Online Appendix for:

"Where Have the Middle-Wage Workers Gone?
A Study of Polarization Using Panel Data"

Appendix A Model Details

This Appendix develops the model outlined in Section 2. It is based on Jung and Mercenier (2012), and extends their analysis by presenting a formal derivation of the general equilibrium effects of RBTC, and by focusing on the implied effects for individual workers in terms of occupational switching patterns and wage changes.

Household Preferences

There is a single representative household composed of a continuum of workers. There are two consumption goods, Y_1 and Y_2, and the household's utility is given by:

$$U(Y_1, Y_2) = (1-\beta)\ln Y_1 + \beta \ln Y_2 \tag{A.1}$$

where $0 < \beta < 1$. The Y_1 good will be the numeraire, so $p_1 = 1$.

Firms

Both industries Y_1 and Y_2 are perfectly competitive. Y_1 is produced by labor performing non-routine manual tasks (which empirically correspond mainly to low-skill service occupations). The production function is linear in labor: $Y_1 = L_M$, where L_M denotes the total labor input of non-routine manual tasks (in efficiency units).

Y_2 requires the combination of two different types of tasks: routine and non-routine cognitive. Routine task services are supplied by labor and by physical capital (machines, computers), while non-routine cognitive tasks are performed only by labor. Specifically, let the production function for the Y_2-good be:

$$Y_2 = \left[(\kappa_R L_R)^{\frac{\sigma-1}{\sigma}} + L_C^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{A.2}$$

where L_R and L_C denote total labor input of routine and non-routine cognitive tasks, respectively (in efficiency units). σ is the elasticity of substitution between routine and non-routine cognitive tasks, and it is assumed that $\sigma \in (0, 1)$. κ_R is the capital stock, which is exogenously given and is available at no cost.[1]

[1] Alternatively, κ_R may be interpreted as a factor-augmenting technology parameter.

Let λ_j denote the wage per efficiency unit for task $j \in \{M, R, C\}$. Because the industries are competitive, wages will equal the value of the marginal product of labor. For the Y_1 industry, using the normalization $p_1 = 1$, this implies:

$$\lambda_M = 1 \tag{A.3}$$

For the Y_2 good, in equilibrium relative labor demand for the two tasks will be given by:

$$\frac{L_R}{L_C} = \kappa_R^{\sigma-1}\left(\frac{\lambda_R}{\lambda_C}\right)^{-\sigma} \tag{A.4}$$

Note that due to the assumption that $\sigma < 1$, an exogenous increase in κ_R will lead to a decrease in the relative demand for labor performing routine tasks.

Labor Productivity

Workers supply labor, and are differentiated by their skill level z, which has an exogenous cumulative distribution $G(z)$ with support $[z_{min}, z_{max}]$. Each worker may perform one of three distinct tasks: non-routine manual (M), routine (R), or non-routine cognitive (C).

Let $\varphi_j(z)$ denote the productivity (in terms of supplied efficiency units) of a worker of skill z performing task $j \in \{M, R, C\}$. $\varphi_j(z)$ is continuous and increasing in z so that a worker with a higher skill level is more productive than a worker with a lower skill level when performing the same task (absolute advantage). It is also assumed that workers with a higher skill level have a comparative advantage in performing more complex tasks (where non-routine cognitive tasks are assumed to be more complex than routine tasks, and these in turn are assumed to be more complex than non-routine manual tasks). The productivity differences are assumed to hold not only in levels but also in logs. This means that:

$$0 < \frac{d\ln\varphi_M(z)}{dz} < \frac{d\ln\varphi_R(z)}{dz} < \frac{d\ln\varphi_C(z)}{dz} \tag{A.5}$$

Assume $\varphi_j(z_{min}) = 1$ for $j \in \{M, R, C\}$.

Worker Sorting and Wages

Workers will choose which task to perform based on the total potential wage they would receive in each occupation, which is given by the competitively determined wage per efficiency unit, and the number of efficiency units supplied by the worker in that task. That is:

$$w_j(z) = \lambda_j\varphi_j(z) \tag{A.6}$$

where $w_j(z)$ is the potential wage in occupation $j \in \{M, R, C\}$ for an individual of skill level z.

The equilibrium will feature two endogenously determined skill thresholds z_0 and z_1 (where $z_{min} < z_0 < z_1 < z_{max}$), such that the least skilled workers will find it optimal to select into the non-routine manual occupation; the middle-skill workers into the routine occupation; and the most skilled workers into the non-routine cognitive occupation.

The cutoffs z_0 and z_1 are determined in equilibrium so that the marginal workers have no incentives to relocate between tasks. Formally, this means:

$$\lambda_M \varphi_M(z_0) = \lambda_R \varphi_R(z_0) \tag{A.7}$$

$$\lambda_R \varphi_R(z_1) = \lambda_C \varphi_C(z_1) \tag{A.8}$$

Equilibrium wages will therefore satisfy:

$$w(z) = \begin{cases} \lambda_M \varphi_M(z) & \text{for } z_{min} \leq z \leq z_0 \\ \lambda_R \varphi_R(z) & \text{for } z_0 < z < z_1 \\ \lambda_C \varphi_C(z) & \text{for } z_1 \leq z \leq z_{max} \end{cases}$$

Total labor supply for each task will be given by:

$$L_M = \int_{z_{min}}^{z_0} \varphi_M(z) dG(z) \tag{A.9}$$

$$L_R = \int_{z_0}^{z_1} \varphi_R(z) dG(z) \tag{A.10}$$

$$L_C = \int_{z_1}^{z_{max}} \varphi_C(z) dG(z) \tag{A.11}$$

Equilibrium

To complete the model, note that household income (denoted by I) is given by total labor compensation.[2] That is:

$$I = \lambda_M L_M + \lambda_R L_R + \lambda_C L_C \tag{A.12}$$

Given the production function for Y_1 and the household demand for this good obtained from the maximization of equation (A.1), where the household takes total income as given, the market clearing condition for the Y_1 good is:

$$L_M = (1 - \beta)(\lambda_M L_M + \lambda_R L_R + \lambda_C L_C) \tag{A.13}$$

[2] Recall that capital is assumed to be available at no cost and therefore does not generate any return.

And given the production function for Y_2 and the household demand obtained from the maximization of equation (A.1), the market clearing condition for this good is given by:

$$p_2\left[(\kappa_R L_R)^{\frac{\sigma-1}{\sigma}}+L_C^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}=\beta(\lambda_M L_M+\lambda_R L_R+\lambda_C L_C) \tag{A.14}$$

Equations (A.3), (A.4), (A.7), (A.8), (A.9), (A.10), (A.11), (A.13), and (A.14) determine the equilibrium levels of the endogenous variables λ_M, λ_R, λ_C, L_M, L_R, L_C, z_0, z_1, p_2.

