Task Specialization within Establishments and the Decline of Routine Employment

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Abstract

The prevailing explanation for job polarization maintains that technology reduces the demand for routine middle-skill employment, but there is limited evidence on occupational changes at the firm level. This paper uncovers a rich new set of facts about the way in which establishments are organized from a task perspective, and the establishment-level patterns underlying the observed changes in the employment composition of the economy. Using workplace-level data from the UK, we show that establishments tend to specialize in particular tasks, with a substantial fraction of their employment concentrated within one broad occupational category. There is considerable variation in task specialization across establishments within industries, in contrast with the recurrent assumption of homogeneity in the technology of production within industries. We show that occupational specialization increased over time, and the fraction of private sector workplaces specializing in non-routine tasks increased sharply between 1998 and 2011. These changes account for most of the changes in aggregate employment shares, while changes in the intensity of use of different tasks conditional on specialization play a relatively minor role. Establishment entry and exit accounts for an important fraction of the change in the specialization composition of establishments. We also document a large increase in the use of computers in non-routine manual workplaces and find no support for the hypothesis that the adoption of new technologies is associated with a lower propensity to increase employment.

1 Introduction

In recent decades labor markets in many developed countries have become increasingly polarized: the share of employment in middle-wage occupations has declined, while employment in both high- and low-wage occupations has increased (Acemoglu and Autor, 2011). A growing literature since Autor et al. (2003) links the decline in middle-wage employment to the task content of occupations. Workers in middle-wage occupations tend to perform tasks that are very "routine" in nature, i.e. they involve following a well-defined set of procedures and are relatively easy to automate. Increasing automation therefore has important implications for the composition of employment and wage inequality. A pessimistic view even argues that the speed of recent technological change is likely to result in a net reduction in employment, fueling a wave of what has been termed "new technological anxiety" (Autor (2015), Mokyr et al. (2015)).

In spite of the central role for the demand side of the labor market in the proposed explanation for the decline in middle-wage employment, most of the literature has focused on the analysis of aggregate or individual-level data (e.g. Autor et al. (2006); Acemoglu and Autor (2011); Firpo et al. (2011); Goos et al. (2014); Cortes (2016)). This paper uncovers a rich new set of facts related to the decline of routine employment from an establishment-level perspective. Our unique contribution is to focus on the occupational composition of employment within establishments.[1] We present new information about the way in which workplaces are organized from a task perspective. Our findings also provide new insights about the changes over time occurring at the establishment level which underlie the observed aggregate employment polarization patterns.

Understanding how the decline in routine employment has come about at the establishment level is important in terms of formulating appropriate conceptual frameworks that can help us understand the driving forces behind the observed changes in the occupational composition of the economy. Polarization theories suggest that firms will substitute workers for capital in performing routine tasks (Autor et al., 2003), but direct evidence at the firm level is very limited. Given the widespread availability of new technologies and the secular decline in the cost of computing one might expect similar adjustments in the occupational composition of employment to occur across all firms in the economy. However, a separate strand of the literature finds that firm heterogene-

[1] Previous literature has considered the extent of skill dispersion within firms (e.g. Iranzo et al. (2008)), but not the extent of occupational heterogeneity.

ity is very widespread, even within narrowly defined industries (Melitz and Redding (2014), Bloom and Van Reenen (2011)). Recent work on wage inequality also finds that most of the increase in inequality in Germany and the United States is accounted for by growing differences in wages across (rather than within) establishments (Card et al. (2013); Barth et al. (2014); Song et al. (2015)). Studying firm-level patterns is therefore particularly relevant in light of this evidence, as it suggests that the adjustments may differ substantially between different types of firms. Understanding these differences provides new insights into the polarization phenomenon, and focusing on the task composition of establishments may in turn provide useful information about a potential mechanism underlying the increased heterogeneity in wages between firms.

We use data from the Workplace Employment Relations Survey (WERS) from the United Kingdom, which provides establishment-level data including the occupational composition of employment within establishments. Cross-sectional data is available for 1998, 2004 and 2011. We also exploit the availability of follow-up questionnaires, which provide information on survival rates and employment growth between waves for most establishments in each cross-section.

Our first key finding is that establishments tend to be highly specialized in particular occupations. 90% of private sector establishments in 2011 employ at least half of their workers in one of four broad task groups. We show that this is not driven by small establishments. We also show that specialization rates are similarly high among independent establishments that are not part of larger firms. The fraction of workplaces with more than 50% of their employment in one broad occupational group has increased over time alongside the intensity of use of the main occupation within specialized workplaces. This is consistent with the evidence for the United States presented in Handwerker et al. (2015), who show that occupational concentration increased in the 2000s, and can explain a small amount of wage inequality growth between establishments during this time period. The changes in the occupational specialization patterns that we find are also consistent with the outsourcing of certain tasks, such as what has been documented for Germany by Goldschmidt and Schmieder (2015).

Our next key finding is that there is widespread heterogeneity in task specialization across workplaces. Strikingly, over 60% of this variation is concentrated within industries. The task mixes that are observed at the industry level are therefore the result of the aggregation across a very heterogeneous set of workplaces, rather than being informative about a representative firm. We also find that establishment characteristics – namely, establishment age, size, and the region in which they are located –

provide little explanatory power in terms of the heterogeneity in specialization within industries. This heterogeneity reflects differences in the way in which different workplaces produce similar goods, which may be due to differences in the extent to which the firm has invested in technology and capital, differences in managerial practices and the organizational structure of the firm, or differences in the technology of production for different varieties of goods within an industry. Our results put into question the common assumption made in the polarization literature of homogeneity in technology within industries, which is a crucial assumption in order to interpret within-industry changes as reflecting changes in technology rather than in output mix.[2]

When analyzing the changes in specialization patterns over time, we find that the proportion of workplaces specializing in a non-routine task has increased swiftly in the private sector from 30% to 50%. These changes are only partly explained by changes in industrial composition. We perform a decomposition to show that these changes in the population of firms in terms of their task specialization account for most of the changes in aggregate occupational shares, both overall and within industries. Changes in the intensity of use of different tasks conditional on task specialization play a relatively minor role.

We then provide additional insights on the importance of differential survival and growth rates between workplaces in driving the changes in specialization that we observe. We find evidence that non-specialized workplaces are more likely to shut down, but no clear indication that routine workplaces are more likely to close or reduce employment than non-routine ones. When comparing the specialization patterns for firms that shut down to those of new entrants, we find that establishment entry and exit plays a major role in accounting for the large decline in the fraction of establishments specializing in routine manual tasks observed throughout our sample period. Changes in specialization among continuing establishments play a more important role in terms of the increase in the fraction of non-routine cognitive establishments between 2004 and 2011.

Finally, we provide evidence on technology use and adoption at the workplace level and find no support for the hypothesis that the net impact of technology adoption on workplace employment is negative. While computer use continues to be higher in cog-

[2]For a recent discussion of these issues in the context of firms' responses to local labor supply shocks, see Dustmann and Glitz (2015). See Goos et al. (2014) for a recent example of a paper on job polarization in which the distinction between changes between and within 1-digit industries have substantive implications.

nitive workplaces, we document a large increase within non-routine manual workplaces in a relatively short period of time: between 2004 and 2011, the average share of employees using a computer more than doubled (from 16% to over 33%) in non-routine manual workplaces. Further analysis shows that non-routine manual workplaces are the least likely to report the adoption of new technology, but they also had the largest increase in the proportion doing so before the recession. Non-routine manual workplaces that reported the adoption of technology were less likely to shut down, while a similar association is not present for other workplaces. Moreover, the adoption of new technology is correlated with a subsequent decline in the establishment's share of non-routine manual employment. These facts are particularly interesting in light of the fact that the literature on routine-biased technological change is generally agnostic on the relationship between technology and non-routine manual low-skill employment.

