Male High School Dropouts* | | | | | | |
| Age 20-29 | 1.90 | 0.89 | –1.01 | 61.58 | 37.87 | –23.70 |
| Age 30-49 | 4.12 | 2.06 | –2.06 | 63.19 | 48.94 | –14.25 |
| Age 50-64 | 4.68 | 1.51 | –3.17 | 43.09 | 32.92 | –10.17 |
| *Male High School Graduates* | | | | | | |
| Age 20-29 | 6.27 | 3.82 | –2.45 | 61.36 | 34.99 | –26.36 |
| Age 30-49 | 7.51 | 6.60 | –0.91 | 55.11 | 44.39 | –10.72 |

***Panel B: Routine Cognitive***

| | **Population Share (%)** | | | **Fraction in RC (%)** | | |
|---|---|---|---|---|---|---|
| | 1989 | 2014 | Change | 1989 | 2014 | Change |
| *Female High School Graduates* | | | | | | |
| Age 20-29 | 5.82 | 3.05 | –2.77 | 32.61 | 22.73 | –9.89 |
| Age 30-49 | 10.58 | 5.57 | –5.01 | 32.68 | 23.81 | –8.87 |
| *Female with Some College* | | | | | | |
| Age 20-29 | 3.88 | 4.70 | 0.82 | 36.77 | 24.46 | –12.31 |
| Age 30-49 | 5.48 | 6.32 | 0.84 | 33.04 | 25.50 | –7.54 |

*Note*: The table presents the change in the population share and the propensity to be employed in routine manual and routine cognitive occupations for the key demographic groups identified in Table 5.
*Source*: CORTES, JAIMOVICH, and SIU (2017).

Panel B documents the analogous patterns for the groups of women with intermediate levels of education that are important in accounting for the decline in routine cognitive employment propensities. All four groups experience obvious declines in their probability of working in routine cognitive jobs, falling from approximately one-third in 1989 to one-quarter in 2014.

Given that these key groups have experienced substantial movement out of routine employment, it is of interest to determine where they have sorted into instead. We illustrate this in Table 7 by presenting the *change* in the share of each demographic group across labor market states. The results in Panel A indicate that the dramatic decline in the probability of working in routine manual for the key demographic groups is offset primarily by increases in non-employment and, to a smaller extent, increases in non-routine manual employment. Clearly individuals from these demographic groups have not benefited from the increase in employment in high-paying, non-routine cognitive occupations observed in the aggregate.

TABLE 7 – **Change in the Fraction of Workers in Each Group (p.p.)**

***Panel A: Routine Manual, 1979-2014***

| | NRC | RC | RM | NRM | Not Working |
|---|---|---|---|---|---|
| *Male High School Dropouts* | | | | | |
| Age 20-29 | –1.10 | 2.16 | –23.70 | 7.47 | 15.17 |
| Age 30-49 | –4.95 | 0.62 | –14.25 | 9.02 | 9.55 |
| Age 50-64 | –6.31 | –0.12 | –10.17 | 2.66 | 13.95 |
| *Male High School Graduates* | | | | | |
| Age 20-29 | –3.81 | 5.22 | –26.36 | 7.79 | 17.16 |
| Age 30-49 | –8.37 | 0.64 | –10.72 | 5.32 | 13.13 |

***Panel B: Routine Cognitive, 1989-2014***

| | NRC | RC | RM | NRM | Not Working |
|---|---|---|---|---|---|
| *Female High School Graduates* | | | | | |
| Age 20-29 | –2.58 | –9.89 | –4.39 | 7.06 | 9.79 |
| Age 30-49 | –2.05 | –8.87 | –3.34 | 6.28 | 7.99 |
| *Female with Some College* | | | | | |
| Age 20-29 | –4.42 | –12.31 | –1.16 | 9.94 | 7.96 |
| Age 30-49 | –3.78 | –7.54 | –0.24 | 7.44 | 4.11 |

*Note*: The table details the changes in the fraction of workers in each occupational category and not working among the groups identified as accounting for the majority of the decline in routine manual employment and routine cognitive employment propensity. NRC stands for Non-Routine Cognitive, RC for Routine Cognitive, RM for Routine Manual, and NRM for Non-Routine Manual.
*Source*: CORTES, JAIMOVICH, and SIU (2017).

In Panel B we find that the decline in the probability of working in routine cognitive occupations among the key groups of women with intermediate levels of education has also not been met by an increase in the propensity to work in high-paying, non-routine cognitive occupations. Instead, they have increased their propensities for non-employment and employment in non-routine manual occupations (with the former more prevalent among high school graduates, and the latter among those with some college). Relative to the male groups in Panel A, we generally observe smaller increases in non-employment rates among the female groups that account for the bulk of the decline in routine cognitive propensity.

## Aggregate Importance of These Demographic Groups

How much of the aggregate change in other labor market outcomes can be accounted for by the propensity change of the key demographic groups that account for the bulk of the decline in routine employment? To determine this, we perform some simple counterfactual exercises in Table 8. The first column reproduces the change in the population share of routine employment, non-routine manual employment, and non-employment, as shown in Column (3) of Table 4. The second column reproduces the propensity effect from Column (5) of Table 4. This represents a counterfactual holding the population shares of all demographic groups constant at their benchmark level (1979 in Panel A, 1989 in Panel B) and allowing *all* group-specific propensities to change as empirically observed.

Table 8 – **Observed and Counterfactual Changes in Population Shares (p.p.)**

| | Observed (1) | Propensity (2) | Accounting CF (3) | Mitigating CF (4) |
|---|---|---|---|---|
| ***Panel A: 1979-2014*** | | | | |
| Routine | –9.30 | –7.67 | –6.20 | –5.37 |
| Non-Routine Manual | 3.85 | 6.55 | 4.17 | 0.85 |
| Non-Employment | –1.27 | 4.03 | 3.14 | –2.81 |
| ***Panel B: 1989-2014*** | | | | |
| Routine | –9.37 | –7.90 | –5.68 | –5.36 |
| Non-Routine Manual | 2.71 | 4.68 | 2.81 | 0.57 |
| Non-Employment | 3.14 | 5.88 | 4.21 | 0.24 |

*Note*: Column (1) shows the total observed change in the fraction of the population in different labor market categories, based on individuals aged 20-64 from the monthly *Current Population Survey*, excluding those employed in agriculture and resource occupations. Column (2) shows the counterfactual changes that are obtained when allowing for changes in the propensities to enter different labor market categories among all demographic groups, holding the composition of demographic groups in the population at benchmark levels. Column (3) shows the counterfactual changes (CF) that are obtained when holding the composition of all demographic groups in the population at benchmark levels, and holding the propensities at benchmark levels for all groups except those identified as being key for the decline in routine employment. Column (4) shows the counterfactual changes that are obtained when allowing the composition of demographic groups to change as in the data, while holding the propensities at benchmark levels only for the groups identified as being key for the decline in routine employment.
*Source*: Cortes, Jaimovich, and Siu (2017).

The third column presents the result of a counterfactual in which only the propensities of the *key groups* are allowed to change; demographic composition and all other propensities are held constant at benchmark levels. This allows us to determine how much of the changes in Columns (1) and (2) are accounted for by the behavioral changes in our key groups. We find that about 65% of the fall in *per capita* routine employment is accounted for by the propensity change of our key groups. This confirms the aggregate quantitative importance of the propensity change in the groups that we have identified.

More interestingly, even though the demographic groups were chosen solely based on their importance in accounting for the decline in *routine employment*, Table 8 shows that the behavioral change of these groups is also important in accounting for the aggregate changes in *non-routine manual employment and non-employment*. The propensity change of our key groups accounts for more than 100% of the observed increase in non-routine manual employment, and about 60% of the overall propensity effect. Moreover, as Panel B indicates, the propensity change of our key groups accounts for more than 100% of the observed increase in non-employment, and about 70% of the propensity effect.

In the fourth column we perform a counterfactual in which the demographic composition of the economy is allowed to change as observed in the data, and we also allow all propensities to change, except those of the key groups, which are held constant at benchmark levels. This allows us to assess how much of the observed changes can be *mitigated* by omitting the behavioral change of our key groups. As indicated in Panel A, if the propensity change of the key groups responsible for the decline of routine employment had not occurred, non-routine manual employment would only have risen by 0.85 percentage points. This mitigates 78% of the observed increase. Similarly, in Panel B, omitting the key demographic groups mitigates 92% of the observed increase in non-employment.