Effects of Routine-Biased Technical Change

Routine-biased technical change (RBTC) is modeled as an exogenous increase in κ_R. Consider first the comparative statics analysis of the effects of a change in κ_R on the ability cutoffs z_0 and z_1. We can use equations (A.9) to (A.11) to explicitly write the equilibrium levels of the different tasks as a function of the cutoffs: $L_M(z_0)$, $L_R(z_0,z_1)$ and $L_C(z_1)$. Using this, along with equations (A.4) and (A.8), we have:

$$\frac{L_R(z_0,z_1)}{L_C(z_1)}=\kappa_R^{\sigma-1}\left(\frac{\varphi_R(z_1)}{\varphi_C(z_1)}\right)^{\sigma} \tag{A.15}$$

And combining equations (A.3), (A.7), (A.8) and (A.13), we have:

$$L_M(z_0)=\left(\frac{1-\beta}{\beta}\right)\left(\frac{\varphi_M(z_0)}{\varphi_R(z_0)}\right)\left(L_R(z_0,z_1)+\frac{\varphi_R(z_1)}{\varphi_C(z_1)}L_C(z_1)\right) \tag{A.16}$$

Equations (A.15) and (A.16) are a two-equation system with two unknowns z_0 and z_1. Taking logs, the system becomes:

$$\begin{aligned}\ln L_R(z_0,z_1)-\ln L_C(z_1)-\sigma\ln\alpha_1(z_1) &= (\sigma-1)\ln\kappa_R && \text{(A.17)}\\ \ln L_M(z_0)-\ln\alpha_0(z_0)-\ln\left[L_R(z_0,z_1)+\alpha_1(z_1)L_C(z_1)\right] &= \ln\left(\frac{1-\beta}{\beta}\right) && \text{(A.18)}\end{aligned}$$

where the following definitions have been used: $\alpha_0(z_0)\equiv\varphi_M(z_0)/\varphi_R(z_0)$, and $\alpha_1(z_1)\equiv\varphi_R(z_1)/\varphi_C(z_1)$.

Taking total derivatives of equations (A.17) and (A.18) we have:

$$\begin{bmatrix}\frac{\varphi_R(z_0)g(z_0)}{L_R(z_0,z_1)} & -g(z_1)\left(\frac{\varphi_R(z_1)}{L_R(z_0,z_1)}+\frac{\varphi_C(z_1)}{L_C(z_1)}\right)+\frac{\sigma\alpha_1'(z_1)}{\alpha_1(z_1)}\\ g(z_0)\left(\frac{\varphi_M(z_0)}{L_M(z_0)}+\frac{\varphi_R(z_0)}{L_R(z_0,z_1)+\alpha_1(z_1)L_C(z_1)}\right)-\frac{\alpha_0'(z_0)}{\alpha_0(z_0)} & -\alpha_1'(z_1)\left(\frac{L_C(z_1)}{L_R(z_0,z_1)+\alpha_1(z_1)L_C(z_1)}\right)\end{bmatrix}\begin{bmatrix}dz_0\\ dz_1\end{bmatrix}$$

$$=\begin{bmatrix}-(\sigma-1)\\ 0\end{bmatrix}d\ln\kappa_R \tag{A.19}$$

where the fundamental theorem of calculus has been used to obtain the derivatives of L_M, L_R and L_C with respect to z_0 and z_1.

Proposition 1 (Effect of RBTC on ability cutoffs): The general equilibrium effects of $d\ln\kappa_{rt}$ on the cutoffs z_0 and z_1 are given by:

$$\frac{dz_0}{d\ln\kappa_R} = \frac{1}{\Delta}(\sigma-1)\,\alpha_1'(z_1)\left(\frac{L_C(z_1)}{L_R(z_0,z_1)+\alpha_1(z_1)L_C(z_1)}\right) > 0 \quad \text{(A.20)}$$

$$\frac{dz_1}{d\ln\kappa_R} = \frac{1}{\Delta}(\sigma-1)\left[g(z_0)\left(\frac{\varphi_M(z_0)}{L_M(z_0)}+\frac{\varphi_R(z_0)}{L_R(z_0,z_1)+\alpha_1(z_1)L_C(z_1)}\right)-\frac{\alpha_0'(z_0)}{\alpha_0(z_0)}\right] < 0 \quad \text{(A.21)}$$

where Δ is the determinant of the matrix on the left-hand-side of the system of Equations (A.19).

Proof:

Based on the assumptions on absolute and comparative advantage across skill groups in Equation (A.5), we have that α_0 and α_1 are decreasing functions in their respective arguments: The relative productivity of non-routine manual relative to routine workers is falling as z increases, and the same is true about the relative productivity of routine relative to non-routine cognitive workers. More formally:

$$\alpha_0'(z_0) = \frac{\varphi_M(z_0)}{\varphi_R(z_0)}\left[\frac{\partial\ln\varphi_M(z_0)}{\partial z_0}-\frac{\partial\ln\varphi_R(z_0)}{\partial z_0}\right] < 0 \quad \text{(A.22)}$$

$$\alpha_1'(z_1) = \frac{\varphi_R(z_1)}{\varphi_C(z_1)}\left[\frac{\partial\ln\varphi_R(z_1)}{\partial z_1}-\frac{\partial\ln\varphi_C(z_1)}{\partial z_1}\right] < 0 \quad \text{(A.23)}$$

All other terms in the matrix on the left-hand-side of Equation (A.19) are positive. Therefore, we have that, in that matrix, cell (1,1) is positive, cell (1,2) is negative, cell (2,1) is positive and cell (2,2) is positive. It follows that $\Delta > 0$. The sign of Equation (A.20) follows from the fact that $\sigma < 1$ and $\alpha_1'(z_1) < 0$. The sign of Equation (A.21) follows from the fact that $\sigma < 1$ and that the term in the square brackets is positive because $\alpha_0'(z_0) < 0$.

■

Proposition 1 states that an increase in κ_R (RBTC) will lead to an increase in z_0 and a decrease in z_1. This implies employment polarization: the share of routine jobs in total employment will decrease, while the share of non-routine manual and the share of non-routine cognitive jobs will increase. It also implies the following in terms of switching patterns:

Corollary 1 (Switching Patterns induced by RBTC): Let the new ability cutoffs after the change in κ_R be z_0' and z_1'. An increase in κ_R will lead to the following switching pattern: Workers at the bottom of the ability distribution within routine jobs, that is, those with $z \in (z_0, z_0')$, will switch to non-routine manual jobs, while workers at the top of the ability distribution within routine jobs, that is, those with $z \in (z_1', z_1)$, will switch to non-routine cognitive jobs.

Next, consider the changes induced by RBTC on the wage per efficiency unit λ_j in each occupation. Using the comparative statics results on the effects of κ_R on z_0 and z_1, along with equations (A.7) and (A.8), we have the following result:

Proposition 2 (Changes in wage per efficiency unit induced by RBTC):

$$\frac{d\ln\lambda_M}{d\ln\kappa_R} = 0 \qquad \frac{d\ln\lambda_R}{d\ln\kappa_R} < 0 \qquad \frac{d\ln\lambda_C}{d\ln\kappa_R} > 0$$

Proof:

Because of marginal cost pricing $\lambda_M = p_1$, and p_1 is normalized to 1 in any equilibrium, so λ_M does not change, i.e. $d\ln\lambda_M/d\ln\kappa_R = 0$. All of the wage changes should be interpreted as being relative to this normalization.