Our paper is part of an emerging literature on the establishment-level patterns underlying job polarization. Gaggl and Wright (2015) exploit a discontinuity in a temporary tax incentive in order to estimate the effects of ICT investment on the employment of different occupational groups within establishments. Petri et al. (2013) and Pekkala Kerr et al. (2015) use panel data from Finland to analyze the importance of within and between firm changes in contributing to the overall changes in the occupational composition of the economy. Meanwhile, Harrigan et al. (2015) develop a new measure of the propensity of firms to adopt new technologies, and use administrative data from France to analyze the link between this measure and changes in the occupational composition of employment within firms. Our results complement the findings from these recent papers by emphasizing the pervasiveness of specialization within establishments and by showing how changes over time in the specialization patterns are linked to the polarization of employment observed at the aggregate level.

2 Data and occupational shares

We use data from three cross-sections of the British Workplace Employment Relations Survey (WERS) of 1998, 2004, and 2011 (BIS, 2015). The survey covers a representative sample of workplaces in Great Britain with at least 5 employees (at least 10 in 1998) in all sectors of the economy except agriculture and mining. To maximize consistency over time we restrict our attention to establishments with at least 10 employees.[3] We use

[3]We check the robustness of our results (when possible) to the use of workplaces with more than 5 employees.

data from the Management Questionnaires, which provide a wide range of establishment characteristics, including the composition of employment within the workplace. A workplace – which is our unit of observation – is defined as an enterprise or part thereof (for example a workshop, factory, warehouse, office, mine or depot) situated in a geographically identified place. A workplace comprises the activities of a single employer at a single set of premises.

The weighted WERS sample is representative of 35% of all workplaces in Britain in 2011, due to the exclusion of small workplaces. However, these workplaces account for 90% of total employment, so changes in these establishments will clearly be the main drivers of changes in the overall employment patterns of the economy.[4]

Crucially for our analysis, managers are asked how many employees at the workplace can be classified in each one of nine occupational groups. In each year, managers were provided with descriptions of each occupational group and these descriptions are highly consistent over time, as we discuss in Appendix B. These ten groups map easily into those used in much of the analysis in Acemoglu and Autor (2011) and we follow their approach in aggregating these occupations as follows:

1. Non-routine cognitive (NRC): Managers; Professionals; Technicians.

2. Routine cognitive (RC): Administrative and secretarial occupations, Sales and customer service occupations.

3. Routine manual (RM): Skilled trades occupations; Process, plant and machine operatives and drivers.

4. Non-routine manual (NRM): Caring, leisure and other personal service occupations; Other unskilled occupations.

Table 1 presents the aggregate share of each of these four occupational groups over time obtained from the workplace-level data for the whole economy (in Panel A) and then separately in the public and private sector (in Panels B and C), using establishments with at least 10 employees. Between 1998 and 2011, routine employment declined entirely because of the decline in routine manual employment which lost about 10pp from the initial level of about 23%. This was mostly compensated by the growth of

[4] The dataset provides two sets of weights – one based on employment size and the other calibrated to ensure the sample is representative of the population of workplaces above the size threshold. We indicate in the different parts of the analysis which weights we use and provide further details in Appendix A. More information about the survey can be found at http://www.wers2011.info/.

non-routine cognitive occupations which gained 8pp, reaching just under 39% of employment in 2011. The share of employment in non-routine manual occupations was stable at around one fifth of total employment.

While the public and private sector differed substantially in terms of their initial occupational composition, in both sectors we see a decline in routine manual employment and a pronounced increase in non-routine cognitive employment. Meanwhile, the share of non-routine manual employment declined in the public sector, whereas it increased slightly in the private one, from 17.6% in 1998 to 19.5% in 2011. It is also clear (and unsurprising) that the private sector accounts for most of the decline in routine manual employment, which almost halved its share from the initial level of just over 30% to just under 17%. Routine cognitive employment appears to have gained employment shares in both sectors in this data.

Overall, the results that (i) routine employment has declined mainly because of routine manual employment and (ii) that this has mostly been compensated by an increase in non-routine cognitive employment, are both in line with the patterns presented in Salvatori (2015) using UK Labour Force Survey data on all workers for roughly the same period. This confirms the reliability of our data in capturing these key aggregate employment trends, enabling their analysis from an establishment-level perspective. The main difference with the findings from nationally representative data lies in the fact that Salvatori (2015) reports that routine cognitive employment has also lost in employment share, while the WERS data show that this has not been the case in workplaces with at least 10 employees.[5]

3 Task specialization of establishments

This section provides new evidence on the occupational composition of employment within establishments. We begin by classifying establishments according to their occupational specialization. If more than 50% of an establishment's employment is concentrated in one occupational category (out of the four broad categories described above), we classify it as being specialized in that occupation. Otherwise, we classify the establishment as being non-specialized.

[5]The analysis at the level of the 1-digit occupations presented in Appendix Table A.1 reveals that the increase in routine cognitive employment is due entirely to the growth of sales occupations, while clerical occupations have lost shares. Using LFS data, Salvatori (2015) reports that the employment share in clerical occupations fell by about 2pp during the 2000s, while the employment share of sales occupations remained roughly constant.

Table 2 provides an interesting picture of the specialization patterns across firms and how this changes over time. Columns (1) to (3) show the fraction of establishments with different types of specialization for each of the three years in the sample. Panel A considers the economy as a whole, while Panels B and C focus on the public and private sectors separately. A first striking result is that over 80% of establishments are specialized in one of the four occupational groups according to our measure of specialization. For example, in 2011, only 12% of establishments employed a mix of workers where less than half were in one of the four occupational groups.

The degree of establishment specialization could be driven by particularly small establishments. To rule this out, Columns (4) to (6) of Table 2 weight establishments by their size. The figures in these columns represent the fraction of aggregate employment in establishments with different types of specializations. The Table shows that the fraction of specialized establishments does not fall dramatically when weighting by employment. In particular, around 85% of workers in 1998 are in specialized establishments, with the figure increasing above 90% by 2011. We can therefore conclude that the high degree of specialization observed in the data is not exclusively driven by small establishments.

In addition to the decline in non-specialized establishments, Table 2 also shows a clear increase over time in the fraction of establishments specializing in non-routine occupations, and a sharp decline in the fraction specializing in routine occupations – both cognitive and manual. Workplaces dominated by non-routine cognitive occupations became the largest group in 2011 gaining nearly 9pp from the 20% level of 1998 when they were the third group behind the two types of routine workplaces. The share of workplaces specializing in non-routine manual occupations grew by over 50% climbing from 16% in 1998 to over 25% in 2011. However, interestingly, the corresponding increase in employment in these workplaces has been more modest (from 17% to 20%). This implies that these establishments are relatively small in scale.

The proportion of routine cognitive workplaces has declined from 25.6% to 21.5%, but the proportion of employment accounted for by such establishments has actually slightly increased, suggesting that the average size of these workplaces has gone up. Meanwhile, the fraction of establishments specializing in routine manual occupations falls dramatically, as does the fraction of employment in these establishments.

Hence, overall, we see a much more pronounced polarization pattern in terms of workplace specialization than we see in terms of aggregate employment shares, and the decline in routine workplaces involves workplaces specializing in both manual and cognitive tasks. These patterns are observed both in the public and private sectors as shown in Panels B and C of Table 2, but the magnitude of the changes in specialization appear more dramatic in the private sector. In fact, while almost 60% of workplaces in the public sector were already specialized in non-routine occupations in 1998, the equivalent figure was only 30% in the private sector and reached 49% by 2011, amounting to a proportional increase of over 60 per cent. Over this time period, the share of employment accounted for by workplaces specializing in non-routine cognitive occupations in the private sector doubled from 15% to over 30%. For the remainder of the paper we focus on the private sector – which represents over 70% of overall employment in our sample – as the explanations that have been proposed in the literature for job polarization appear to be most relevant for this sector.