To summarize, the changes in employment and occupational choice of a small subset of demographic groups account for a large share of the decline in routine employment. These same groups are also key in understanding the rise of non-employment in the U.S. observed in the past 25 years and, to a slightly lesser extent, the rise of non-routine manual employment observed since 1979. This suggests that these long-run labor market changes are closely linked phenomena.

The evidence reviewed in this paper shows that the decline in routine employment has had very heterogeneous effects across different subsets of workers. Using longitudinal data for male workers, in CORTES (2016) I show that routine workers of relatively high ability are more likely to switch to non-routine cognitive jobs, while routine workers of relatively low ability are more likely to switch to non-routine manual ones. I also find that workers staying in routine jobs perform significantly worse in terms of their long-run wage growth than workers who switch to other occupations. In other words, conditional on remaining employed, the workers who are hardest hit in the long run by the effects of technological change are those who stay in routine jobs, not those who switch to other occupations. These findings suggest that it may be a more promising public policy tool to try to retrain workers who are currently in declining routine occupations, rather than trying to help them stay in their current jobs.

The evidence based on repeated cross-sectional data in CORTES, JAIMOVICH, and SIU (2017), meanwhile, highlights the fact that the majority of the decline in routine employment can be traced back to changes among a small subset of demographic groups. Specifically, most of the decline in routine manual employment is driven by changes among men with low levels of education, while most of the decline in routine cognitive employment is driven by changes among women with intermediate levels of education. Routine jobs used to be a major source of employment for workers from these demographic groups, and this has changed dramatically over the past three or four decades. Even though we know that, in aggregate, employment has been growing strongly in high-paying non-routine cognitive jobs, we find that the key demographic groups that we have identified have not benefited from this employment growth. Instead, they have become more likely to work in low-paying non-routine manual jobs, or to be out of work altogether. In fact, we find that a substantial proportion of the increase in non-employment observed in the U.S. since the late 1980s can be traced back to the small set of demographic groups that are key in accounting for the decline in routine employment.

Overall, the findings illustrate the fact that, as the structure of the labor market changes, there are both winners and losers. Our results can help guide public policy by identifying the segments of the population that have been most negatively impacted by the decline of routine employment. Evaluating specific policies that may help those who are being negatively affected by these changes in the structure of the labor market would be a promising avenue for future research.

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# Globalization, Job Tasks and the Demand for Different Occupations*

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Globalization has increased in recent decades, resulting in structural changes of production and labor demand. This paper examines how the increased global engagement of firms affects the structure of the workforce. We find that the aggregate distribution of occupations in Sweden has become more skilled between 1997 and 2013. Moreover, firms with a high degree of international orientation have a relatively skilled distribution of occupations and firms with low international orientation have a relatively unskilled distribution of occupations. High- and low-skilled occupations have increased in importance whereas middle-skilled occupations have declined with a resulting job polarization. We also discuss and analyze the role played by new technology and automatization.

International economic integration has increased substantially over the last decades and is presumably higher than ever before. One consequence of this is that a large share of workers are employed in foreign-owned firms, in firms that own foreign affiliates, and in exporting and offshoring firms. Globalization leads to an increased level of specialization in countries' production. Furthermore, globalization also results in increased competition, which, in turn, forces firms to engage in streamlining and improving their activities. Finally, globalization enables firms to benefit from economies of scale in production, which is particularly important for firms in relatively small countries. These effects of globalization have resulted in increased economic growth, higher incomes and improved living standards for large segments of the

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population (Frankel, Romer, 1999). However, what benefits individual countries, and the majority of people, does not necessarily benefit everyone. There are groups whose situation is rendered more difficult by the structural changes following increased levels of globalization.[1]

Furthermore, it appears that the nature of globalization has gradually changed. More specifically, structural change takes place within firms and between firms in the same industries, and not as before between different industries (Baldwin, 2016). This change has an impact on the relative demand for different types of labor: some occupations face decreasing demand when their tasks are relocated to foreign countries, whereas others experience an increase in demand as a result of globalization.

New research shows that when China joined the World Trade Organization (WTO), it had a significant impact on the US labor market. Many American jobs disappeared because of increased imports from China, while approximately the same number of new American jobs were added when US exports increased (Feenstra, Sasahara, 2017; Feenstra *et al.*, 2017). But even if the net effect was marginal, the economic consequences were in many cases serious and long-lasting for the American workers who lost their jobs (Autor *et al.*, 2014). While high-skilled workers managed relatively well and soon got new jobs in expanding industries, the low-skilled workers were severely affected. Decreasing incomes and increasing unemployment subsequently result in various negative effects, such as poor health, increased mortality and a decline in the number of new marriages and fertility (Autor *et al.*, 2017; Pierce, Schott, 2016).[2]

Hence, it is clear that possible negative labor market effects may come with significant socioeconomic costs. This highlights the need for a better understanding of the mechanisms set in motion by increased globalization. It should be noted that the effect is more complex than what is captured by, for instance, the educational level of the workers: the effect of globalization is not uniformly benefitting skilled workers and hurting unskilled workers. Instead, the character of the job tasks carried out by different workers seems important in determining the effect of globalization. Some job tasks can be offshored to cheaper production sites in low-income countries whereas other tasks cannot. The latter include both high- and low-skilled tasks and many previous empirical studies show that it is primarily middle-skilled tasks that are declining. As a result, job polarization tends to increase (see e.g. Goos *et al.*, 2014, for an overview).

This paper analyzes the effects of increased globalization with a particular focus on the relative demand for different occupations. Our analysis focuses on changes within firms and how these, in turn, alter the demand for different types of employees. The focus on firms allows us to present evidence on how these shape job polarization.

1. See, for example, Milanovic (2016) for an overview of the relationship between globalization and increased inequality. See also Saval (2017).

2. The increased globalization also has political implications. Citizens negatively affected by globalization have a tendency to be attracted to parties of a more protectionist or populist nature (Rodrik, 2018; Autor *et al.*, 2016; Dippel *et al.*, 2015; Colantone, Stanig, 2018a, 2018b).

More specifically, it enables us to look at how organizational changes within firms influence the trend towards a more polarized labor market, and how the main explanations for job polarization are related to firm dynamics. We also briefly discuss and analyze the role played by new technology and automatization.

The tendency of increased job polarization has been shown in a large number of studies for different countries. Two early studies are Goos, Manning (2007) and Goos *et al.* (2009). They look at the relationship between wages and employment at the level of individual occupations and the extent to which they are characterized as routine intensive. They find that occupations characterized as routine are in the middle of the wage distribution, while occupations not characterized as routine are in both the upper and lower end of the wage distribution. This indicates a potential improvement in employment opportunities for highly skilled occupations with relatively high wages as well as for low-skilled and low-wage occupations, as well as a less favorable development for middle-level occupations, mainly various white-collar occupations involving routine tasks. Hence, relative employment change is positively correlated with occupations that are non-routine and cognitive in nature and negatively correlated with occupations characterized as routine. This result is consistent with the task-biased technological change (TBTC) hypothesis and is one of the main explanations for the job polarization pattern observed in many countries.[3] TBTC stresses that new technology affects occupations and job tasks differently. Some job tasks are complements and some are substitutes to new technology. Many occupations that are substitutes to new technology and that are routine-intensive are in the middle of the wage distribution. The decrease in demand for these occupations is in line with job polarization due to routine-biased (or task-biased) technological change. It is important to note that skill-biased technological change (SBTC), which for many years was the leading explanation for how relative labor demand and wage inequality were affected by changes in technology, is not able to explain job polarization because the task content of jobs is not part of the SBTC framework. This implies that SBTC cannot explain how globalization and new technology can affect relative labor demand differently in different parts of the wage distribution –in accordance with job polarization.

A number of studies have subsequently confirmed an improvement in employment opportunities for relatively high and relatively low wages and a weaker development for middle-level occupations, mainly various white-collar occupations (see, for example, Autor *et al.*, 2006; Acemoglu, Autor, 2011; Asplund *et al.*, 2011; Autor, Dorn, 2009, 2013; Spitz-Oener, 2006; Michaels *et al.*, 2014; Adermon, Gustavsson, 2015; Heyman, 2016).

We add to the literature above by putting a special focus on labor demand and job polarization in firms with different degrees of international integration. There are good reasons to believe that this factor may make a difference. For instance, the type of tasks required for operations on the domestic market might differ from the

3. Also commonly referred to as *routine-biased technological change* (RBTC).

tasks required for export, offshoring, and other international activities. International finance and marketing, logistics, and other similar tasks required to run international operations are presumably of a high-skilled and non-routine character. As a result, there might be relatively more non-routine job tasks in globalized firms. Secondly, firms with for instance foreign affiliates are presumably in a relatively good position to divide the production chain and place different tasks in different countries. If this assumption is correct, we would expect relatively fewer routine- and low-skilled job tasks in multinational firms. At the opposite, local firms are not in the same position to use imported inputs, which means that the share of routine- and low-skilled employees can be expected to be comparably higher (see, for example, Becker *et al.*, 2013 and Hakkala *et al.*, 2014).