From Equation (A.7),

$$\begin{aligned}\ln\lambda_R &= \ln\left(\frac{\varphi_M(z_0)}{\varphi_R(z_0)}\right) + \ln\lambda_M \\ &= \ln\alpha_0(z_0) + \ln\lambda_M\end{aligned}$$

So:

$$\begin{aligned}\frac{d\ln\lambda_R}{d\ln\kappa_R} &= \left(\frac{\alpha_0'(z_0)}{\alpha_0(z_0)}\right)\frac{dz_0}{d\ln\kappa_R} + \frac{d\ln\lambda_M}{d\ln\kappa_R} \\ &= \left(\frac{\alpha_0'(z_0)}{\alpha_0(z_0)}\right)\frac{dz_0}{d\ln\kappa_R}\end{aligned}$$

From Proposition 1 and its proof, $dz_0/d\ln\kappa_R > 0$ and $\alpha_0'(z_0) < 0$. Therefore, $d\ln\lambda_R/d\ln\kappa_R < 0$.

From Equation (A.8),

$$\begin{aligned}\ln\lambda_C &= \ln\left(\frac{\varphi_R(z_1)}{\varphi_C(z_1)}\right) + \ln\lambda_R \\ &= \ln\alpha_1(z_1) + \ln\lambda_R\end{aligned}$$

So:

$$
\begin{aligned}
\frac{d\ln\lambda_C}{d\ln\kappa_R} &= \left(\frac{\alpha_1'(z_1)}{\alpha_1(z_1)}\right)\frac{dz_1}{d\ln\kappa_R} + \frac{d\ln\lambda_R}{d\ln\kappa_R} \\
&= \left(\frac{\alpha_1'(z_1)}{\alpha_1(z_1)}\right)\frac{dz_1}{d\ln\kappa_R} + \left(\frac{\alpha_0'(z_0)}{\alpha_0(z_0)}\right)\frac{dz_0}{d\ln\kappa_R}
\end{aligned}
$$

From Proposition 1 and its proof, $\alpha_1'(z_1) < 0$, $dz_1/d\ln\kappa_R < 0$, $\alpha_0'(z_0) < 0$ and $dz_0/d\ln\kappa_R > 0$, so the first term is positive and the second term is negative. However, we can use Equations (A.20) and (A.21) to substitute for $dz_0/d\ln\kappa_R$ and $dz_1/d\ln\kappa_R$ to obtain:

$$
\begin{aligned}
\frac{d\ln\lambda_C}{d\ln\kappa_R} &= \frac{1}{\Delta}(\sigma-1)\alpha_1'(z_1)\left[\frac{1}{\alpha_1(z_1)}g(z_0)\left(\frac{\varphi_M(z_0)}{L_M(z_0)} + \frac{\varphi_R(z_0)}{L_R(z_0,z_1)+\alpha_1(z_1)L_C(z_1)}\right)\right. \\
&\qquad \left. + \frac{\alpha_0'(z_0)}{\alpha_0(z_0)}\left(\frac{L_C(z_1)}{L_R(z_0,z_1)+\alpha_1(z_1)L_C(z_1)} - \frac{1}{\alpha_1(z_1)}\right)\right] \\
&= \frac{1}{\Delta}(\sigma-1)\frac{\alpha_1'(z_1)}{\alpha_1(z_1)}\left[g(z_0)\left(\frac{\varphi_M(z_0)}{L_M(z_0)} + \frac{\varphi_R(z_0)}{L_R(z_0,z_1)+\alpha_1(z_1)L_C(z_1)}\right)\right. \\
&\qquad \left. - \frac{\alpha_0'(z_0)}{\alpha_0(z_0)}\left(\frac{L_R(z_0,z_1)}{L_R(z_0,z_1)+\alpha_1(z_1)L_C(z_1)}\right)\right]
\end{aligned}
$$

Given the facts that $\Delta > 0$, $\sigma < 1$, $\alpha_1'(z_1) < 0$ and $\alpha_0'(z_0) < 0$, this expression is unambiguously positive.

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Proposition 3 (Wage changes induced by RBTC for workers of different ability levels): The wage changes induced by a positive shock to $\ln\kappa_R$ are as given in the following equations, where the final column indicates each worker's occupation before and after the shock.

$$
\begin{array}{llllll}
\frac{d\ln w(z)}{d\ln \kappa_R} & = \frac{d\ln \lambda_M}{d\ln \kappa_R} = 0 & \text{if } z_{min} \leq z \leq z_0 & M \to M \\
\frac{d\ln w(z)}{d\ln \kappa_R} & > \frac{d\ln \lambda_R}{d\ln \kappa_R} & \text{if } z_0 < z < z_0' & R \to M \\
\frac{d\ln w(z)}{d\ln \kappa_R} & = \frac{d\ln \lambda_R}{d\ln \kappa_R} < 0 & \text{if } z_0' \leq z \leq z_1' & R \to R \\
\frac{d\ln w(z)}{d\ln \kappa_R} & > \frac{d\ln \lambda_R}{d\ln \kappa_R} & \text{if } z_1' < z < z_1 & R \to C \\
\frac{d\ln w(z)}{d\ln \kappa_R} & = \frac{d\ln \lambda_C}{d\ln \kappa_R} > 0 & \text{if } z_1 \leq z \leq z_{max} & C \to C
\end{array}
$$

Proof:

The wage change for a worker of skill level z is given by:

$$\frac{d\ln w(z)}{d\ln \kappa_R} = \frac{d\ln \lambda_{j'}}{d\ln \kappa_R} + \mathbb{1}(j \neq j'|z)\left[\ln \lambda_{j'} - \ln \lambda_j + \ln \varphi_{j'}(z) - \ln \varphi_j(z)\right] \tag{A.24}$$

where j denotes the occupation that a worker of skill level z optimally chooses before the change in κ_R, and j' indicates his optimal choice after the shock. $\mathbb{1}(j \neq j'|z)$ is an indicator function equal to 1 if $j \neq j'$ for a worker of skill level z.

For workers who do not switch occupations, $j = j'$, and the wage change induced by the change in κ_R is equal to the change in the wage per efficiency unit λ_j in their occupation.

For workers who do switch occupations, the wage change is equal to the change in $\lambda_{j'}$ (change in wage per efficiency unit in their new occupation) plus the difference between the wage they would have received before the shock in occupation j' and the wage they were receiving in occupation j.

Based on the results from Proposition 1, and using z_0' and z_1' to denote the new cutoff skill levels (after the shock to κ_R), we have that:

$$\mathbb{1}(j \neq j'|z) = \begin{cases} 0 & \text{if } z_{min} \leq z \leq z_0 \text{ or } z_0' \leq z \leq z_1' \text{ or } z_1 \leq z \leq z_{max} \\ 1 & \text{if } z_0 < z < z_0' \text{ or } z_1' < z < z_1 \end{cases}$$

For non-switchers, the proof of Proposition 3 follows directly from Proposition 2. For switchers, the proof is as follows.

Consider first switchers to non-routine manual, that is, workers with ability $z \in (z_0, z_0')$. The first term, $d\ln \lambda_M / d\ln \kappa_R$ is zero, so the wage change for workers in this range is equal to $\ln \lambda_M - \ln \lambda_R + \ln \varphi_M(z) - \ln \varphi_R(z)$. Now, recall that before the shock to κ_R, all workers with $z \in (z_0, z_1)$ were optimally sorting into routine jobs, meaning that, given their skill level and the pre-shock equilibrium values of λ_M and λ_R, the wage they would have earned in non-routine manual jobs was lower than the wage they were earning in routine jobs. Formally, this means: $\ln\lambda_R + \ln\varphi_R(z) > \ln\lambda_M + \ln\varphi_M(z)$ for all workers with ability $z \in (z_0, z_0')$. It follows that the wage change for workers in this ability range is unambiguously negative. Note also that $\ln\lambda_M - \ln\lambda_R + \ln\varphi_M(z) - \ln\varphi_R(z)$ is decreasing in z due to the assumption in Equation (A.5), implying that workers of higher ability will experience larger wage cuts. The wage cuts for this group will be at most equal to $d\ln\lambda_R/d\ln\kappa_R$, which is the wage cut experienced by a worker with ability $z = z_0'$ who is indifferent between working in a routine or a non-routine manual job.