One reason why establishments appear to be so specialized might be because of the workplace concept used in the survey, which refers to a specific set of premises, rather than a firm as a whole. If firms perform different parts of their production process at different geographical locations, this would make establishments appear very specialized in the data. In order to explore this possibility, we consider the specialization patterns for workplaces that report that they are independent establishments, rather than being part of a larger organization. These represent between 30 and 40% of all establishments in the sample. The specialization patterns for these independent establishments are shown in Panel D of Table 2. The most noteworthy pattern is that independent establishments are also very specialized: over 83% of independent establishments in the private sector specialize in one of the four task groups. Thus, the high degree of establishments specialization observed among all workplaces does not seem to be particularly driven by multi-establishment firms that assign the performance of different tasks to different geographical locations. It is also noteworthy that independent establishments are less likely to specialize in routine cognitive tasks as compared to all private sector establishments. This suggests that many of the establishments that specialize in this task are part of larger organizations.

Figure 1 shows the composition of employment by occupation for establishments in each specialization category. The figure confirms the extent to which employment in these establishments is concentrated in their main occupational group. On average across specialized establishments, the largest occupational group accounts for 71%-80% of the establishment's total employment. Although it is not evident from the figure, employment is also fairly concentrated in particular occupational categories among non-specialized establishments. Within this group, the share of employment in the largest occupational group is 44% on average. The fairly even composition of occupations observed in the figure is in fact the result of aggregating across a set of workplaces with fairly high levels of occupational concentration.

Figure 1 also shows that specialized establishments are, if anything, becoming even more specialized over time, in the sense that the fraction of employment in their largest occupational group increases between 1998 and 2011. On average across all establishments (including the non-specialized ones), the fraction of employment in the largest occupational group within the establishment increases slightly over time, from 70% in 1998 to 73% in 2011.

Another interesting pattern that emerges from Figure 1 is that manual workers are rarely found in establishments specializing in cognitive tasks, whereas non-routine cognitive workers in particular tend to be present to some extent in all types of establishments. The figure also shows that the fraction of routine workers in establishments specialized in routine tasks does not fall over time. We have already seen that the proportion of workplaces specializing in routine employment has declined; however, the results here show that the intensity of use of routine employment in the remaining specializing firms has remained stable. This may seem surprising in light of the standard routine-biased technical change (RBTC) hypothesis: One would expect that firms which use routine workers most intensively would have the strongest incentive to invest in new technologies which would allow them to reduce their use of workers for routine tasks – given that these workers would represent a large share of their wage bill.[6]

The results in Figure 1 make it clear that the occupational mix that is observed at the aggregate level is due to the aggregation of employment across very heterogeneous firms, rather than being informative about a "representative" firm. Interestingly, this is also true when restricting the analysis to the within-industry composition of establishments, as we discuss below.

As further evidence of the extent of task specialization within establishments, we consider specialization patterns at the 1-digit occupation level. Appendix Table A.1 shows the evolution of overall employment shares by 1-digit occupation over time. As before, we define a workplace as being specialized if over 50% of its employment falls into one occupational category, where the categories are now each of the nine 1-digit occupation groups available in the data. Table 3 presents the results for private sec-

[6]See for example Autor and Dorn (2013), who consider heterogeneity across local labor markets (LLMs). Their model predicts that LLMs with greater initial routine shares will experience more IT adoption and more displacement of labor from routine tasks.

tor establishments. Given the finer level of aggregation that we are now considering, it is not surprising that the fraction of non-specialized establishments in this case is higher; however, non-specialized establishments still represent less than one third of total establishments and comprise less than one third of total employment. They are also declining in magnitude over time, from 27.5% to 24.6% between 1998 and 2011. The patterns of specialization across the 1-digit occupational groups tend to move in line with the broader patterns reported in the paper: there is a decline in the fraction of establishments specializing in each of the routine occupations (including cognitive ones) and more specialization in non-routine ones (with the exception of managerial occupations – which represent over 50% of employment in very few workplaces).

A final piece of evidence of the increase in occupational specialization within establishments can be obtained by computing a Herfindahl index of occupational concentration, as in Handwerker et al. (2015). For the median establishment in our sample, this concentration index increases from 0.46 in 1998 to 0.49 in 2004 and 0.51 in 2011.

3.1 Explaining variation in task specialization across workplaces

In the previous section we documented widespread and increasing task specialization among British workplaces, and highlighted a dramatic shift towards specialization in non-routine tasks which is particularly strong in the private sector. We now investigate the extent to which variation in specialization across workplaces and over time reflects differences across industries and other observable workplace characteristics. It is a common practice in the literature to assume that firms within a given industry use similar technology and therefore changes observed within industries are generally interpreted as reflecting changes in technology rather than changes in output mix.[7] As Dustmann and Glitz (2015) emphasize, if firms within an industry produce heterogeneous products, this interpretation may be incorrect. Here we show that there is a large amount of heterogeneity within industries in the occupational specialization of establishments.

As a motivating example for the extent of this heterogeneity in task specialization within industries, Table 4 shows the specialization patterns within two broadly defined private sector industries: manufacturing and services. Unsurprisingly, manufacturing is characterized by a large fraction of workplaces specializing in routine manual tasks; however, a non-negligible fraction of establishments within manufacturing specialize in

[7]See for example Goos, Manning, and Salomons (2014).

other tasks as well. We also observe that there was a considerable increase in the fraction of workplaces specializing in non-routine cognitive employment within the manufacturing sector, as their share increased more than two and half times from 6% in 1998 to 16% in 2011. While in manufacturing the proportion of non-specialized workplaces has remained stable at around 22%, in services the equivalent figure has fallen from just over 15% to 11%. At the same time, routine cognitive workplaces have gone from being the largest group (at 34%) to accounting for roughly the same fraction of workplaces as non-routine cognitive and non-routine manual ones, as in 2011 these groups comprised about 26% of workplaces each. The largest proportional increase in the service sector is seen for non-routine manual workplaces, whose share increased by almost 60 per cent. Hence, the service sector has seen an increase both in the fraction of specialized establishments, and in the dispersion of specialization across workplaces.

To account more formally for the extent of variation in specialization patterns within and between industries, we estimate a series of regressions of the different specialization indicators on a full set of 2-digit industry dummies. The R^2 from these regressions ranges between 0.32 and 0.39, showing that more than 60% of the variation in specialization occurs across establishments within 2-digit industries.

Table 5 reports the results from similar OLS regressions of the specialization indicator variables on a set of workplace characteristics, including 2-digit industry dummies, as well as establishment age, size, and region. Each regression pools all three waves together and includes time dummies. The R^2 from these regressions does not increase much relative to the regressions that include only the industry dummies, which implies that the additional regressors (establishment age, size and region) do not offer much additional explanatory power in terms of the observed specialization patterns, and a large amount of heterogeneity in specialization exists within cells defined by these establishment characteristics.[8]

The coefficients on the time dummies reflect changes over time in the probability that an establishment specializes in each of the task categories, conditional on establishment characteristics. The reduction in the probability of specializing in routine tasks and the increase in the probability of specializing in non-routine tasks between 1998 and 2011 are large and statistically significant. Comparing these coefficients to the overall

[8]These results show very little sensitivity to the introduction of further controls for firm characteristics available in WERS, such as type of ownership, level of competition of the product market, or the use of external contractors. They are also very similar when we focus on independent establishments only.

(unconditional) change in specialization probabilities, we can see that more than half of the overall increase in specialization in both non-routine manual and non-routine cognitive tasks occurs within cells defined by industry and establishment characteristics. Changes in the industrial composition play a relatively larger role in explaining the decline in specialization in routine manual occupations, as the coefficient on the 2011 dummy is reduced by around 60% relative to the unconditional change between 1998 and 2011. Below we provide further details on the changes in specialization probabilities occurring within and between industries.

4 Changes in establishment specialization and aggregate polarization

In the previous sections we documented a high and increasing level of task specialization in British workplaces and showed that there has been a significant increase in the proportion of workplaces specializing in non-routine occupations. In fact, we have noted that the pattern of polarization is clearer when one looks at establishment specialization than at aggregate employment shares. In this section, we investigate the relationship between the two.