Our paper is structured as follows. We start by describing the mechanisms behind globalization and changes in labor demand. We also briefly discuss the link between new technology and relative labor demand. We then show how the distribution of occupations in firms has changed over time, depending on whether the firm is more or less globalized. This section also presents evidence on within-firm job polarization. We end with a discussion on how globalization and new technology affect job polarization.

## Globalization, Firms and the Labor Market

Firms in specific industries differ considerably in a number of aspects. Some firms are large, use sophisticated technology and enjoy a high level of productivity, whereas others are small and have lower productivity. Furthermore, some firms have considerable international exposure with exports, imports of inputs and perhaps affiliates located abroad. Other firms are entirely focused on using domestic inputs and selling in the domestic market.

It is a stylized fact that multinational enterprises (MNEs) are more productive, pay higher wages, and perform more R&D than domestic firms (e.g. Bernard, Jensen, 1997 and Navaretti, Venables, 2004). In his seminal work, Dunning (1981) provided an early explanation for this pattern, arguing that MNEs possess unique knowledge of production methods, management practices, or technologies. With the ownership of such firm-specific assets, MNEs are able to maintain the sales, profits, and productivity levels that are required to cover the additional costs associated with foreign expansion. Firm-specific assets have also been integrated into more formal models with heterogeneous firms in which firms select among different entry modes into a foreign market conditional on the quality of their firm-specific assets (see e.g. Helpman *et al.*, 2004).

In Helpman *et al.* (2004) firms first draw their productivity from a given productivity distribution and then sort into three firm types according to their productivity draws. With fixed cost of entry being the lowest in the home market, firms in the lower part of the productivity distribution choose only to serve the home market (domestic firms). Firms in the middle part of the productivity distribution earn enough profit to cover a fixed exporting or marketing cost to also reach consumers in foreign markets by exporting (exporting firms). Firms in the top-end of the source country productivity distribution can additionally cover the fixed cost of opening an affiliate in the foreign market, and avoid variable trade costs associated with exporting. Thus, MNEs are the most productive firm type, local firms the least productive, and exporters have an intermediate productivity level. In our empirical analysis, we will focus on these three firm types.

Developments in information and communication technology (ICT) have resulted in firms being able to more easily break up production chains and move different tasks to different geographical locations. The main reason is that it has become easier to communicate over long distances and manage logistical needs across national boundaries. As a result, firms have become more complex. MNEs have been at the forefront of a process where different parts of the production are located in different facilities and frequently also to different countries. To an increasing extent, different components are produced in different geographical locations and then shipped to other factories where they are assembled into finished products and exported worldwide. This division applies not only to the production of goods, such as components and other inputs, but also to the production of services, such as design, logistics, and marketing. Firms may increase their profitability by separating the production and locating each task where it is the cheapest and the most effective.

In the recent academic literature on global value chains, the concept of *trade in tasks* is frequently used as a complement to defining production units in terms of produced goods or inputs (Grossman, Rossi-Hansberg, 2008, 2012). Characteristics other than knowledge intensity and formal training then lead to the decision whether or not a task may be carried out at a longer distance from the head office. For instance, the degree of routine tasks and the need for close communications are important determinants of what may be relocated to other countries and what needs to be located in the home country. There are tasks that can easily be codified and do not require close monitoring or interaction with the head office or other parts of the production. Many, but not all, such tasks are routine in nature and can be carried out by low-skilled labor. Computer programming is an example of the opposite; this work requires a high level of education but may easily be performed by an engineer working in, for example, India. Cleaning and repair services, on the other hand, are examples of tasks often performed by low-skilled labor, but which are difficult to relocate far away from the rest of the operations.

All in all, this means that the relationship between the knowledge intensity of job tasks and how suitable they are for relocation is complex, which in turn means that job tasks and occupations involving both a high and a low level of knowledge are affected by increased globalization (Blinder, 2006; Blinder, Krueger, 2013; Hakkala *et al.*, 2014).

Globalization represents an important explanation for changes in demand for different types of labor, even though globalization clearly is not the only explanation. Technological development is frequently presented as another important factor behind changes in the labor market. Technology and globalization are, however, closely linked, thereby making it difficult to distinguish their effects. More specifically, new technology increases the degree of globalization, but there is also an effect of increased globalization on the development of new technology. New technological developments can therefore potentially amplify or change the way globalization impacts workers and firms. Similarly, changes in globalization can influence how new technology affects workers and firms. We will take this possible effect into account in the empirical analysis by including measures on technology.

Extensive research has shown, in accordance with SBTC, that technology shifts are associated with a higher demand for skilled workers since mastering new and more complex technology often requires a higher level of education. In recent years, however, many studies have shifted the view that education is crucial to the way technology affects different groups, particularly since SBTC is unable to explain a number of important phenomena in the labor market observed in recent years. As mentioned above, one important reason for this is that the analysis based on SBTC does not take into account the task content of jobs. Instead, and as discussed above, TBCT emphasizes the nature of the tasks performed by workers (see Leamer, Storper, 2001; Autor *et al.*, 2003 and Levy, Murmane, 2004 for three early contributions).

The job task literature and TBCT stress that the specific task contents in occupations determine how new technologies affect the relative labor demand.[4] Different types of tasks can either complement new technology or be substituted by it and this, rather than formal education, is precisely what will determine how different jobs are affected. Well-defined tasks that may be described in the form of clear rules, jobs of a so-called routine nature, could be substituted by new technologies. Tasks characterized as complex and requiring elements such as problem-solving (i.e. non-routine jobs) instead serve as complements to new technology. The increased use of ICT may thus be expected to reduce the demand for workers with routine jobs and increase the demand for non-routine jobs, which may be seen as complementing new technology. This development is in line with the extensive international evidence on job polarization. However, it should be emphasized that the relationship between new technology and demand for labor is complex and routine tasks can also be difficult to automate (Autor, 2014).[5]

4. See also Acemoglu, Autor (2011) for a more developed model incorporating SBTC and the importance of specific tasks (demand for routine and non-routine jobs). Autor (2013) is a summarizing paper on how job task contents and technology affect labor markets.

5. Autor (2014) discusses the relationship between digitalization and the demand for different types of tasks on the basis of the so-called Polanyi's Paradox. Polanyi's Paradox says that many simple tasks may be surprisingly difficult to automate. Autor (2014) further argues that complementary effects between new technology and labor may be significant.

Globalization is also closely related to the routinization of jobs. A large empirical literature has presented evidence on how globalization affects the relative demand for routine jobs (see e.g. BECKER *et al.*, 2013; BAUMGARTEN *et al.*, 2013; and HAKKALA *et al.*, 2014). These papers show that increased globalization tends to increase the demand for non-routine jobs and jobs characterized by personal interaction. For instance, results in HAKKALA *et al.* (2014) indicate that MNEs employ a higher share of non-routine jobs and that acquisitions of local firms by MNEs tend to increase the relative demand for non-routine and interactive job tasks. This suggests that foreign direct investments (FDI) increase the demand for non-routine and interactive tasks, hence a link between globalization and de-routinization of jobs. Another link between globalization and routinization of jobs, analyzed in e.g. BAUMGARTEN *et al.* (2013), is how offshoring affects the relative demand for jobs in terms of their routine content. Since routine tasks and tasks that do not require personal interaction can be more easily located at a distance from the home country, this implies that increased offshoring leads to a de-routinization of jobs in the home country.

We now continue by presenting empirical evidence on how globalization affects labor markets with a particular focus on relative demand for different occupations and job polarization. We also discuss our results in relation to the international evidence on relative labor demand and job polarization.