Now consider switchers to non-routine cognitive occupations, that is, workers with ability $z \in (z_1', z_1)$. First consider a worker of ability z_1'. As z_1' is the new cutoff, it must be the case that this worker is indifferent between working in a routine or a non-routine cognitive job, or in other words, the wage change he experiences if he switches or he stays should be the same. This implies:

$$\frac{d\ln w(z_1')}{d\ln\kappa_R} = \frac{d\ln\lambda_R}{d\ln\kappa_R} < 0$$

This shows that a worker of ability z_1' will experience a wage cut equal to that experienced by stayers in routine occupations. Now consider a worker of ability z_1. Before the shock these workers would have been indifferent between routine and non-routine cognitive jobs, meaning that $\ln\lambda_C + \ln\varphi_C(z_1) = \ln\lambda_R + \ln\varphi_R(z_1)$. It follows then that:

$$\begin{aligned}\frac{d\ln w(z_1)}{d\ln\kappa_R} &= \frac{d\ln\lambda_C}{d\kappa_R} + \ln\lambda_C + \ln\varphi_C(z_1) - (\ln\lambda_R + \ln\varphi_R(z_1))\\ &= \frac{d\ln\lambda_C}{d\ln\kappa_R} > 0\end{aligned}$$

This shows that the wage change for a worker of ability z_1 will be unambiguously positive. Due to the fact that $\ln\lambda_C - \ln\lambda_R + \ln\varphi_C(z) - \ln\varphi_R(z)$ is increasing in z (Equation (A.5)), we can conclude that, among workers who switch to non-routine cognitive jobs, the wage change is increasing in the worker's ability level, with the lowest ability switchers experiencing wage cuts and the highest ability switchers experiencing wage increases. In all cases their wage change will be greater than the wage change experienced by workers staying in routine occupations.

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Appendix B Model Extension: Two-Dimensional Skills

This section describes how the model can be extended to account for two-dimensional skills that are rewarded differently in different occupations. It is shown that, by imposing certain restrictions on the variances of those skills in the population and the differences in the returns across occupations, the predictions of the model are still valid in expectations.

Assume that workers are endowed with a certain level of cognitive skills z_i^C and manual skills z_i^M. The marginal productivity of these skills varies across occupations. For simplicity, assume that only cognitive skills are productive in non-routine cognitive occupations, and only manual skills are productive in non-routine manual occupations. Both types of skills are productive in routine occupations.

The marginal productivity of an individual with skills $\{z_i^C, z_i^M\}$ is given by:

$$\ln \varphi_j(z_i) = \begin{cases} b_M^M z_i^M & \text{in non-routine manual jobs} \\ b_R^M z_i^M + b_R^C z_i^C & \text{in routine jobs} \\ b_C^C z_i^C & \text{in non-routine cognitive jobs} \end{cases}$$

where the subscript on b indicates the occupation and the superscript indicates the type of skill.

The predictions of the model in terms of the sorting patterns and the switches induced by routinization will still be true if the following conditions hold:

$$Cov\left\{w_C(z_i^M, z_i^C) - w_R(z_i^M, z_i^C), w_R(z_i^M, z_i^C)\right\} > 0 \tag{A.25}$$

$$Cov\left\{w_M(z_i^M, z_i^C) - w_R(z_i^M, z_i^C), w_R(z_i^M, z_i^C)\right\} < 0 \tag{A.26}$$

where $w_j(z_i^M, z_i^C)$ are the (potential) wages received in occupation j by a worker of skills $\{z_i^C, z_i^M\}$. The covariances imply that routine workers with higher wages will in expectation be the ones with more to gain from switching to non-routine cognitive jobs, while the workers with relatively lower wages will in expectation be the ones with more to gain from switching to non-routine manual ones.

Assume that the endowments of the two types of skills are independently distributed in the population, so that $Cov(z_i^M, z_i^C) = 0$. The variances of each of the two types of skills are denoted σ_M^2 and σ_C^2. Using these assumptions, along with the equation for log wages (A.6) and the assumption for $\ln \varphi_j(z_i)$, Equation (A.25) implies:

$$\begin{aligned} Cov\left\{\theta_C - \theta_R + (b_C^C - b_R^C) z_i^C - b_R^M z_i^M, \theta_R + b_R^C z_i^C + b_R^M z_i^M\right\} > 0 \\ (b_C^C - b_R^C) b_R^C \sigma_C^2 - (b_R^M)^2 \sigma_M^2 > 0 \end{aligned}$$

That is:

$$(b_C^C - b_R^C) b_R^C \sigma_C^2 > (b_R^M)^2 \sigma_M^2 \tag{A.27}$$

And Equation (A.26) implies:

$$\begin{aligned} Cov\left\{\theta_M - \theta_R + (b_M^M - b_R^M) z_i^M - b_R^C z_i^C, \theta_R + b_R^C z_i^C + b_R^M z_i^M\right\} < 0 \\ (b_M^M - b_R^M) b_R^M \sigma_M^2 - (b_R^C)^2 \sigma_C^2 < 0 \end{aligned}$$

That is:

$$(b_M^M - b_R^M)b_R^M\sigma_M^2 < (b_R^C)^2\sigma_C^2 \tag{A.28}$$

Equations (A.27) and (A.28) provide restrictions on the dispersion of skills in the population, and on the returns to skills in the different occupations. As long as these two equations hold, the predicted patterns of occupational switching described in the paper go through.

Note that the restrictions allow for returns to manual skills to be largest in non-routine manual occupations (that is $(b_M^M - b_R^M) > 0$), as long as the variance of cognitive skills in the population is large enough relative to the variance of manual skills. Note also that under the two-dimensional skills assumption there may be some overlap in the wage distributions across the three occupations.

Appendix C Grouping of Occupation Codes

Table A.1 describes the mapping of 3-digit occupation codes into the broad categories used in the main specification in the paper. The mapping is based on aggregating 3-digit codes into 1-digit categories, and then labeling them according to their main task (Acemoglu and Autor, 2011).