To formally account for the aggregate changes in occupational shares and how this relates to establishment specialization, we perform a decomposition to determine the contribution of (1) changes in the composition of the firm population in terms of specializing in different occupations and (2) changes in the intensity of use of different occupations in firms with different specializations. Specifically, we can write the aggregate employment share in a particular task, say routine manual (RM) as:

$$E^{RM} = \sum_j e_j E_j^{RM} \tag{1}$$

where $j \in \{NRC, RC, RM, NRM, X\}$ indexes specialization categories, with X being non-specialized, e_j is the share of aggregate employment in establishments specialized in category j, and E_j^{RM} is the (average) routine manual employment share among establishments specialized in j. Using this equation, the change in the routine manual employment share can be decomposed as:

$$\Delta E^{RM} = \sum_j \Delta e_j E_j^{RM} + \sum_j e_j \Delta E_j^{RM} + \sum_j \Delta e_j \Delta E_j^{RM} \tag{2}$$

The first component captures changes *between* specialization categories in the share of total employment that they account for (weighted by each type's initial routine manual employment share), while the second component captures changes *within* specialization categories in their routine manual employment share (weighted by each type's initial size). Analogous decompositions can be performed for each of the four tasks.

Panel A of Table 6 shows the overall changes in the employment shares in each task between 1998 and 2011 in our sample, while Panel B presents the results from the decomposition. For non-routine cognitive employment, over 75% of the increase in the employment share comes from a change in the composition of establishments with different specializations, namely the shift towards establishments specializing in non-routine cognitive employment and away from those specializing in routine manual jobs. The remainder is due to the increase in the employment of non-routine cognitive workers in all types of establishments, and particularly so in those that were already specializing in this type of occupation.

For routine manual employment, the shift in the composition of establishments with different specializations accounts for 85% of the fall in this occupation's aggregate employment share. Decreases in the use of routine manual workers within specialization groups account for most of the rest of the change.

The results for non-routine manual employment are also interesting. They highlight the fact that the stability in the employment share in aggregate for this group is the result of two offsetting forces. The shift in the composition of establishments tends to push the non-routine manual share up, but the reduction in the use of non-routine manual workers in establishments that do not specialize in this task (see Figure 1) tends to push the non-routine manual share down. We note that this pattern is consistent with a trend of increasing outsourcing of non-routine manual tasks, as non-routine manual employment appears increasingly concentrated in specialized workplaces.

To determine the extent to which these changes in the composition of establishment specializations are due to changes in the industrial composition, we perform a further set of decompositions. Panel C of Table 6 performs a standard decomposition of the changes in the employment share of each of the four task groups into the between industry and the within industry components. As has been documented elsewhere, changes in the industrial composition account for an important fraction of the changes in employment shares, but there is also an important role for changes in employment shares in each task within industries. In Panel D we focus on the within-industry component, in order to determine the extent to which changes in the composition of establishment specializations play a role within industries. Specifically, we perform a decomposition analogous to Equation (2) for the within-industry component only. The results show that the change in specialization composition is the main driver of the within-industry decline in routine manual employment, and also accounts for more than half of the within-industry increase in non-routine cognitive tasks.

Overall these results confirm that the reduction in the fraction of employment in establishments that specialize in routine manual tasks, and the compensating increase in the fraction of employment in establishments that specialize in non-routine cognitive tasks, have played an important role in driving changes in aggregate occupational shares, both between and within industries. The results also suggest that changes in employment shares conditional on establishment specialization are relatively less important as a driver of the observed aggregate changes.

The changes in the composition of the workplace population in terms of their task specialization result from the combination of the following components:

1. Differential growth rates among establishments with different specializations (holding the proportions specializing in each task constant);

2. Changes in the proportion of workplaces specializing in different occupations due to differential specialization of workplaces entering and exiting the market

3. Changes in the proportion of workplaces specializing in different occupations due to changes in specialization among surviving workplaces

Although the panel component of our dataset is relatively small, we can exploit additional information available in the cross-sectional data to provide insights on the relative importance of each of these three channels. In particular, follow-up questionnaires provide information on changes in employment size, as well as survival probabilities for all establishments in the cross-sectional surveys. We exploit this information in the following sub-section.

4.1 Task specialization and changes in establishment size

The 2004 survey provides information on the change in total employment for all 1998 workplaces that survive and are located in 2004. We use this information to determine whether establishments with different types of specialization in 1998 experience differential growth rates of employment between 1998 and 2004. Table 7 reports the results from OLS regressions of annualized changes in log of employment on the specialization indicators, with workplaces specializing in non-routine cognitive tasks as the omitted category. Column (1) presents a specification that only includes the specialization dummies, while Column (2) includes controls for 2-digit industries, and Column (3) adds additional controls for region, age of the establishment and employment size.

The Table shows some evidence that workplaces specializing in routine tasks tend to grow less than those specializing in non-routine cognitive tasks, although the differences are not statistically significant. The point estimates suggest that routine workplaces grow by about 10-15% of a standard deviation less than non-routine cognitive ones. Meanwhile workplaces specializing in non-routine manual tasks tend to grow significantly less, conditional on their characteristics. These results are suggestive that differential growth rates by task specialization are likely to play only a partial role in explaining the changes in aggregate occupational shares.

4.2 Survival probability

All workplaces included in each cross-section of WERS are recontacted at the time of the following wave to establish whether they are still in operation. This allows us to see whether workplaces with different task specializations experience differential closing rates.[9] Table 8 shows the proportion of workplaces closing down for the two time periods available.

These data reveal large differences in the closing probability of workplaces specializing in the two types of routine employment. In fact, workplaces specializing in routine cognitive tasks were the least likely to close down in both years, while those specialized in routine manual tasks were the most likely to close down (among all specialized workplaces in 1998, and among all workplaces in 2004). Interestingly, non-specialized workplaces have very high closing rates in both years – in fact between 1998 and 2004 they had the highest recorded rate of all groups at over 29%.

Table 9 reports the results from OLS regressions of the probability of closing between waves, pooling the two waves together. The first specification only includes dummies for task specialization, while the successive columns introduce industry and firm characteristics as well. These estimates confirm that non-specialized workplaces

[9]The response rate to the follow-up questionnaires is above 98.5%.

are generally more likely to close down than non-routine cognitive establishments, as are non-routine manual ones. The lower closing probability for routine cognitive establishments vanishes when controlling for industries – pointing to the fact that the lower closure rate of these workplaces is due to differences in closure rates between industries rather than between specialization categories within industries. The positive coefficient on routine manual establishments also becomes smaller when industries and establishment characteristics are controlled for.

Overall, there is no strong indication that workplaces specializing in routine tasks are more likely to close. The main distinction seems to be between non-routine cognitive establishments, which have particularly low closing probabilities – consistent with the increase in the proportion of these workplaces that we have already documented – and non-routine manual and non-specialized establishments which both have particularly high closing probabilities.

4.3 Establishment entry and exit and changes for continuing establishments

Although routine establishments do not appear to be disproportionately likely to exit the market, it may be the case that the specialization profile of new establishments is quite different from that of existing ones, leading to changes in the establishment composition. In order to understand the role of establishment entry and exit it is therefore important to contrast the specialization composition of exiting establishments to that of establishments that enter the market between waves. We do this in Columns (1) and (2) of Table 10. Column (1) presents the fraction of establishments specializing in each of the task categories for establishments that were in existence in the base period (1998 in Panel A and 2004 in Panel B), but are no longer in business by the time of the next wave of the survey, while Column (2) presents the specialization composition of new establishments, where an establishment is defined as being new if it reports having been in operation for less than 6 years in 2004, or less than 7 years in 2011 (the time interval between survey waves).

Contrasting the shares in Column (1) to the overall Private Sector shares in Table 2 shows that establishments that shut down between surveys are disproportionately likely to be non-specialized or to specialize in one of the manual tasks, as confirmed in the previous sub-section. The specialization profile of exiting firms is also quite different from that of new firms: new establishments are much more likely to specialize in non-routine tasks compared to establishments that exit the market, and they are less likely to specialize in routine manual tasks or to be non-specialized.