## Globalization and the Organization of Firms: Empirical Evidence

### Swedish Matched Employer-Employee Data

We will use detailed, register-based, matched employer-employee data from Statistics Sweden (SCB) to examine how globalization shapes the relative demand for different occupations. The database includes data on firms and individuals, which are linked with unique identification numbers and cover the period from 1996 to 2013. The firm data contain detailed information on all Swedish firms, including variables such as value added, capital stock (book value), number of employees, wages, ownership status, sales, and industry. The data on individuals originate from Sweden's official wage statistics and contain detailed information on a representative sample of the labor force, including full-time equivalent wages, education, occupation, and gender. Occupations are based on the *Swedish Standard Classification of Occupations* (*SSYK96*) which in turn is based on the *International Standard Classification of Occupations (ISCO-88).*

Firm-level data on exports and imports by product and country of origin come from the Swedish Foreign Trade Statistics, collected by Statistics Sweden.[6] Based on

6. These data cover the period 1997-2013.

compulsory registration at Swedish Customs, the data cover all the trade transactions from outside the EU. Trade data for EU countries are available for all firms with a yearly import or export of around 1.5 million SEK[7] and above. Material imports are defined at the 5-digit level according to NACE Rev 1.1 and grouped into Main Industrial Groupings (MIGs) based on intended use. Based on the MIGs definition of intermediate inputs we identify offshoring using import data at the firm and product level.

Information on foreign MNEs operating in Sweden comes from the Swedish Agency for Economic and Regional Growth (Tillväxtanalys). The Agency uses definitions that are in accordance with definitions concerning similar data from the OECD and Eurostat. A firm is classified as a foreign-owned MNE if more than 50% of the equity are foreign-owned. Finally, Swedish MNEs are defined as firms reporting positive exports to other firms within the corporation.

All data sets are matched by unique identification codes. We restrict our analysis to firms with at least ten non-farm private sector employees who are observed throughout the period.

## Relative Demand for Different Occupations Over Time

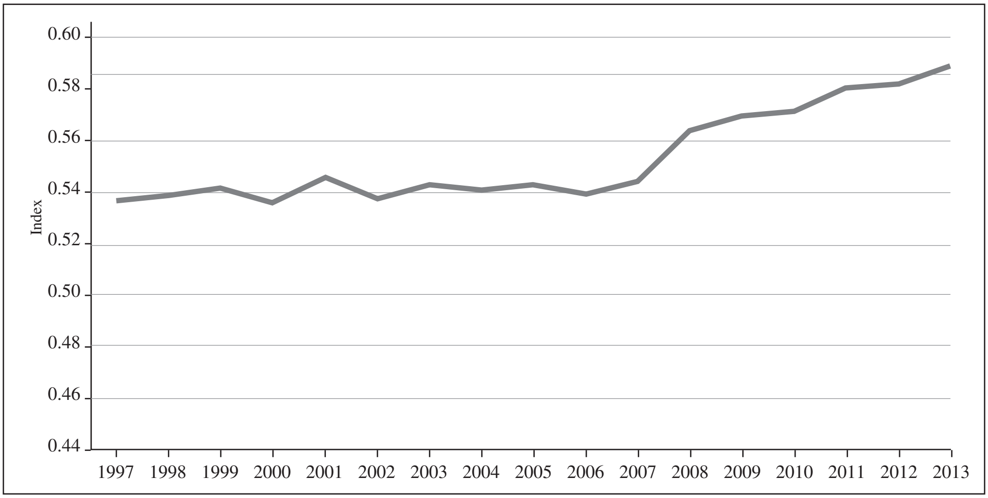
As discussed above, there are reasons to expect that increased internationalization has an effect on how firms organize production. Below, we compare the relative occupational structures in firms with different degrees of international involvement in order to examine the effect of globalization on the occupational composition.

We first rank occupations by average wage level over the period 1997-2013 at the national level.[8] The highest average wages (highest ranks) are found for chief executive officers (CEOs), lawyers, and healthcare specialists. The lowest average wages are observed for cleaners, and kitchen and restaurant workers. We then measure the share of the workforce in the different occupations at the firm level. For each firm, we compute an index that summarizes the ranks of the occupations weighted by their share in the firm's workforce. The firm index varies between 0.01 and 1, and a high index means a high level of employment in high-wage occupations.[9]

Figure 1 shows the average national index for the period 1997-2013. The index was stable up until 2007. After 2007, the index has continuously increased: it was about 0.54 in 2007, while it had increased to about 0.59 by 2013. This means that the occupational composition has become more skilled: an increasing share of the workforce is working in relatively skilled occupations and a decreasing share in relatively less skilled occupations.

7. Swedish Krona (around 140,000 Euros).
8. See Davidson *et al.* (2017) for results and details regarding different alternative occupational rankings. These include ranking (i) on the basis of wages in non-MNEs (in order to take higher wages in MNEs into account), (ii) on the basis of education, and (iii) on the basis of a regression approach where we take various individual characteristics into account. The results are robust and do not change depending on our choice of ranking.
9. See Davidson *et al.* (2017) for details regarding this index.

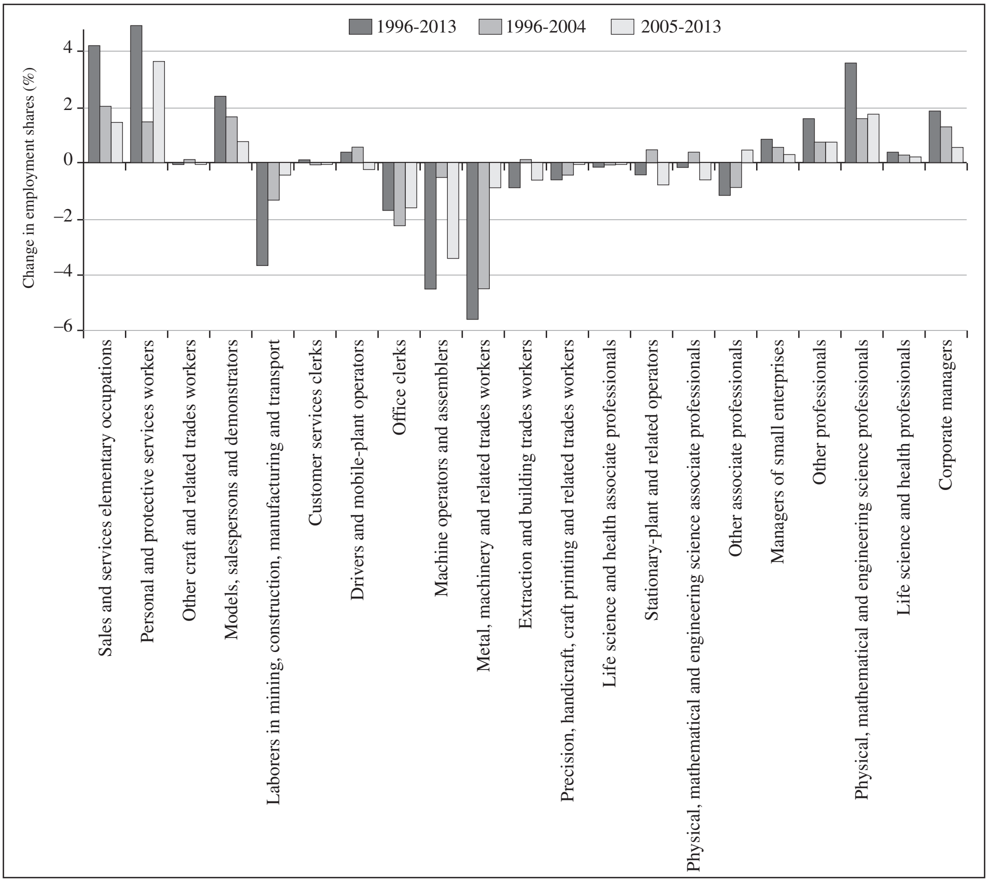
Figure 1 – **Evolution of the Occupational Composition in Sweden 1997–2013 (Index)**




*Note*: The index is estimated at the firm level. A high value represents a relatively skilled occupational composition. The figure shows annual averages at the national level. See Davidson *et al.* (2017) for details.

A similar picture is presented in Figure 2, showing the evolution in employment shares for 21 specific occupational categories. In order to be able to make a comparison with the work by Goos *et al.* (2009, 2014) on job polarization, we have applied the same grouping of occupations. Figure 2 suggests that the pattern in Figure 1 is more complex than an increase in the share of the most skilled employees and a decrease in the lowest skilled employees. The general trend is an increase in the skill level (Figure 1) but there are dramatic changes in the skill distribution (Figure 2). More specifically, the largest increase is seen for both occupations at the top and at the bottom of the wage distribution. For low-wage occupations, we see an increase in employment shares for occupations in the service, care and security sectors and for different types of services requiring a low level of education only. High-wage occupations increasing in employment shares include various specialist and managerial occupations. We also note a reduction in relative shares for a number of occupations, several of which are located in the middle of the wage distribution. These include occupations in machine and assembly work in addition to metal and repair work. All in all, the changes in Figure 2 support the presence of job polarization, i.e. the simultaneous growth of high-skilled, high-wage jobs and low-skilled, low-wage jobs at the expense of middle-skilled jobs.