Appendix C.1 Alternative Classification of Occupations

In order to test the robustness of the results to the way in which occupations are grouped, I also use an alternative classification of occupations in which I directly use task data from the Dictionary of Occupational Titles (DOT), and follow a procedure similar to Autor and Dorn (2009) to assign occupations to the broad task categories (non-routine manual, routine and non-routine cognitive). I use data from the 4th Edition of the DOT, which was published in 1977 and is available in electronic format through the Interuniversity Consortium for Political and Social Research (ICPSR, 1981). The DOT provides precise measures of the different abilities that are required in different occupations, as well as the different work activities performed by job incumbents. The DOT-77 has its own coding scheme, which is much more disaggregated than the Census Occupation Codes (COC) used in the PSID. To aggregate to the 1970-COC level, I follow Autor et al. (2003). I use the April 1971 CPS Monthly File, in which experts assigned individuals both with 1970-COC and DOT-77 codes. Using the CPS sampling weights, I calculate means of each DOT task measure at the 1970-COC occupation level. Each DOT score is rescaled to have a (potential) range from zero to 10. I then generate an index of relative routine task intensity for each occupation j (RTI_j) as follows:

$$RTI_j = \frac{rt_j}{max\{nr\_cog_j, nr\_man_j\}} \tag{A.29}$$

where, following Autor et al. (2003), rt_j is the mean score for 'Dealing with set limits, tolerances and standards' and 'Finger dexterity'; nr_cog_j is the mean score for 'Mathematics' and 'Direction, control and planning'; and nr_man_j is the score for 'Eye-Hand-Foot Coordination'. I attach the task measures to the 1970 Census (downloaded from David Autor's website) and label the occupations in the top third of the employment-weighted distribution of RTI as intensive in routine tasks.[3] Among the remaining occupations, I generate an index of relative non-routine cognitive task intensity (CTI_j) as follows:

$$CTI_j = \frac{nr\_cog_j}{nr\_man_j} \tag{A.30}$$

I label the occupations above the median of the employment-weighted distribution (among the remaining occupations) of CTI as intensive in non-routine cognitive tasks, and the remaining occupations as intensive in non-routine manual tasks. Once I have each 1970-COC labeled with its main task, I can attach these task labels to the PSID data up to 2001 (which is the period for which PSID occupation were coded using 1970-COC).

Figure A.1 plots the switching probabilities for routine workers into the two non-routine categories. With this alternative classification of occupations the measured switching rates are higher, but the general pattern in the direction of switches across ability quintiles remains robust. Meanwhile, Figure A.2 shows the estimated changes in occupation wage premia from the estimation of Equation (5) using the alternative occupation classification. The Figure confirms the robustness of the result on the falling wage premium in routine occupations relative to either non-routine category.

Appendix D A Simple Decomposition of the Changes in the Share of Routine Employment

There are (at least) three different ways in which the changes in the share of routine employment can be decomposed in order to assess the relative importance of occupational mobility, and entry and exit from the employment pool (for example due to retirement of older workers or entry decisions of new workers).

First, consider the decomposition of the change in the share of routine employment into the portion that would have occurred due to occupational mobility if the total employment pool had remained constant, and the additional effect due to changes in the employment pool

[3] The weights are equal to the product of the Census sampling weight, weeks worked last year and usual weekly hours.

(entry and exit). This leads to:

$$
\begin{aligned}
\frac{E_t^R}{E_t} - \frac{E_{t-1}^R}{E_{t-1}} &= \left[\frac{E_{t-1}^R + Occ_{t-1}^R}{E_{t-1}} - \frac{E_{t-1}^R}{E_{t-1}}\right] + \left[\frac{E_{t-1}^R + Occ_{t-1}^R + N_{t-1}^R}{E_{t-1} + N_{t-1}^R + N_{t-1}^{NR}} - \frac{E_{t-1}^R + Occ_{t-1}^R}{E_{t-1}}\right] \\
&= \left[\frac{Occ_{t-1}^R}{E_{t-1}}\right] + \left[\frac{E_t^R}{E_t} - \frac{E_{t-1}^R + Occ_{t-1}^R}{E_{t-1}}\right] \\
&= \left[\frac{Occ_{t-1}^R}{E_{t-1}}\right] + \left[\frac{E_t^R}{E_t} - \frac{E_{t-1}^R}{E_{t-1}} - \frac{Occ_{t-1}^R}{E_{t-1}}\right]
\end{aligned}
$$

where E_t^R is the stock of routine employment at time t, E_t is the total stock of employment at time t, Occ_{t-1}^R represents total net inflows into routine employment from non-routine occupations between $t-1$ and t (i.e. the total number of workers observed in non-routine employment in $t-1$ and in routine employment in t, minus the total number of workers observed in routine employment in t and in non-routine employment in $t-1$), and N_{t-1}^R and N_{t-1}^{NR} stand for net inflows into employment in routine and non-routine occupations, respectively, between $t-1$ and t.

Next, consider a decomposition where we first allow for changes in the employment pool due to exit, then allow for occupational mobility, and then allow for entry into employment. This leads to:

$$
\begin{aligned}
\frac{E_t^R}{E_t} - \frac{E_{t-1}^R}{E_{t-1}} = &\left[\frac{E_{t-1}^R - X_{t-1}^R}{E_{t-1} - X_{t-1}^R - X_{t-1}^{NR}} - \frac{E_{t-1}^R}{E_{t-1}}\right] \\
&+ \left[\frac{E_{t-1}^R - X_{t-1}^R + Occ_{t-1}^R}{E_{t-1} - X_{t-1}^R - X_{t-1}^{NR}} - \frac{E_{t-1}^R - X_{t-1}^R}{E_{t-1} - X_{t-1}^R - X_{t-1}^{NR}}\right] \\
&+ \left[\frac{E_{t-1}^R + Occ_{t-1}^R + N_{t-1}^R}{E_{t-1} + N_{t-1}^R + N_{t-1}^{NR}} - \frac{E_{t-1}^R - X_{t-1}^R + Occ_{t-1}^R}{E_{t-1} - X_{t-1}^R - X_{t-1}^{NR}}\right] \\
= &\left[\frac{E_{t-1}^R - X_{t-1}^R}{E_{t-1} - X_{t-1}^R - X_{t-1}^{NR}} - \frac{E_{t-1}^R}{E_{t-1}}\right] + \left[\frac{Occ_{t-1}^R}{E_{t-1} - X_{t-1}^R - X_{t-1}^{NR}}\right] \\
&+ \left[\frac{E_t^R}{E_t} - \frac{E_{t-1}^R - X_{t-1}^R + Occ_{t-1}^R}{E_{t-1} - X_{t-1}^R - X_{t-1}^{NR}}\right]
\end{aligned}
$$

where X_{t-1}^R and X_{t-1}^{NR} represent exit from employment (to non-employment) out of routine and out of non-routine occupations respectively, between $t-1$ and t. Note that the term in the first set of square brackets is the difference between the share of routine employment among individuals who remain in the employment sample between $t-1$ and t relative to the routine employment share in the full employment sample in $t-1$. Meanwhile, the term in the final set of square brackets is the difference between the share of routine employment at time t in the full sample and the share of routine employment at time t among the susbset of workers who were in the employment sample in $t-1$.

Finally, consider a decomposition where we first allow for net entry into employment and then allow for occupational mobility given the composition of employment induced by the new net entrants. This leads to:

$$\begin{aligned}
\frac{E_t^R}{E_t} - \frac{E_{t-1}^R}{E_{t-1}} &= \left[\frac{E_{t-1}^R + N_{t-1}^R}{E_{t-1} + N_{t-1}^R + N_{t-1}^{NR}} - \frac{E_{t-1}^R}{E_{t-1}}\right] \\
&\quad + \left[\frac{E_{t-1}^R + N_{t-1}^R + Occ_{t-1}^R}{E_{t-1} + N_{t-1}^R + N_{t-1}^{NR}} - \frac{E_{t-1}^R - N_{t-1}^R}{E_{t-1} + N_{t-1}^R + N_{t-1}^{NR}}\right] \\
&= \left[\frac{E_{t-1}^R + N_{t-1}^R}{E_t} - \frac{E_{t-1}^R}{E_{t-1}}\right] + \left[\frac{Occ_{t-1}^R}{E_t}\right]
\end{aligned}$$

Each decomposition provides a slightly different term for the component attributable to occupational mobility:

$$\text{A:} \quad \frac{Occ_{t-1}^R}{E_{t-1}} \qquad\qquad \text{B:} \quad \frac{Occ_{t-1}^R}{E_{t-1} - X_{t-1}^R - X_{t-1}^{NR}} \qquad\qquad \text{C:} \quad \frac{Occ_{t-1}^R}{E_t}$$

Each of these terms can be computed from the data and aggregated over any relevant time horizon. I compute them over consecutive two-year windows from 1977 to 2007 and accumulate them over the ten-year periods from Figure 2. The results are presented in Figure A.3.