In Columns (3) and (4) of Table 10 we analyze the changes in specialization profiles occurring among continuing establishments. Column (3) presents the specialization composition in the base year for establishments that are still in operation by the time of the next survey wave, while Column (4) presents the specialization composition at the time of the next survey wave for establishments that have been in operation at least since the time of the previous survey. Although these are not exactly the same establishments, the representativeness of the sample through the use of establishment weights ensures that these figures are comparable and informative about the changes occurring among continuing establishments. The most striking patterns are for the period between 2004 and 2011, where we observe a large shift among continuing establishments from specialization in routine cognitive tasks to specialization in non-routine cognitive tasks.

Overall, the findings in Table 10 help us understand how the changes in specialization composition documented in Table 2 have come about. The large increase in the fraction of establishments specializing in non-routine cognitive tasks between 2004 and 2011 is due to both an important entry effect and a substantial change in specialization among continuing establishments. The decline in the fraction of establishments specializing in routine cognitive tasks over this same period is entirely due to a change in specialization among continuing establishments.

Meanwhile, the large decline in the fraction of establishments specializing in routine manual tasks throughout our sample period is due to both entry and exit and changes among continuing establishments, with the former playing a much more important role than the latter. The rise in the fraction of establishments specializing in non-routine manual tasks is primarily due to entry in the first period, and both entry and changes among continuing establishments in the second period.

5 Technology adoption and use

As discussed earlier, the main theories proposed to explain the decline in routine employment are related to the use of new technologies. Our dataset allows a unique opportunity to provide direct evidence on technology use and adoption at the workplace level, and its relationship with the employment of different occupations. In particular, we have information on the proportion of employees who use computers as part of their normal work duties (in 2004 and 2011), as well as information reported by managers one whether the workplace has introduced or upgraded to new technologies (including computers) in recent years.[10]

In Table 11 we examine how these variables relate to task specialization over time. The first two columns show that the average share of employees using computers in a private sector workplace increased from just under 48% in 2004 to over 61% in 2011. The increase occurred within all workplaces, but was particularly pronounced in those specializing in manual tasks (which started from relatively low levels of computer usage). While the share using computers remains much higher in cognitive workplaces (reaching 90% in non-routine cognitive ones), the gap with manual workplaces has shrunk substantially as the figures more than doubled in non-routine manual workplaces (going from 16% to over 33%) and increased by 40% in routine manual workplaces (from 26.7% to 37.6%).

The remaining three columns of table 11 show the fraction of workplaces reporting the adoption of new technology in the previous five years for 1998 and in the previous two years for 2004 and 2011. Between 1998 and 2004, technology adoption increased among workplaces of all specializations and particularly among non-routine manual workplaces.[11] In 2011, however, the proportion of workplaces reporting recent technological change fell significantly, presumably as a result of the Great Recession. Overall, only 55% of workplaces reported having adopted technology in 2011 compared to 71% in 2004. The largest declines were not confined to either routine or non-routine workplaces, but occurred in routine cognitive workplaces and in non-routine manual ones. Both of these groups saw a reduction of over 30% in the fraction of workplaces reporting the adoption of new technology. In each year, however, non-routine cognitive workplaces were the most likely to report the recent adoption of new technology and non-routine manual ones were the least likely.

[10] In 1998 managers are asked about changes over the past five years; in 2004 and 2011 about changes over the past two years.

[11] This conclusion holds even net of the comparability issues due to different time frames of the questions, as one would expect the 1998 figures to be biased upwards as a result of this.

5.1 Technology, employment change and the probability of closing

Table 12 looks at the correlation between technology adoption and two workplace-level outcomes, namely the probability of closing and the probability of increasing the level of employment. The standard RBTC hypothesis suggests that the adoption of new technologies leads to a reduction in employment for routine workers. A pessimistic view emphasizes the destructive nature of recent technological change arguing that it is likely to result in a net decline in employment. However, the adoption of new technologies may also lead to efficiency gains which are associated with employment growth at the establishment level. Hence, the nature of the relationship between the adoption of new technologies and overall employment growth at the establishment level is ultimately an empirical question. While we cannot provide reliable causal estimates, our data allow us to provide unique evidence on the correlation between technology adoption and workplace employment and survival. We do so by looking at workplaces specializing in different tasks separately in light of the widely accepted observation that technology interacts with labor in different ways depending on the specific tasks that characterize a job.

In the first column of Panel A of Table 12 we find a negative but statistically insignificant correlation between reporting the adoption of new technology in a given wave and the probability of having closed down by the time of the subsequent wave (i.e. 6 or 7 years later). However, when we break down the sample by establishment specialization we find that this negative correlation is not pervasive. In fact, NRC workplaces which report the adoption of new technology in a given wave are significantly more likely to have closed down by the time of the successive wave. Only for non-routine manual workplaces is the negative correlation statistically significant. This is an interesting result given that the literature on RBTC is generally agnostic on the relationship between technology and non-routine manual employment.

In Panel B, we use the probability of increasing employment between 1998 and 2004 as the dependent variable. This is based on the information from the follow-up questionnaire which was also used in Table 7. Column (1) shows that the correlation between technology adoption and the probability of increasing employment is positive and significant at the 5% level for the whole sample.[12] When we break down the sample

[12]The analogous relationship for the 2004-2011 period can only be estimated using the limited panel dimension of the survey (551 observations). For that period, we also find a positive relationship

by task specialization, the positive correlation is statistically significant only for manual workplaces.

Overall, there is no evidence that technology adoption reduces employment growth at the workplace level. In other words, the efficiency effect which leads to the expansion of establishments due to the adoption of new technology seems to dominate any labor-replacing effects of the new technologies.

Table 13 explores the evidence on whether technology adoption is correlated with changes in the occupational composition of employment within the establishment by exploiting the limited panel dimension in the data. The dependent variable is the annualized within-establishment change in the employment share of a given occupational group between waves $t-1$ and t, and the main regressor of interest is whether the establishment reports having recently adopted new technologies at the time of the $t-1$ survey. The regression in Column (1) considers the within-establishment change in the non-routine cognitive employment share and, in addition to the technology variable includes a year dummy only. The regression in Column (2) adds controls for the initial non-routine cognitive employment share within the establishment (in order to control for potential heterogeneities in share changes according to initial conditions), as well as controls for the establishment's industry, region, age, and size in the base period. The remaining columns consider analogous specifications for each of the other occupation groups.

Interestingly, the recent adoption of new technologies is correlated with very little subsequent change in the share of employment in non-routine cognitive occupations within the establishment. Surprisingly, the adoption of new technology is associated with an increase in the use of routine tasks within the establishment – although the effect is not significant in the case of routine manual tasks. The strongest effect that we observe is that establishments that adopt new technologies tend to subsequently reduce the share of employment in non-routine manual tasks. Conditional on establishment characteristics, including their initial non-routine manual share, the result in Column (8) implies that the adoption of new technologies is associated with a 1.2 percentage point annual decline in the establishment's share of non-routine manual employment.

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between recent technological adoption and subsequent employment growth probabilities (coefficient: 0.106), although the effect is not statistically significant (p-value: 0.131).

6 Conclusions

This paper offers a rich new set of facts about the way in which workplaces are organized along task dimensions. We provide insights about the establishment-level patterns underlying the decline in middle-wage employment. We document widespread and increasing task specialization at the workplace level, as well as widespread heterogeneity in the tasks that different establishments specialize in within industries. Such heterogeneity is likely to reflect differences in technology and organization across workplaces and cautions against the common practice in the literature of assuming a common technology within industries which leads to the interpretation of within-industry changes as reflecting changes in technology.

We show that the fraction of non-specialized workplaces declined between 1998 and 2011, in line with the evidence that occupational concentration increased in the US over the same time period (Handwerker et al., 2015). The changes in the occupational specialization patterns that we find are also consistent with the outsourcing of non-routine manual tasks, such as what has been documented for Germany by Goldschmidt and Schmieder (2015), and with increased trade in tasks between firms enabling increased firm specialization. Importantly, we show that the high degree of specialization is not due to firms dividing their task inputs between different geographic locations, as the specialization rates are also very high among independent establishments.

The proportion of private sector workplaces specializing in non-routine tasks increased between 1998 and 2011 from 30% to almost 50%. These changes are only partly explained by changes in industrial composition and play a major role in explaining the changes in aggregate occupational shares, both between and within industries. On the other hand, changes in the intensity of use of different occupations conditional on specialization play a relatively minor role.