FIGURE 2 – **Changes in Employment Shares for Different Occupational Categories 1996-2013**




*Note*: The occupational distribution is identical to the one used in GOOS *et al.* (2014). The least skilled occupation on the basis of wages is found on the left and the most skilled on the right.
*Source*: HEYMAN (2016).

## Job Polarization within Firms

The job polarization literature typically focuses on employment changes in different occupations, with no consideration given to how firms shape the labor demand process, but there are a few exceptions. One is HEYMAN (2016) who uses detailed matched firm-worker data for Sweden spanning the period 1996-2013 to investigate the role played by firms in the recent trend toward a more polarized labor market. The study presents results that show novel evidence on within-firm job polarization. Accordingly, KERR *et al.* (2016) find evidence of job polarization within Finnish firms and that this polarization is also influenced by the entry and exit of firms. They also find that increased trade and offshoring play a role in terms of job polarization. Finally, HARRIGAN *et al.* (2016), who study French firms, find that job polarization occurs both within and between firms.

Changes in employment can be decomposed into a within-industry component and a between-industry one. GOOS *et al.* (2014) find that both components are qualitatively important in terms of explaining the overall pattern in their study on 16 European countries. Hence, job polarization is driven by both employment dynamics within industries as well as between industries. We present similar results based on our

FIGURE 3 – **Changes in Employment Shares 1996-2013**

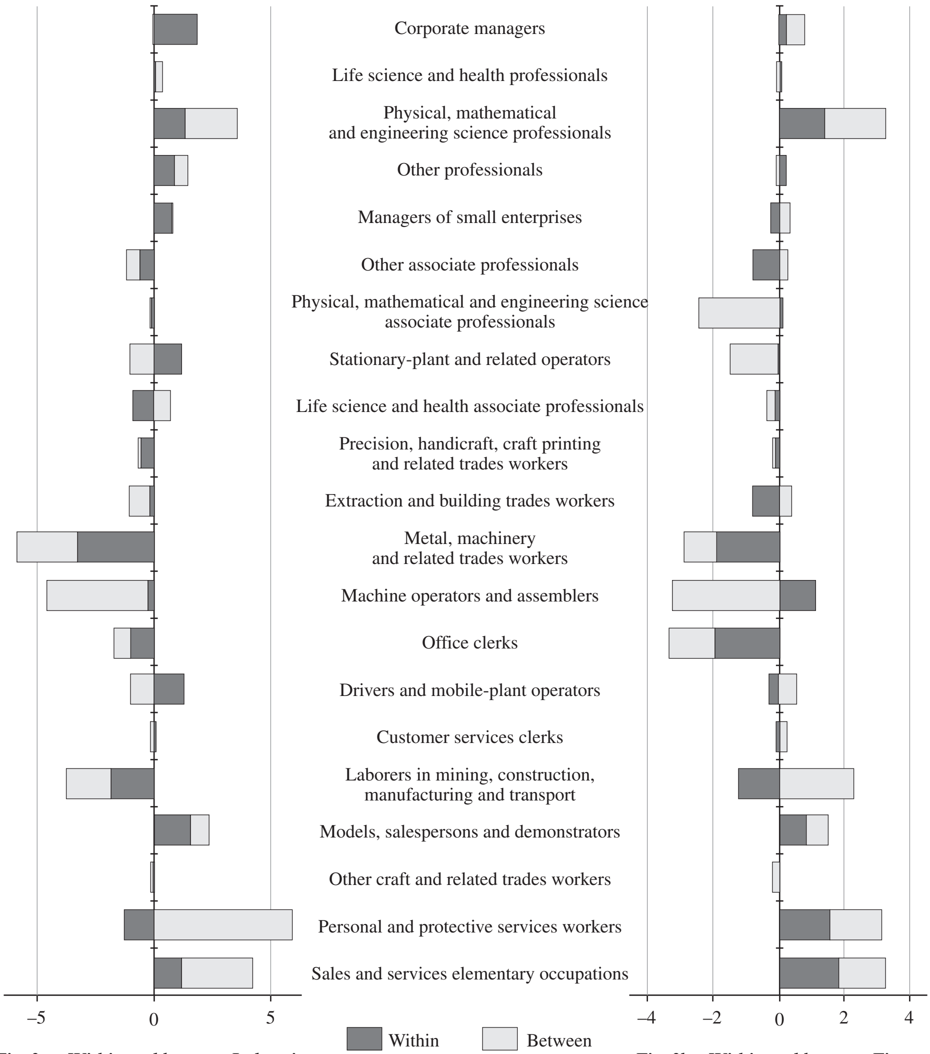



**Fig. 3a – Within and between Industries**

**Fig. 3b – Within and between Firms**

*Note*: The figures show decompositions of changes in employment shares for the period 1996-2013. Occupations are based on ISCO-88 and are ordered by their mean wage in the first year (1996). Each bar represents percentage point changes in employment shares between 1996 and 2013.
*Source*: HEYMAN (2016).

matched-employer-employee data to see if the same pattern is present in Sweden.[10] In addition to studying industry components, we extend the analysis in Goos *et al.* (2014) by looking at employment dynamics at the firm level and the importance of within-firm and between-firm components of overall job polarization. Figure 3a presents results using industry decomposition and Figure 3b shows corresponding results at the firm level. Both industry components are typically positive for high-wage and low-wage occupations and are mostly negative for the group of middle-wage occupations.

Occupations are also divided into three wage groups as in Goos *et al.* (2009, 2014). We observe a 6.7 percentage point increase in the employment share for the high-wage group, a decrease in the middle-wage group equal to 17.8 percentage points and an increase in the low-wage group equal to 11.1 percentage points. Both industry components are positive for the high-wage and low-wage groups and are negative for the middle-wage group. These results are in accordance with results in Goos *et al.* (2014) and indicate that overall job polarization originates from both within- and between-industry reallocation.

Similar patterns can also be traced at the firm level (Figure 3b). One difference is related to changes in employment shares for low-wage jobs. For this wage group, the intra and inter components are generally stronger at the firm level than at the industry level, suggesting that the increasing demand for low-wage jobs is much more due to reallocation at the firm level, both within and between firms, than reallocations within and between sectors. These results are in accordance with recent research stressing the importance of firm heterogeneity (see, for example, Melitz, 2013).

After showing descriptive evidence on overall job polarization in Sweden, we now present regression results at the firm-level. We estimate within-firm regression models where the shares of workers in the three wage groups are regressed on year dummies. All regressions also include time-varying firm characteristics and firm fixed-effects. Details can be found in Heyman (2016).

Figure 4 presents the results. The figure plots the estimated coefficients for the year dummies for the three different wage groups.[11] Hence, Figure 4 shows annual changes in employment shares and not the overall change in employment between 1996 and 2013. There is an increasing trend in the share of employees in the high-wage group, while at the same time, the share of middle-wage group workers decreases within firms over time. These two developments are consistent with within-firm job polarization. The annual changes in low-wage employment are less clear. However, the estimated coefficients are systematically positive during the period for the low-wage group and are added up to positive changes observed in accordance with the results in Figures 2 and 3. Overall, the evidence in Figure 4 points to a divergence in employment dynamics across occupations at different parts of the wage distribution.

10. The results and discussion in this section are based on results in Heyman (2016).
11. The exact estimates are available upon request.

FIGURE 4 – **Within-Firm Job Polarization in Sweden, 1996-2013**


*Note*: Job polarization in Sweden 1996-2013. Estimated coefficients on occupation group-year dummies. The figure plots estimated year coefficients obtained from equation (1) in HEYMAN *et al.* (2016). Stars denote the level at which the estimated coefficients are significantly different from zero. To allow for within-firm correlation over time, standard errors are adjusted for clustering at the firm level. ***, **, * show significance at the 1%, 5%, and 10% level, respectively.
*Source*: HEYMAN (2016).

## How are the Different Occupational Categories Affected by Globalization?

We continue our analysis by looking in more detail at the extent to which changes in globalization are related to changes in the relative demand for different occupations (Table 1). The classification into low- and high-skilled occupations is based on the average wage over the period 1997-2013, as shown in column 1. Managerial employees have the highest average wage and laborers have the lowest. The difference in wages between these two groups is approximately 130 percent. Column 2 shows the shares of total employment for the occupational categories, and column 3 shows the corresponding wage cost shares.

Columns 4-7 show the corresponding shares in the manufacturing industry and the service sector, respectively. The largest differences are found in the less skilled occupations: machine operators represent a large group within the manufacturing sector but a very small group in the service sector, whereas service and sales workers represent a large group in the service sector but are non-existent in the manufacturing sector.