All three decompositions show very similar results. Over all three decades there are net outflows from routine towards non-routine occupations among workers who remain in the employment sample. Moreover, the falls in the routine employment share are almost entirely driven by net outflows to other occupations rather than entry and exit from the employment pool. Note that the portion attributed to entry and exit could also include occupational switchers who go through a period when they are out of the employment sample (either because of unemployment, labor force non-participation or attrition from the PSID).

Appendix E Patterns for Women

The paper focuses on male workers in order to abstract from the selectivity issues related to changes in female labor force participation and their access to different occupations. These issues notwithstanding, this section explores the occupational mobility and wage patterns for female routine workers. Given that women have high employment shares in certain occupations that are intensive in routine tasks (such as clerical and administrative support jobs), RBTC may also have important impacts on women.

Data is available in the PSID from 1979 onwards for female household heads and for wives or partners of household heads. Table A.2 presents summary statistics for this sample. Routine occupations are also in the middle of the wage distribution for women, and their employment share has also fallen substantially over time as shown in Figure A.4. Most of the compensating increase in employment share has occurred in non-routine cognitive occupations, and to a smaller extent since the 1990s in non-routine manual occupations.

I estimate Equation (5) using the sample of women. Figure A.5 uses the results of this estimation to plot the transition patterns for women in routine occupations. As was the case for men, women in the top ability quintile are more likely to switch to non-routine cognitive jobs than women at other parts of the ability distribution, while women at the bottom of the ability distribution within the routine occupation are relatively more likely to transition to non-routine manual jobs.

Figure A.6 plots the estimated changes in the occupation fixed effects. Interestingly, for women, there is no evidence of a fall in the routine occupation wage premium relative to non-routine manual occupations over time. The routine occupation wage premium falls over time relative to non-routine cognitive occupations only.[4]

Finally, Table A.3 provides evidence on the wage changes for female routine workers switching to non-routine jobs relative to stayers. The results are similar to those found for men: Switchers to non-routine cognitive occupations experience faster wage growth than stayers over all time horizons. Switchers to non-routine manual occupations experience slower wage growth over horizons up to 4 years, but faster wage growth over 10-year horizons.

Appendix F Other Model Implications

As can be seen from the depiction of the model predictions in Figure 1, there are also theoretical implications about the wages of workers who switch out of routine occupations relative to other workers in their *destination* occupations. Specifically, workers who switch from routine to non-routine cognitive occupations should be at the bottom of the wage distribution in their new occupation, while workers who switch to non-routine manual occupations should be at the top of the wage distribution in that occupation.

Table A.4 tests these predictions. Columns (1) and (2) show the results of a regression of log real wages on dummies for individuals' occupation in period $t-2$. Column (1) uses the sample of non-routine cognitive workers in period t, and workers who were already in non-routine cognitive occupations in period $t-2$ are the omitted category. The coefficient estimates show that workers who switch from routine to non-routine cognitive occupations between years t and $t-2$ have significantly lower wages than those who remain in non-routine cognitive occupations over the same period. Meanwhile, Column (2) is a similar regression for the sample of workers who are in non-routine manual occupations in period t. The results

[4] This is robust to controlling for changes in the return to education.

show that workers who switch from routine to non-routine manual occupations between period t and $t-2$ earn on average significantly lower wages than workers who remain in non-routine manual jobs over the same period. Columns (3) and (4) verify the robustness of these results when using individuals' estimated occupation spell fixed effects as the dependent variable. We can conclude that switchers to non-routine cognitive occupations tend to be at the bottom of the wage distribution in their destination occupation, as predicted by the model. However the model prediction that switchers to non-routine manual jobs are at the top of the wage distribution in that occupation is not satisfied in the data.

These results can be contrasted with the findings in Groes et al. (2010). They do find that workers who experience an occupation downgrade (i.e., switch to an occupation that on average pays lower wages) earn higher wages than stayers in the destination occupation. However, this finding is based on all occupation downgrades, not specifically on workers switching out of occupations that are experiencing a decline in productivity (as it the case for routine occupations). Given that the transition patterns out of occupations that experience productivity declines are different than those from other occupations, it may be the case that the wage changes for this particular subset of switchers are different in their dataset as well.

Another implication of the model which can be inferred from Figure 1 is that, because of the selection patterns induced by RBTC, wage inequality should fall within routine occupations and rise within non-routine occupations. Figure A.7 plots the variance of log real wages within each occupation over time in the top panel, and the variance of the estimated occupation spell fixed effects in the bottom panel. We do observe an increasing trend in within-occupation inequality in the two non-routine occupations. However, there is also evidence of increasing inequality within the routine occupations, although at a slower rate than in the non-routine ones.

Table A.1: Occupation code groupings

Task label	Occupations included	3-digit Census Codes 1970-COC	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: The 1970 Census Occupation Codes (COC) were used in the PSID up to 2001. Since 2003, the 2000 coding system has been used. Task labels are based on Acemoglu and Autor (2011). Occupation code groupings and details on the 3-digit codes can be found in the Working Paper version of Kambourov and Manovskii (2008) and on the IPUMS website (King et al., 2010): See `http://usa.ipums.org/usa/volii/97occup.shtml` for the 1970 codes and `http://usa.ipums.org/usa/volii/00occup.shtml` for the 2000 codes.

Table A.2: Summary statistics, women

	Non-Routine Cognitive			Routine			Non-Routine Manual		
	1979-1986	1987-1996	1997-2007	1979-1986	1987-1996	1997-2007	1979-1986	1987-1996	1997-2007
Nr of Obs	3,472	7,458	6,451	5,693	8,609	5,656	1,868	3,000	2,145
Share	0.31	0.39	0.45	0.52	0.45	0.40	0.17	0.16	0.15
Nr of Indiv	1,030	1,823	2,372	1,657	2,184	2,293	689	1,039	1,125
Averages:									
Real Wages	6.65	7.91	8.92	4.53	5.26	5.71	3.48	4.06	4.54
Residual Wages	0.088	0.160	0.160	0.001	-0.058	-0.092	-0.173	-0.248	-0.250
Age	36.21	38.29	40.64	36.09	37.49	39.84	37.42	37.57	37.59
Fractions within the occupation group:									
Union	0.14	0.13	0.14	0.14	0.12	0.11	0.09	0.09	0.09
H.S. Dropout	0.01	0.01	0.01	0.09	0.06	0.05	0.22	0.14	0.12
H.S. Grad	0.15	0.18	0.19	0.53	0.51	0.45	0.48	0.51	0.48
Some Coll.	0.24	0.26	0.27	0.28	0.33	0.37	0.23	0.27	0.31
College	0.60	0.55	0.53	0.11	0.10	0.14	0.06	0.08	0.09
Task measures:									
Non-Routine Cognit.	5.06	5.19	5.22	1.76	1.86	1.98	1.36	1.45	1.42
Routine	3.10	3.05	2.99	5.60	5.39	4.95	2.76	2.61	2.53
Non-Routine Manual	1.06	0.96	0.94	0.44	0.39	0.38	1.57	1.46	1.53

Note: Sample includes females (household heads or wives) 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. Real wages are in 1979 dollars. Residual wages are obtained from a regression of log real wages on age, age squared, and dummies for education, union status, marital status, race, urban area, region and year. See Table 1 for details on the task measures.