Our analysis of the probability of survival and employment changes reveals that there is no indication that routine workplaces are less likely to survive or to increase employment. Differences in the specialization patterns of new establishments relative to continuing and exiting ones play a major role in the changes in the composition of establishment specialization observed over time. Specialization changes among continuing establishments are also important, particularly in accounting for the increase in non-routine cognitive workplaces between 2004 and 2011.

Finally, we have a number of results that point to an increasingly important role of technology in manual workplaces. In particular, while computer use continues to be higher in cognitive workplaces, we document that between 2004 and 2011, the average share of employees using a computer more than doubled (from 16% to over 33%) in non-routine manual workplaces. Moreover, we find that, conditional on a wide set of establishment characteristics, those that report the adoption of new technologies tend to subsequently decrease their share of employment in non-routine manual occupations. These facts are interesting in light of the fact that the literature on routine-biased technological change is generally agnostic on the relationship between technology and non-routine manual low-skilled employment. Furthermore, we find no evidence to support the pessimistic view that technology adoption is associated with reduced employment growth at the workplace level.

Our results open a number of interesting avenues for future research. The extent of heterogeneity in task composition across establishments within industries is striking and deserves further analysis in order to understand its drivers. For example, it would be interesting to determine whether establishments that use different occupational mixes produce different types of goods within an industry, or whether there is heterogeneity in the input mix even among firms producing the same type of detailed good. Establishing the link between this heterogeneity and the increased dispersion in wages across establishments documented in recent literature (e.g. Song et al. (2015)) would also be important. Establishment-level panel data would also enable the analysis of the specific ways in which particular establishments change their occupational composition over time and how this is linked to other changes over time within the establishment.

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Figure 1: Composition of employment

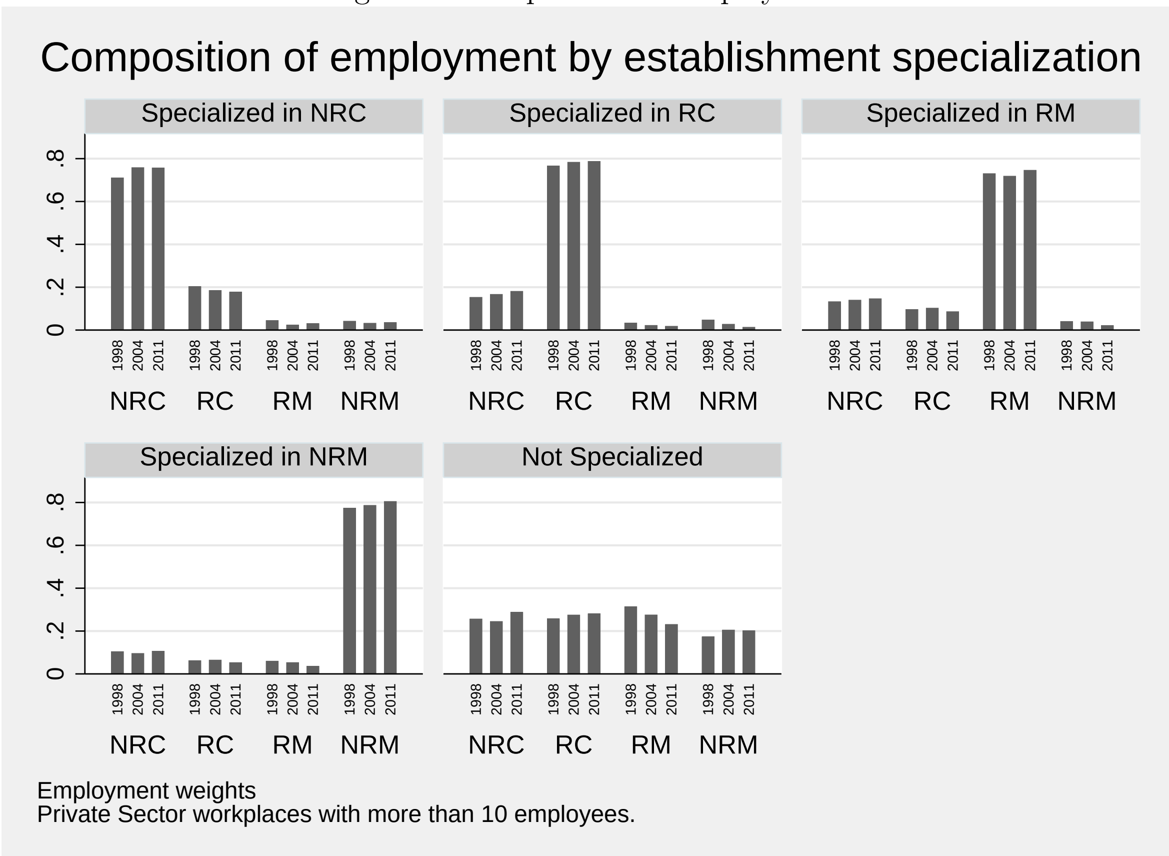

Table 1: Employment shares by occupational group

	NRC	RC	RM	NRM
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
1998	0.304	0.254	0.234	0.207
2004	0.319	0.298	0.165	0.217
2011	0.388	0.274	0.134	0.204
Panel B: Public Sector				
1998	0.446	0.205	0.071	0.279
2004	0.480	0.218	0.046	0.257
2011	0.501	0.234	0.031	0.234
Panel C: Private Sector				
1998	0.242	0.276	0.306	0.176
2004	0.272	0.322	0.201	0.205
2011	0.353	0.286	0.167	0.195

Table 2: Establishment specialization

	Proportion of establishments			Proportion of employment		
	1998	2004	2011	1998	2004	2011
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Sample						
Specialized in NRC	19.9	21.2	28.6	25.7	27.4	37.6
Specialized in RC	25.6	25.8	21.5	18.1	22.5	19.8
Specialized in RM	20.9	15.5	13.0	23.6	15.9	12.9
Specialized in NRM	16.1	22.2	25.1	17.1	20.0	19.8
Not Specialized	17.6	15.3	11.8	15.5	14.2	9.9
Panel B: Public Sector						
Specialized in NRC	34.6	49.9	43.9	49.0	54.3	56.4
Specialized in RC	13.7	10.5	10.7	10.9	10.3	14.6
Specialized in RM	6.3	1.5	2.1	4.9	3.1	1.5
Specialized in NRM	24.5	24.4	34.2	21.3	18.1	19.2
Not Specialized	20.9	13.7	9.1	14.0	14.2	8.2
Panel C: Private Sector						
Specialized in NRC	16.0	15.2	25.4	15.5	18.7	31.1
Specialized in RC	28.7	29.0	23.7	21.3	26.4	21.6
Specialized in RM	24.7	18.5	15.3	31.8	20.0	16.8
Specialized in NRM	13.9	21.7	23.3	15.3	20.7	20.0
Not Specialized	16.7	15.6	12.4	16.1	14.3	10.4
Panel D: Private Sector Independent Establishments						
Specialized in NRC	16.2	14.1	28.9	18.5	16.5	36.2
Specialized in RC	16.3	15.6	14.4	10.3	13.0	9.8
Specialized in RM	35.5	23.7	22.2	29.1	24.4	20.3
Specialized in NRM	17.9	29.7	20.7	27.7	30.5	20.9
Not Specialized	14.1	16.9	13.8	14.4	15.6	12.8

Note: Proportion of employment refers to the fraction of aggregate employment in establishments with different types of specialization.