Next, we divide our firms into three types and estimate regressions at the firm level to compare firms with different levels of international engagement. As previously mentioned, our firm types are MNEs, which are the most globally integrated firms; non-MNEs that do not export (i.e. local firms), which are the least globally integrated; and

TABLE 1 – **Differences between Firm Types in Employment Shares (Percent) for Different Occupational Categories, 1997-2013**

| | | | | **Manufacturing** | | **Service** | | Employment Share | | Wage Share | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean Wage (1) | Employment Share (2) | Wage Share (3) | Employment Share (4) | Wage Share (5) | Employment Share (6) | Wage Share (7) | $\alpha_k^M$ (8) | $\alpha_k^X$ (9) | $\alpha_k^M$ (10) | $\alpha_k^X$ (11) |
| ***Higher-Skilled Occupations*** | | | | | | | | | | | |
| Managers | 38,988 | 6.41% | 10.75% | 6.48% | 11.23% | 6.37% | 10.44% | 0.041*** | 0.030*** | 0.071*** | 0.047*** |
| Research Professionals | 32,651 | 7.72% | 10.84% | 8.00% | 11.10% | 7.54% | 10.68% | 0.044*** | 0.029*** | 0.044*** | 0.029*** |
| Business Professionals | 28,009 | 9.83% | 11.85% | 8.54% | 10.15% | 10.64% | 12.95% | 0.086*** | 0.049*** | 0.083*** | 0.049*** |
| Technicians | 25,691 | 10.20% | 11.27% | 11.94% | 12.93% | 9.10% | 10.19% | 0.043*** | 0.029*** | 0.037*** | 0.026*** |
| Other Professionals | 24,533 | 3.37% | 3.55% | 1.78% | 2.00% | 4.37% | 4.58% | –0.010*** | –0.013*** | –0.012*** | –0.014*** |
| ***Lower-Skilled Occupations*** | | | | | | | | | | | |
| Craft | 20,778 | 11.18% | 9.99% | 12.06% | 10.21% | 10.62% | 9.85% | –0.094*** | –0.049*** | –0.091*** | –0.049*** |
| Machine Operators | 20,177 | 14.62% | 12.69% | 35.01% | 29.81% | 1.75% | 1.48% | 0.028*** | 0.031*** | 0.020*** | 0.027*** |
| Transportation Operators | 19,265 | 4.03% | 3.34% | 1.62% | 1.37% | 5.55% | 4.63% | –0.057*** | –0.047*** | –0.057*** | –0.047*** |
| Information-Processing Clerks | 19,222 | 6.75% | 5.59% | 4.59% | 3.78% | 8.12% | 6.77% | 0.036*** | 0.030*** | 0.024*** | 0.022*** |
| Sales and Service Workers | 18,802 | 12.11% | 9.80% | 0.62% | 0.55% | 19.37% | 15.85% | –0.079*** | –0.066*** | –0.079*** | –0.066*** |
| Other Clerks | 18,340 | 5.13% | 4.04% | 1.67% | 1.41% | 7.31% | 5.77% | –0.003 | –0.004** | –0.007*** | –0.006*** |
| Laborers | 16,880 | 8.65% | 6.28% | 7.67% | 5.46% | 9.26% | 6.82% | –0.034*** | –0.019*** | –0.035*** | –0.020*** |

*Note*: This table lists twelve broad occupation groups based on their functions in production. Column 1 shows the average wages for 1997-2013. Columns 2 and 3 show the employment and wage cost shares. Columns 4-7 show corresponding shares in the manufacturing industry and the service sector. Columns 8-11 report estimates from firm-level regressions, where $\alpha_k^M$ indicates the difference in employment shares (or wage shares) between multinational (MNEs) and local firms, and $\alpha_k^X$ indicates the difference in employment shares (or wage shares) between exporting non-MNEs and local firms. Standard errors are clustered by firm. ***, **, * show significance at the 1%, 5%, and 10% level, respectively.
*Source*: HEYMAN, SJÖHOLM (2018).

non-MNE exporters, which represent an intermediate degree of global integration. The dependent variable is the occupational share, and the regressions control for time and industry variation as well as for a variety of firm characteristics, such as size, capital intensity, firm age and labor productivity (see Davidson *et al.*, 2017, for details).

The results for MNEs and exporters are shown in columns 8–11 and are based on both employment shares and wage shares. $\alpha_k^M$ is an estimate of the share of a given occupational category working in MNEs in comparison with the share employed in local firms after we have taken the above mentioned firm-specific factors into account. A positive coefficient means that MNEs have a relatively large share of the occupational category in question compared to similar local firms. A negative coefficient means that they have a relatively small share in relation to local firms. In the same way, $\alpha_k^X$ captures the share of an occupational category in exporting firms compared to the share in local firms.

For instance, looking at managers, and on the basis of employment shares, we observe that the estimated coefficient for $\alpha_k^M$ is equal to 0.04. This means that in comparison with local firms, the share of managers is 4 percentage points higher for MNEs. The corresponding estimate for exporters, $\alpha_k^X$, is approximately 0.03, indicating that the share of managerial employees is on average 3 percentage points higher for exporters compared to local firms.

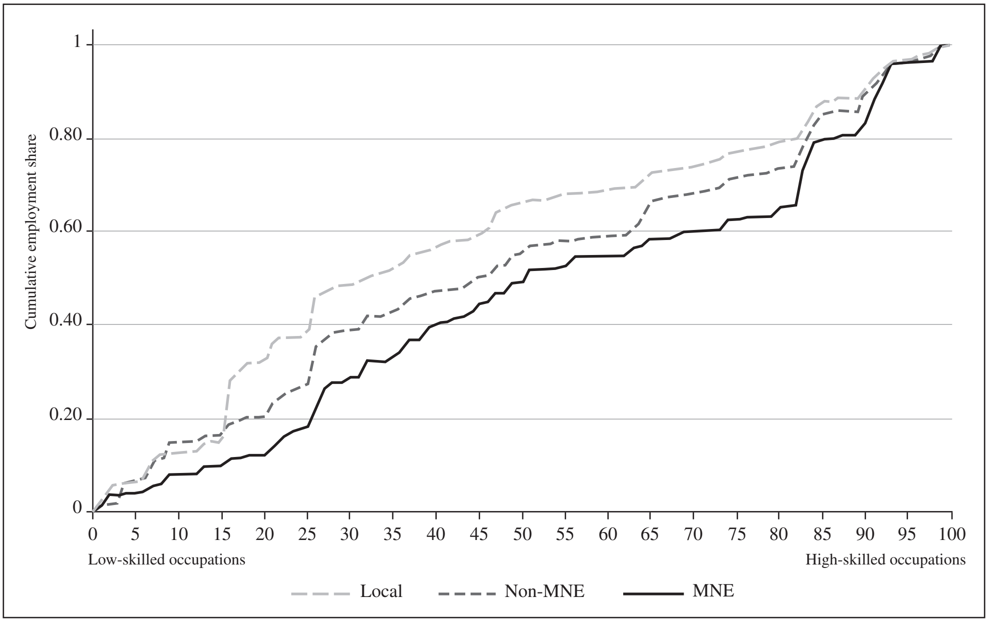
As we can see in Table 1, MNEs and exporters have a larger share of employees within highly skilled occupations compared to local firms. The difference between local and globalized firms is particularly significant with regard to legal and financial specialists; MNEs employment share is close to 4 percentage points larger than local firms. Furthermore, we see that the coefficient for $\alpha_k^M$ in all high-skilled occupational categories. This means that the shares are larger in MNEs than in exporting firms. In other words, we observe the largest shares of high-skilled occupations in MNEs followed by exporting firms and then by local firms.

The results for less-skilled occupations are basically a mirror image of the above results. MNEs and exporting firms generally have a relatively low share of low-skilled jobs. The exceptions are machine operators and information assistants, of which local firms have relatively low shares. The difference between local firms and globalized firms is particularly significant for construction workers and for service and sales workers. Furthermore, the coefficient for MNEs tends to be smaller than the coefficient for exporting firms. This indicates that for less skilled occupational categories, MNEs tend to have the smallest employment shares, local firms the largest shares and exporting firms somewhere in-between.