Table A.3: Wage changes for female 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:	1979-1997	1979-2007	1979-2007	1979-2007	1979-1991	1991-2007
	(1)	(2)	(3)	(4)	(5)	(6)
to non-routine cognitive	.069 (.008)***	.086 (.007)***	.098 (.009)***	.162 (.019)***	.094 (.015)***	.089 (.010)***
to non-routine manual	-.046 (.021)**	-.085 (.021)***	-.041 (.022)*	.052 (.030)*	-.105 (.042)**	-.056 (.033)*
Const.	-.009 (.009)	-.006 (.010)	.072 (.014)***	.161 (.023)***	-.007 (.010)	.046 (.009)***
Obs.	11724	13745	10440	5290	3328	5578
Nr of Indiv.	2318	2784	2290	1454	1338	1993
R^2	.017	.029	.029	.036	.034	.032

Panel B: 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:	1979-1997	1979-2007	1979-2007	1979-2007	1979-1991	1991-2007
	(1)	(2)	(3)	(4)	(5)	(6)
to non-routine cognitive	10.01	14.62	14.61	14.33	12.35	17.34
to non-routine manual	2.53	3.64	3.51	3.93	2.82	4.30

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) excluded. Standard errors are clustered at the individual level.

Table A.4: Wage levels for switchers relative to other workers in their destination occupation

Dependent Variable:	Log real wages		Occ Spell Fixed Effect	
Occupation at t:	non-routine cognitive	non-routine manual	non-routine cognitive	non-routine manual
	(1)	(2)	(3)	(4)
from routine	-.359 (.015)***	-.360 (.033)***	-.302 (.014)***	-.300 (.030)***
from non-routine manual	-.605 (.039)***		-.548 (.034)***	
from non-routine cognitive		-.127 (.053)**		-.063 (.048)
Const.	2.384 (.021)***	1.865 (.048)***	.424 (.018)***	-.037 (.047)
Obs.	17768	2574	17637	2560
Nr of Indiv.	2781	730	2769	726
R^2	.083	.089	.167	.16

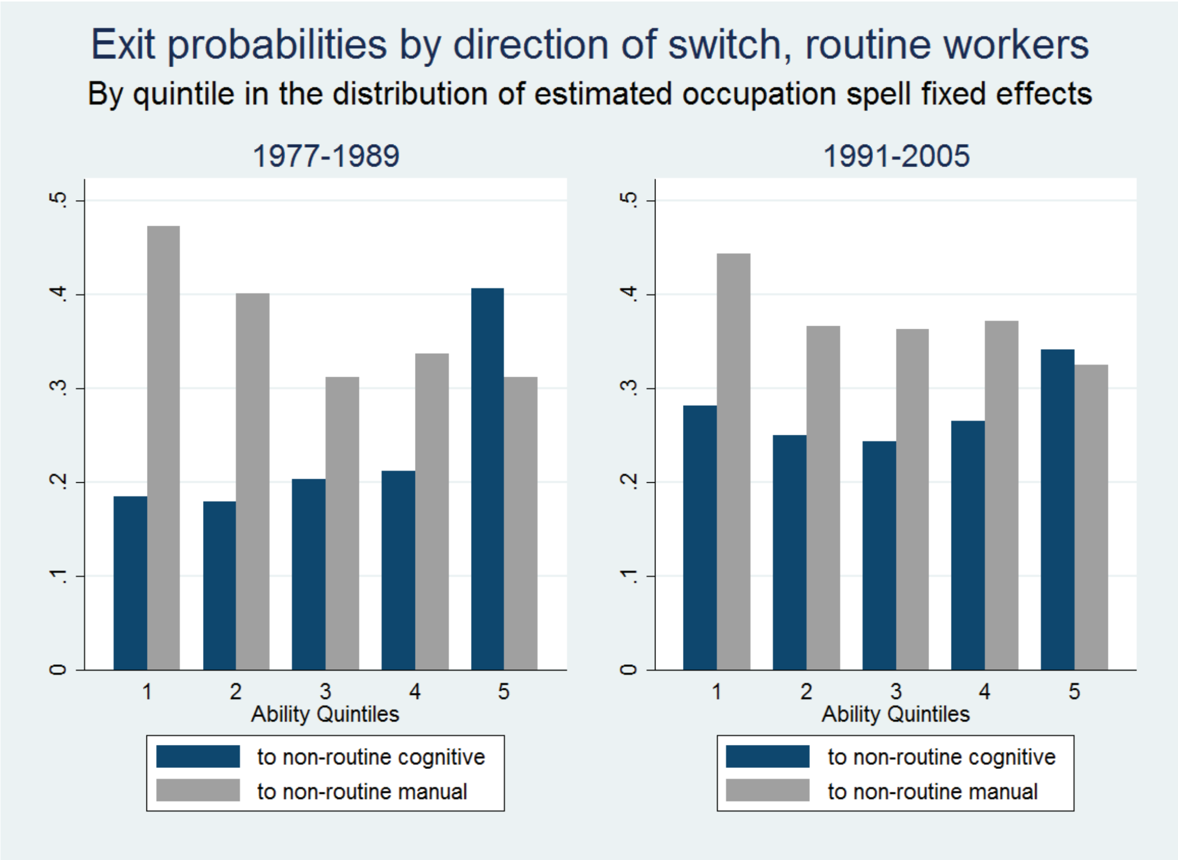
Note: Columns (1) and (3) use the sample of workers in non-routine cognitive occupations at time t and regress wages and estimated occupation spell fixed effects, respectively, on dummies for individuals' occupation in period $t-2$. Columns (2) and (4) are analogous regression for the sample of workers in non-routine manual occupations at time t. Non-switchers (workers who were already in the occupation in period $t-2$) are the omitted category. All regressions include year dummies. Observations with log real hourly wages below 0.1 ($1.1 1979 dollars) or above 4 ($54.6 1979 dollars) excluded. Standard errors are clustered at the individual level.