Table 3: Establishment specialization in 1-digit occupations, private sector

	Proportion of establishments			Proportion of employment		
	1998	2004	2011	1998	2004	2011
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Routine Cognitive						
Managers	2.3	0.8	0.8	1.1	0.7	0.9
Professionals	5.9	3.5	8.1	3.7	4.5	10.1
Technical	2.4	3.8	5.9	3.2	4.8	5.5
Routine Cognitive						
Clerical	8.0	7.3	6.5	6.0	6.2	5.1
Sales	17.2	18.5	16.2	11.7	16.2	13.8
Routine Manual						
Craft	14.3	8.0	6.5	8.8	5.5	4.3
Operatives	8.5	9.2	7.2	18.1	11.6	10.5
Non-Routine Manual						
Personal services	6.6	8.5	9.7	4.7	6.1	7.7
Unskilled	7.3	13.7	14.6	10.4	15.5	14.0
Not Specialized						
None	27.5	26.7	24.6	32.1	28.8	28.3

Table 4: Establishment specialization by broad industry

	Manufacturing			*Services*		
	1998	2004	2011	1998	2004	2011
	(1)	(2)	(3)	(4)	(5)	(6)
Specialized in NRC	5.93	10.85	16.01	18.19	15.99	26.63
Specialized in RC	3.29	3.68	2.96	34.17	33.31	26.35
Specialized in RM	65.86	54.85	56.36	15.84	12.28	9.93
Specialized in NRM	2.24	3.47	2.12	16.37	24.82	26.02
Not Specialized	22.69	27.16	22.56	15.43	13.60	11.07

Table 5: OLS regression of specialization dummies on workplace characteristics.

	Dependent var: Prob of specializing in...			
	NRC	RC	RM	NRM
	(1)	(2)	(3)	(4)
D2004	-0.0163	-0.0281	-0.0199	0.0636**
	(0.0198)	(0.0258)	(0.0223)	(0.0199)
D2011	0.0507**	-0.0435*	-0.0376*	0.0514**
	(0.0213)	(0.0254)	(0.0214)	(0.0213)
Establishment Age (years):				
7-13	0.0116	-0.0693**	0.0623**	0.0232
	(0.0264)	(0.0336)	(0.0295)	(0.0299)
14-20	0.0182	-0.00271	0.0249	-0.0277
	(0.0284)	(0.0346)	(0.0242)	(0.0263)
21-34	0.00162	-0.0354	0.0266	-0.0271
	(0.0260)	(0.0338)	(0.0320)	(0.0257)
25 or more	-0.00796	0.0688*	0.0308	-0.0841**
	(0.0268)	(0.0374)	(0.0317)	(0.0313)
Establishment Size:				
25-49	-0.0301	-0.0531**	-0.0102	0.0744***
	(0.0186)	(0.0214)	(0.0223)	(0.0182)
50-99	-0.00388	-0.0700**	0.0133	0.0745***
	(0.0206)	(0.0219)	(0.0211)	(0.0192)
100-199	-0.0603**	-0.0633**	0.000847	0.129***
	(0.0229)	(0.0241)	(0.0233)	(0.0214)
200 or more	-0.0271	-0.101***	0.0203	0.127***
	(0.0219)	(0.0237)	(0.0229)	(0.0173)
Cons	0.253**	0.242**	0.139**	0.291***
	(0.0968)	(0.0834)	(0.0563)	(0.0830)
Region	Yes	Yes	Yes	Yes
2-digit Ind	Yes	Yes	Yes	Yes
R2	0.341	0.390	0.397	0.355
N	4390	4390	4390	4390

Note: Data from WERS 1998, 2004, 2011. Private Sector workplaces with at least 10 employees. Robust Standard Errors in parenthesis.

Table 6: Decomposition of changes in occupational employment shares

Panel A: Overall Change

	NRC	RC	RM	NRM
	(1)	(2)	(3)	(4)
1998	0.2420	0.2762	0.3059	0.1758
2011	0.3508	0.2807	0.1687	0.1998
Change	0.1087	0.0045	-0.1372	0.0240
	(0.0130)***	(0.0146)	(0.0172)***	(0.0138)*

Panel B: Decomposition of the Overall Change Between and Within Specialization Categories

	NRC	RC	RM	NRM
	(1)	(2)	(3)	(4)
Between Specialization	0.0821	0.0083	-0.1170	0.0271
	(0.0118)***	(0.0124)	(0.0157)***	(0.0123)**
Within Specialization	0.0228	-0.0004	-0.0173	-0.0051
	(0.0062)***	(0.0060)	(0.0068)**	(0.0058)
Interaction	0.0036	-0.0042	-0.0011	0.0017
	(0.0030)	(0.0029)	(0.0036)	(0.0026)

Panel C: Decomposition of the Overall Change Between and Within Industries

	NRC	RC	RM	NRM
	(1)	(2)	(3)	(4)
Between Industries	0.0378	0.0000	-0.0858	0.0480
	(0.0088)***	(0.0108)	(0.0146)***	(0.0088)***
Within Industries	0.0750	0.0040	-0.0542	-0.0248
	(0.0111)***	(0.0100)	(0.0118)***	(0.0108)**
Interaction	-0.0041	0.0005	0.0028	0.0008
	(0.0093)	(0.0065)	(0.0075)	(0.0072)

Panel D: Decomposition of the Within Industry Component Between and Within Specialization Categories

	NRC	RC	RM	NRM
	(1)	(2)	(3)	(4)
Between Specialization	0.0382	0.0154	-0.0551	-0.0100
Within Specialization	0.0232	-0.0061	-0.0093	-0.0163
Interaction	0.0136	-0.0054	0.0103	0.0015

Table 7: Employment change and task specialization

	Future-Current Log Empl 2004-1998		
	(1)	(2)	(3)
Specialized in RC	-.018	-.019	-.030
	(.021)	(.019)	(.019)
Specialized in RM	-.032	-.021	-.025
	(.026)	(.025)	(.025)
Specialized in NRM	-.022	-.044	-.044
	(.020)	(.021)**	(.021)**
Not Specialized	.023	.005	-.006
	(.031)	(.029)	(.031)
Const.	-.002	.031	.091
	(.017)	(.043)	(.055)*
2-dig Ind Dummies	No	Yes	Yes
Region Dummies	No	No	Yes
Firm Charact	No	No	Yes
Obs.	1240	1240	1220
R^2	.015	.135	.25

Note: Private Sector workplaces with at least 10 employees. Robust Standard Errors in parenthesis. Workplaces specialized in NRC are the omitted category.

Table 8: Proportion of firms closing down by occupational specialization

	1998-2004	2004-2011
Specialized in NRC	15.86	17.23
Specialized in RC	8.41	11.69
Specialized in RM	23.36	24.53
Specialized in NRM	19.61	19.49
Not Specialized	29.56	21.97

Private sector establishments with at least 10 employees.

Table 9: Probability of closing between waves

	Probability of Closing		
	(1)	(2)	(3)
Specialized in RC	-.067	-.001	.006
	(.034)*	(.037)	(.038)
Specialized in RM	.074	.006	.027
	(.050)	(.048)	(.048)
Specialized in NRM	.032	.084	.096
	(.044)	(.044)*	(.045)**
Not Specialized	.106	.088	.093
	(.058)*	(.051)*	(.051)*
Const.	.163	-.036	.032
	(.030)***	(.027)	(.059)
2-dig Ind Dummies	No	Yes	Yes
Region Dummies	No	No	Yes
Firm Charact	No	No	Yes
Obs.	2916	2916	2854
R^2	.028	.097	.146

Note: Private Sector workplaces with at least 10 employees. Robust Standard Errors in parenthesis. Workplaces specialized in NRC are the omitted category.

Table 10: Specialization Composition of Entering, Exiting, and Continuing Establishments

Panel A: 1998-2004

	Exit	Entry	Continuing 1998	Continuing 2004
	(1)	(2)	(3)	(4)
Specialized in NRC	13.67	25.24	16.34	13.88
Specialized in RC	13.18	24.91	32.32	29.04
Specialized in RM	31.43	10.64	23.23	20.45
Specialized in NRM	14.74	27.82	13.61	19.83
Not Specialized	26.99	11.39	14.49	16.80

Panel B: 2004-2011

	Exit	Entry	Continuing 2004	Continuing 2011
	(1)	(2)	(3)	(4)
Specialized in NRC	14.37	22.41	15.31	26.38
Specialized in RC	18.94	26.18	31.73	22.07
Specialized in RM	24.41	11.87	16.65	16.59
Specialized in NRM	23.56	24.63	21.57	23.08
Not Specialized	18.71	14.91	14.74	11.87

Table 11: Technology use and adoption across establishments with different task specializations

	% Employees using PC		Fraction reporting technology adoption		
	2004	**2011**	**1998**	**2004**	**2011**
			Past 5 years	*Past 2 years*	
Specialized in NRC	82.6	90.7	0.74	0.83	0.68
Specialized in RC	63.9	68.5	0.64	0.71	0.48
Specialized in RM	26.7	37.6	0.69	0.71	0.60
Specialized in NRM	16.2	33.2	0.48	0.60	0.39
Not Specialized	53.3	67.3	0.53	0.76	0.61
Total	47.9	61.1	0.63	0.71	0.55

Private sector workplaces with at least 10 employees. Establishment weights.