### A More General Picture of the Occupational Distribution in Different Firm Types

We also analyze how the overall occupational distribution differs between different firm types (Figure 5). Along the x-axis, we have ranked our 100 occupations from the least skilled to the most skilled. Just like before, the ranking is based on the

FIGURE 5 – **Composition of Occupations Based on Skill Levels in Different Firm Types, 1997-2013**




*Note:* "Local" are non-exporters that are not MNEs, "Non-MNE" are exporters that are not MNEs and "MNE" are multinational enterprises. See DAVIDSON *et al.* (2017) for details.

average wage for the occupations throughout the period. The y-axis corresponds to the cumulative employment share of the labor force accounted for by the skill category that is indicated on the x-axis. If all occupations represented the exact same share of the workforce, we would have a 45-degree straight line. The curves for the three firm types differ, indicating differences in the shares of different occupations for different firms. The curve for local firms appears above the curve for exporters and a little more above the curve for MNEs. This is a result of the relatively large share of low-skilled occupations in local firms. For instance, we observe that the 50 percent lowest-skilled occupations account for almost 70 percent of employees in the least globalized firms (local) and about 50 percent in the most globalized firms (MNEs). Exporters have a share located somewhere in-between local and multinational firms. The results in Figure 5 illustrate that firms level of globalization is positively correlated with the share of highly skilled occupations. This in turn implies a positive relationship between the presence of local firms and the relative demand for low-skilled jobs. Overall, the results in Figure 5 are in accordance with a job polarization pattern where globalized firms have employed an increasing number of high-skilled jobs at the same time as local firms have increased their share of low-skilled occupations.

Yet another way of analyzing the difference in occupational composition is to use our previously defined index in regressions with different firm types and different control variables as explanatory variables. In Table 2, we only show the estimated

TABLE 2 – **Differences in Occupational Structures between Different Firm Types. Firm-Level Regressions, 1997-2013**

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| MNE | 0.137*** | 0.116*** | |
| | (0.004) | (0.004) | |
| Non-MNE Exporter | 0.092*** | 0.074 *** | |
| | (0.004) | (0.003) | |
| Offshoring | | 0.050 *** | |
| | | (0.003) | |
| Foreign MNE | | | 0.084 *** |
| | | | (0.004) |
| Swedish MNE | | | 0.083*** |
| | | | (0.005) |

*Note*: This table shows estimated coefficients from regressions with an index of the skill level in the firms' workforce as dependent variable. The regressions are at the firm level and cover the period 1997–2013. The estimated coefficients show the skill level in the occupational composition compared to the composition in local firms. A positive estimated coefficient indicates that a firm type has a more skilled occupational composition than local firms. All regressions control for firm size, capital intensity, value added per employee and firm age. They also control for industry-specific and year-specific factors. The regressions are based on 69,109 observations. To allow for within-firm correlation over time, standard errors are adjusted for clustering at the firm level. ***, **, * show significance at the 1%, 5%, and 10% level, respectively

Source: HEYMAN, SJÖHOLM (2018). See also DAVIDSON *et al.* (2017) for details.

coefficients for our firm types, which show the difference in the skill index for different globalized firms as compared to local firms. For instance, a positive coefficient means that the firm in question has a distribution of occupations more geared towards highly skilled occupations than local firms.

In column 1, we compare MNEs and exporters with local firms. The results show that MNEs have the most skilled occupational composition in comparison with the other firm types: MNEs have more employees in high-wage occupations and fewer employees in low-wage occupations. Non-MNE exporters have an occupational composition between MNEs and local firms.

We previously discussed offshoring as an additional dimension of international integration. In column 2 we examine if offshoring has an impact on the occupational mix. Offshoring is measured by imported inputs as a share of total sales. As shown in column 2, the inclusion of offshoring has little impact on our main results. Although the offshoring coefficient is statistically significant, the main result is driven by the fact that MNEs or exporters employ much more skilled jobs than local firms.

In the last column, we look at occupational differences on the basis of multinational ownership and show differences between different types of MNEs. The results indicate that there is no difference between Swedish and foreign-owned MNEs; both firm types have a relatively skilled occupational composition.

## Do Globalization and New Technology Contribute to Within-Firm Job Polarization?

Figures 2-4 showed job polarization to have increased in Sweden. In Table 3, we examine the main determinants to the increased job polarization. The focus is on the results on within-firm polarization presented above. The results and discussion in this section is based on Heyman (2016).

As discussed above, it is of course difficult to distinguish between the technological effect and that of globalization. Many of the same arguments on how new technology and routineness of jobs influence different occupations can also be applied to the impact of international trade and offshoring. Sorting out the relative importance

Table 3 – **Routineness, Automation, Offshoring and Job Polarization at the Firm Level. Firm-Level Regressions, 1996-2013**

| | **High Wage Group (1)** | **High Wage Group (2)** | **Middle Wage Group (3)** | **Middle Wage Group (4)** | **Low Wage Group (5)** | **Low Wage Group (6)** |
|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High |
| ***Panel a: Routineness*** | | | | | | |
| D_1999-2003 | –0.012*** | 0.006 | 0.014*** | –0.011*** | –0.002 | 0.006* |
| | (0.005) | (0.004) | (0.005) | (0.004) | (0.004) | (0.003) |
| D_2004-2008 | –0.010* | 0.042*** | 0.023*** | –0.056*** | –0.013** | 0.014*** |
| | (0.006) | (0.005) | (0.006) | (0.006) | (0.005) | (0.004) |
| D_2009-2013 | –0.007 | 0.064*** | 0.020*** | –0.078*** | –0.013** | 0.014*** |
| | (0.007) | (0.006) | (0.007) | (0.006) | (0.006) | (0.004) |
| ***Panel b: Offshoring*** | | | | | | |
| D_1999-2003 | 0.008** | –0.008* | –0.008* | 0.004 | 0.000 | 0.005** |
| | (0.004) | (0.004) | (0.005) | (0.005) | (0.004) | (0.002) |
| D_2004-2008 | 0.020*** | 0.023*** | –0.013** | –0.034*** | –0.007 | 0.011*** |
| | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) | (0.003) |
| D_2009-2013 | 0.033*** | 0.036*** | –0.024*** | –0.049*** | –0.009 | 0.012*** |
| | (0.006) | (0.006) | (0.007) | (0.006) | (0.007) | (0.003) |
| ***Panel c: Automation*** | | | | | | |
| D_1999-2003 | 0.003 | –0.004 | –0.006 | 0.002 | 0.004 | 0.002 |
| | (0.005) | (0.004) | (0.005) | (0.005) | (0.003) | (0.003) |
| D_2004-2008 | 0.021*** | 0.023*** | –0.025*** | –0.026*** | 0.004 | 0.003 |
| | (0.006) | (0.005) | (0.006) | (0.006) | (0.003) | (0.005) |
| D_2009-2013 | 0.031*** | 0.039*** | –0.035*** | –0.043*** | 0.004 | 0.003 |
| | (0.007) | (0.006) | (0.006) | (0.007) | (0.004) | (0.006) |
| Firm Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |

*Note*: The dependent variable is the share of high-, medium- and low-wage employees at the firm level. Low and high in columns 1-6 refer to initial values of routineness, automation and offshoring. For each wage group, firms are divided into two groups, high and low, based on initial values of routineness, automation and offshoring. Firm controls include the log of value added per employee and the log of the capital-labor ratio. Firm and year fixed effects are included in all estimations. To allow for within-firm correlation over time, standard errors are adjusted for clustering at the firm level. ***, **, * show significance at the 1%, 5%, and 10% level, respectively.
*Source*: Heyman (2016).

of these factors is difficult and outside the scope of this paper. In this paper, we instead show regression-based evidence on how routineness, offshoring and automation of jobs correlate with the observed pattern of within-firm job polarization. We refer to HEYMAN (2016) for more details.

Panel a in Table 3 shows results on routineness, panel b on offshoring and panel c on automation. To investigate how the degree of routineness of jobs is related to within-firm job polarization we divide firms into two groups according to the intensity of routineness for the firm's workforce in their initial year. Routineness is defined by the routine task-intensity (RTI) index used in e.g. AUTOR (2013), AUTOR, DORN (2013), and GOOS *et al.* (2014). RTI is available at the 2-digit level for the Swedish job classification, SSYK96. A higher value indicates that the occupation is characterized by more routine tasks. We then estimate separate regressions on each wage group and on each group according to the intensity of routineness. The hypothesis is that firms with a high initial share of employees with routine tasks have greater opportunities to reallocate their workforce towards a higher share of non-routine jobs, than firms that initially have a low share of routine jobs. Columns 1, 3 and 5 show estimations on the group of firms with high initial average routineness. The corresponding regressions on low routineness firms are presented in columns 2, 4 and 6.[12]

Looking across the different estimated coefficients, we note that the pattern presented in Figure 4 above –showing evidence on within-firm job polarization– corresponds to firms with high initial routineness among their workforce. For instance, comparing columns 1 and 2 we can see that the increase in employment for the high-wage group comes from firms that initially can be characterized as high-routine. These are firms with high shares of routine jobs at the beginning of the period and in which opportunities for de-routinization have implied a higher relative demand for high-wage jobs. For firms that initially can be characterized as low-routine, we notice a small decline in high-wage jobs at the beginning of the time period that becomes insignificant in the most recent period.

The same pattern is also observed for the demand for low-wage jobs in high-routine firms (compare columns 5 and 6). For these firms, we notice a clear increase in employment for low-wage occupations. These results, in combination with decreasing demand for middle-wage workers in firms with high initial average routineness (column 4), are consistent with routine-biased technological change as an explanation for job polarization. If we instead study firms with low initial average routineness, we do not note any job polarization (columns 1, 3 and 5).

Overall, the results in panel a in Table 3 indicate that the initial composition of the workforce in terms of the degree of routineness and its change over time are systematically related to the observed pattern of within-firm job polarization.

12. See HEYMAN *et al.* (2016) for details.

Panel b shows similar results on the impact of offshorability. The measure of offshorability of jobs is identical to the measure used in e.g. Goos *et al.* (2014) and originates from Blinder, Krueger (2013). We now take into account firms' occupational structure and the offshorability of these occupations to see how this is associated with the relative demand for the three different wage groups. Differences in offshorability among the firms' workforce are not systematically related to job polarization (see columns in panel b). The only exception is for low-wage workers.

Finally, a similar pattern can be seen when we look at automation risks for occupations. Results are presented in panel c. The measure of automation of jobs is the same as in Frey, Osborne (2013). They have estimated the extent to which new technology can replace labor for individual occupations in the US labor market in 2010. Approximately 47 percent of total employment in the US are at risk of being automated within one to two decades. The probabilities of automation have been converted to the Swedish classification of occupations (see Heyman *et al.*, 2016, for details).

Similarly to what is found for the offshorability of jobs, no systematic pattern of job polarization can be observed for automation risks. Given the close relationship between an occupation's routineness and its risk of being automated, we have also analyzed combinations of routineness and automation risks (not shown). For these combinations, the degree of routineness of the initial composition of the workforce is more important than the corresponding classification of firms in terms of automation risks. The same pattern also emerges when we study combinations of firms' workforce in terms of routineness and offshorability. These results again suggest that routine-biased technological change is an important explanation for job polarization.

We conclude that the results in Table 3 indicate that de-routinization is the most important explanation for the observed within-firm job polarization depicted in Figure 4. We also note that the results on high-routine firms and high-wage jobs are in accordance with the previously presented results on skill-upgrading among globalized firms. For instance, acquisitions of local firms by MNEs lead to an increase in high-wage jobs, characterized by less routine.

One puzzle that remains for future research to investigate is the increase in demand for low-wage jobs in firms that initially can be characterized as high-routine. This is, however, offset by a corresponding decrease in demand for low-wage jobs in low-routine firms, implying a rather unchanged share of low-wage occupations when studying within-firm dynamics (Figure 4). In combination with a decreasing demand for middle-wage jobs (originating from firms that initially can be characterized as high-routine), the increase in within-firm employment originates from high-wage firms. This is in accordance with results presented above on a skill-upgrading of globalized firms, with increasing demand for high-skilled occupations (Figures 1, 5 and Table 2). These high-skilled, high wage occupations are also characterized by less routine.

The above results and discussion show that there is a relationship between the level of international activities and the demand for high-skilled occupations. An important question is whether this relationship is a causal relationship. For instance, a firm's technological development could lead both to an increased demand for a highly skilled workforce and increased competitiveness, thereby increasing its international activities.

To estimate the causal effect of increased export shares on the skill mix at firm-level, DAVIDSON *et al.* (2017) use an instrumental variables method and construct instruments for export shares in order to control for time-varying unobserved factors that are correlated with export shares and skill mix. More specifically, they use changes in global supply and demand for goods produced by Swedish firms.[13] The reasoning behind this approach is that when global demand (import) increases, there is a positive export shock for Swedish firms producing these goods. Likewise, an increased global supply of inputs constitutes a positive import shock for Swedish firms using these imported inputs.

The results in DAVIDSON *et al.* (2017) show that there is a causal relationship between international trade and the share of high-skilled workers. However, the mechanism behind this effect looks different for exports compared to the import of inputs (offshoring).

When Swedish firms experiencing an exogenous positive increase in demand (a positive export shock) increase their exports, the share of employees working in high-skilled occupations also increases. One may break down this effect for different employee categories. Such a breakdown shows that the increase applies to both white- and blue-collar workers. In other words, increased exports lead to more white-collar workers working in relatively skilled occupations and fewer in less skilled occupations, and the same applies to blue-collar workers.

The effect of offshoring is a similar increase in the share of white-collar workers and a similar increase in high-skilled white-collar occupations, but it also results in an increase in less skilled blue-collar occupations.

Globalization has increased substantially over the last few decades. As a result, production patterns have changed and with them, the demand for different types of workers. In this paper, we have looked at the effects of some of these changes on the labor market. Firstly, we have shown that the overall distribution of occupations in Sweden has become more skill-intensive over time. There are more people working in relatively skilled occupations today than in the 1990s. The increasingly skilled distribution is not, however, caused by a decline in the lowest skilled occupations. On the contrary, both the lowest and the highest skilled occupations have increased their employment shares. The share of medium skilled occupations has declined, which altogether has led to an increased job polarization.

13. This method is increasingly used in international economics and was first developed by HUMMELS *et al.* (2014).

We have then examined the role of globalization in changing the distribution of occupations. We have found that globalized firms have a more skilled distribution of occupations than less globalized firms. More precisely, multinational firms have a more skilled distribution than firms that only sell their products on the local market. Exporting firms have a distribution which is less skilled than multinational firms but more skilled than local firms. Again, the share of low-skilled employees has increased, which suggests that this share might have increased in local firms, an issue that future research might shed new light on.

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# ABSTRACTS

## Polarization(s) in Labour Markets

### Job Polarization, Structural Transformation and Biased Technological Change

*Zsófia L. Bárány, Christian Siegel*

By reviewing our work in Bárány, Siegel (2018a, 2018b), this article emphasizes the link between job polarization and structural change. We summarize evidence that job polarization in the United States has started as early as the 1950s: middle-wage workers have been losing both in terms of employment and average wage growth compared to low- and high-wage workers. Furthermore, at least since the 1960s the same patterns for both employment and wages have been discernible in terms of three broad sectors: low-skilled services, manufacturing and high-skilled services, and these two phenomena are closely linked. Finally, we propose a model where technology evolves at the sector-occupation cell level that can capture the employment reallocation across sectors, occupations, and within sectors. We show that this framework can be used to assess what type of biased technological change is the driver of the observed reallocations. The data suggests that technological change has been biased not only across occupations or sectors, but also across sector-occupation cells.

KEYWORDS: biased technological change, structural change, employment polarization

JEL: O41, O33, J24

### The Individual-Level Patterns Underlying the Decline of Routine Jobs

*Guido Matias Cortes*

This article reviews the findings from Cortes (2016) and Cortes, Jaimovich, and Siu (2017), which explore the micro-level patterns associated with the decline in middle-wage routine employment in the United States. I show that male workers who remain in routine jobs experience significantly slower long-run wage growth than those who switch to other occupations, even when compared to those who transition to lower-skill non-routine manual jobs. I also show that changes in the employment patterns of men with low levels of education and women with intermediate levels of education account for the majority of the decline in routine employment. Individuals with these demographic characteristics used to predominantly work in routine jobs. In more recent years, they have become increasingly likely to be out of work.

KEYWORDS: labor market polarization, technological change, heterogeneous effects, inequality

JEL: J21, J23, J31, J62

## Globalization, Job Tasks and the Demand for Different Occupations

*Fredrik Heyman, Fredrik Sjöholm*

Globalization has increased in recent decades, resulting in structural changes of production and labor demand. This paper examines how the increased global engagement of firms affects the structure of the workforce. We find that the aggregate distribution of occupations in Sweden has become more skilled between 1997 and 2013. Moreover, firms with a high degree of international orientation have a relatively skilled distribution of occupations and firms with low international orientation have a relatively unskilled distribution of occupations. High- and low-skilled occupations have increased in importance whereas middle-skilled occupations have declined with a resulting job polarization. We also discuss and analyze the role played by new technology and automatization.

Keywords: occupations, job polarization, globalization, multinational enterprises, exporter, automatization
JEL: F10, F16; F23

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