Table 12: Technology adoption, probability of closing and employment growth

	Sample restricted to establishments specialized in...				
	(1)	(2)	(3)	(4)	(5)
	All	**NRC**	**RC**	**RM**	**NRM**
Panel A: Probability of closing between waves					
			1998-2004, 2004-2011		
TechChange (t-1)	-0.0479	0.116*	-0.0528	-0.0743	-0.133**
	(0.0307)	(0.0660)	(0.0353)	(0.0644)	(0.0585)
Obs.	2878	529	720	686	504
R^2	0.141	0.250	0.203	0.253	0.239
Panel B: Probability of increasing employment between 1998 and 2004					
TechChange (1998)	0.191**	-0.147	0.229	0.347***	0.304***
	(0.0630)	(0.118)	(0.142)	(0.0868)	(0.0817)
Obs.	1228	208	314	323	195
R^2	0.201	0.477	0.340	0.504	0.502

Robust standard errors in parenthesis.
All regressions include controls for 2-digit industries, age, employment size, regions and time dummies.

Table 13: Technology and changes in occupational employment shares

	Change in the within-establishment share of employment in...							
	NRC	NRC	RC	RC	RM	RM	NRM	NRM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TechChange (t-1)	.011	.088	.645	.821	.379	.143	-1.035	-1.244
	(.377)	(.283)	(.654)	(.360)**	(.300)	(.280)	(.735)	(.362)***
NRC share (t-1)		-5.247						
		(.993)***						
RC share (t-1)				-7.570				
				(.933)***				
RM share (t-1)						-7.137		
						(.771)***		
NRM share (t-1)								-8.657
								(.977)***
Const.	.083	1.468	-1.136	-.969	-.367	-.469	1.420	7.366
	(.400)	(.893)*	(.716)	(1.451)	(.309)	(1.090)	(.832)*	(1.558)***
Region Dummies	No	Yes	No	Yes	No	Yes	No	Yes
2-d Ind Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Firm Charact	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	1133	1112	1133	1112	1133	1112	1133	1112
R^2	.008	.244	.014	.366	.004	.304	.029	.427

Note: Private Sector workplaces with at least 10 employees. Establishment-weighted regressions. Dependent variables are the annualized within-establishment changes in the employment share for the corresponding occupation. All regressions include a year dummy for 2004. Robust Standard Errors in parenthesis.

Appendix A Weighting in WERS

WERS employs a complex sampling design which involves stratification, unequal sampling fractions across strata, sampling without replacement and post-stratification. The technical documentation for the 2011 wave dropped the previous recommendation of specifying a stratification variable when using statistical software to account for such complex design. This is based on the observation that corrections for stratification (or finite population corrections) have very limited practical impacts on standard errors produced using WERS data.

A choice had to be made as to which version of weights to use for the 2004 cross-section. Along with the 2011 data, a revised set of weights for 2004 was released which were computed using the same approach to non-response adjustment adopted for the 2011 data. However, no revised weights were provided for the 1998 cross-section. We experimented with a number of regressions to see if different versions of the 2004 weights made any appreciable difference and we concluded that they do not (whether we used employment or establishment weights). As a result, we present results using the most recent version of the 2004 weights. For 1998, we also use the most recent version of the weights which came with the release of the subsequent wave of WERS in 2004.

Appendix B Definition of occupations and computation of employment shares

We have information on 9 different occupational groups in each wave. Managers are given an Employees Profile Questionnaires ahead of the actual interview so that they can look up the figures if necessary. The questionnaire includes a definition of what is meant by each occupational group. These descriptions are identical in 2004 and 2011 and there are only minor differences between 1998 and the other two waves which we now discuss briefly. In 1998, police, prison, and fire officers, customs and excise officers are mentioned as examples within the Protective and personal service occupations group, while in 2004 and 2011 junior officers are included in Associate professional and technical occupations and senior offices in Managers and senior officials. In terms of our classification this means that these occupations are moved from the non-routine manual group to the non-routine cognitive group. They might therefore bias the change in NRC employment upwards and that in NRM employment downward between 1998 and 2004.

Exploiting the availability of detailed occupational coding for the largest occupational group in the workplace, we can establish that in 2004 and 2011 there are only 32 and 55 workplaces respectively in which one of these occupational groups is the largest (with more than 10 employees). The figures drop to 1 and 3 respectively when the sample is restricted to the private sector. This suggests that this is likely to be a minor issue for the whole sample and an entirely negligible one for the private sector sample.

In 1998, hairdressing was mentioned as an examples in the crafts and skilled service occupations while in 2004 it was mentioned under caring, leisure, and other personal service occupations. Hence, in terms of our classification, this implies a movement from the routine manual group to the non-routine manual one. The impact of this change is likely to be very small: keeping in mind that we always restrict the sample to workplaces with more than 10 employees, using the detailed codes for the largest occupational group we see that the number of workplaces dominated by hairdressers was 7 in 2004 and 9 in 2011 and the average size of the workplace was around 18 employees in each year.

A change that has no impact on our results given our classification is the move of protective services (i.e. traffic wardens and security guards) between the two occupational groups which we include in the non-routine manual group.

We have information on the absolute number of employees in each of the 9 occupational groups and then, as a separate variable, the total number of employees. There are very few missing values or discrepancies between the total reported number of employees and the total obtained as the sum of occupations. We only use workplaces for which we do not have these issues. In particular, a workplace is in our sample if:

1. It has valid information (no missing values) on all the occupational groups (i.e. workplaces with a missing value for any occupations are discarded);

2. The sum of employment across occupations is within 5% of the total reported employment. For those workplaces within the 5% tolerance interval, we compute the shares using the total based on the sum across occupations. The latter is also the total employment variable we use.

The actual number of workplaces lost due to these rules is small. In 1998, only 26 workplaces do not have valid information for each occupation and another 17 have large discrepancies between the two measures of total employment. In 2004, we lose 19/2295 workplaces due to non-valid information on at least one occupation and 44 are lost due to significant discrepancies in total employment. In 2011, 43/2680 lost due to non-valid occupation data and 1 is lost due to the significant discrepancy in total employment.

Table A.1: Employment shares by 1-digit occupation, sector and year

	Non Routine Cognitive			Routine Cognitive		Routine Manual		Non Routine Manual	
	Managers	Professionals	Technical	Clerical	Sales	Craft	Operatives	Personal Svc	Unskilled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Full Sample									
1998	0.086	0.129	0.088	0.158	0.097	0.105	0.129	0.082	0.125
2004	0.105	0.108	0.107	0.148	0.150	0.072	0.094	0.072	0.145
2011	0.118	0.165	0.105	0.141	0.133	0.058	0.077	0.087	0.117
Panel B: Public Sector									
1998	0.067	0.254	0.124	0.199	0.006	0.045	0.026	0.155	0.124
2004	0.068	0.219	0.193	0.205	0.013	0.029	0.017	0.133	0.123
2011	0.087	0.282	0.132	0.208	0.026	0.019	0.012	0.128	0.107
Panel C: Private Sector									
1998	0.095	0.074	0.073	0.140	0.136	0.132	0.174	0.050	0.126
2004	0.115	0.076	0.081	0.131	0.191	0.084	0.116	0.054	0.152
2011	0.128	0.128	0.097	0.120	0.166	0.070	0.097	0.075	0.120