Table A.5: Descriptive statistics on occupational cycles

Occupation in period:			
t	$t+2$	$t+4$	Fraction
R	R	R	77.3%
R	R	C	7.2%
R	R	M	1.6%
R	C	C	7.2%
R	M	M	1.0%
R	C	R	4.5%
R	M	R	0.8%
R	C	M	0.2%
R	M	C	0.2%

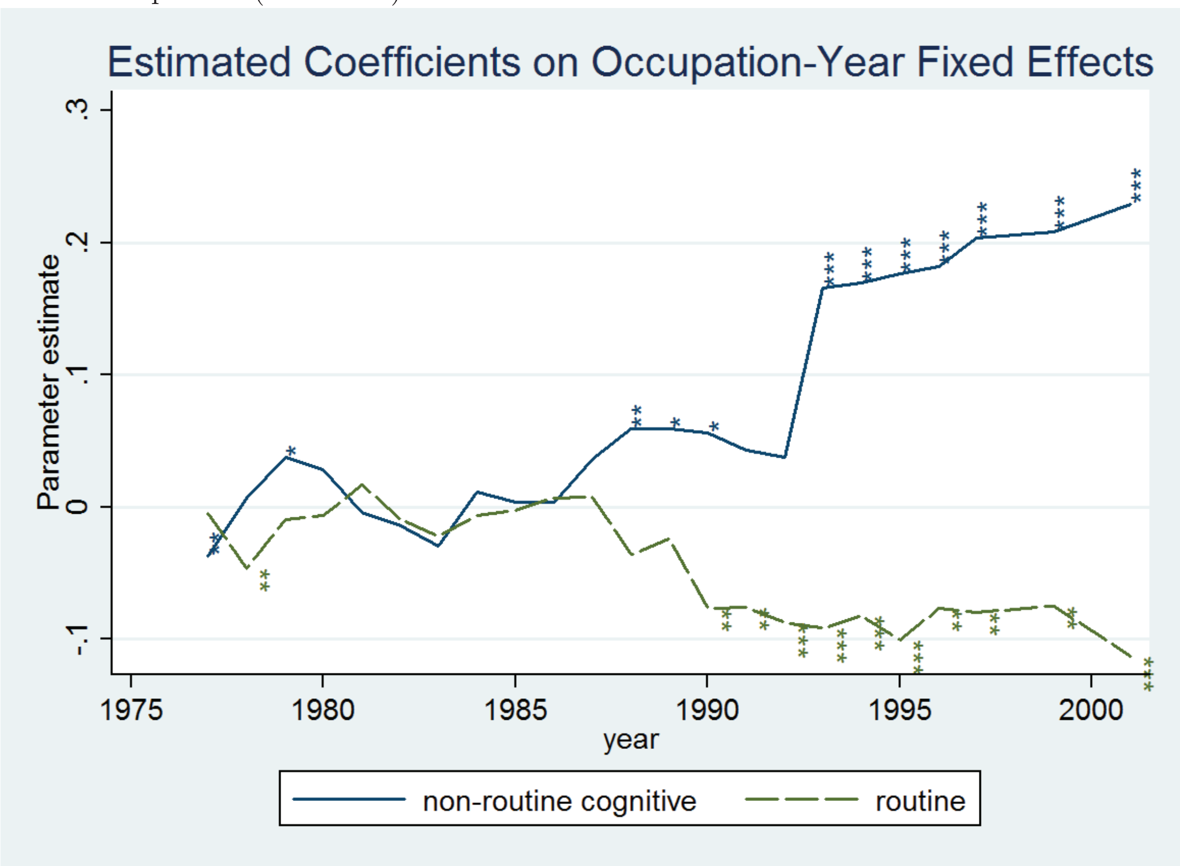
Note: R = Routine, C = Non-Routine Cognitive, M = Non-Routine Manual. The table considers workers who are observed in routine occupations with valid wage data at time t and who also have valid occupation codes in periods $t+2$ and $t+4$. The fraction that follow different occupational trajectories is presented in the final column.

Figure A.1: Direction of switch by ability quintile using the alternative classification of occupations



Note: Sample includes workers in routine occupations, and plots their probability of switching to the different non-routine occupations between years t and $t+2$, according to their ability quintile, using the alternative classification of occupations described in Appendix C.1.

Figure A.2: Estimated coefficients on occupation-year dummies under alternative classification of occupations (1976-2001)



Note: The figure shows the estimates of the time-varying occupation fixed effects $\widehat{\theta}_{rt}$ and $\widehat{\theta}_{cog}$ obtained from the wage equation (5) using the alternative classification of occupations into broad categories described in Appendix C.1. Stars denote the level at which the estimated coefficients are significantly different from zero.

Figure A.3: Decomposition of the changes in the share of routine employment into the fraction due to occupational mobility and the fraction due to net inflows from non-employment

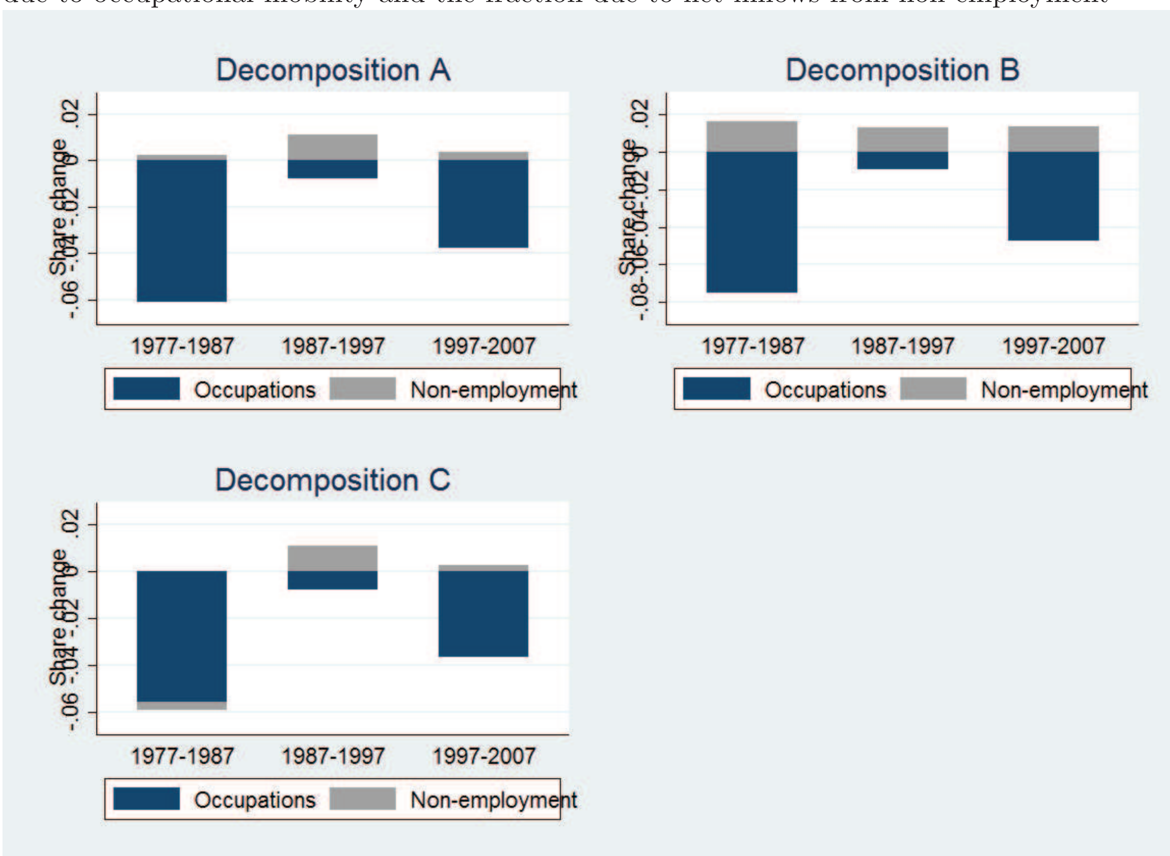
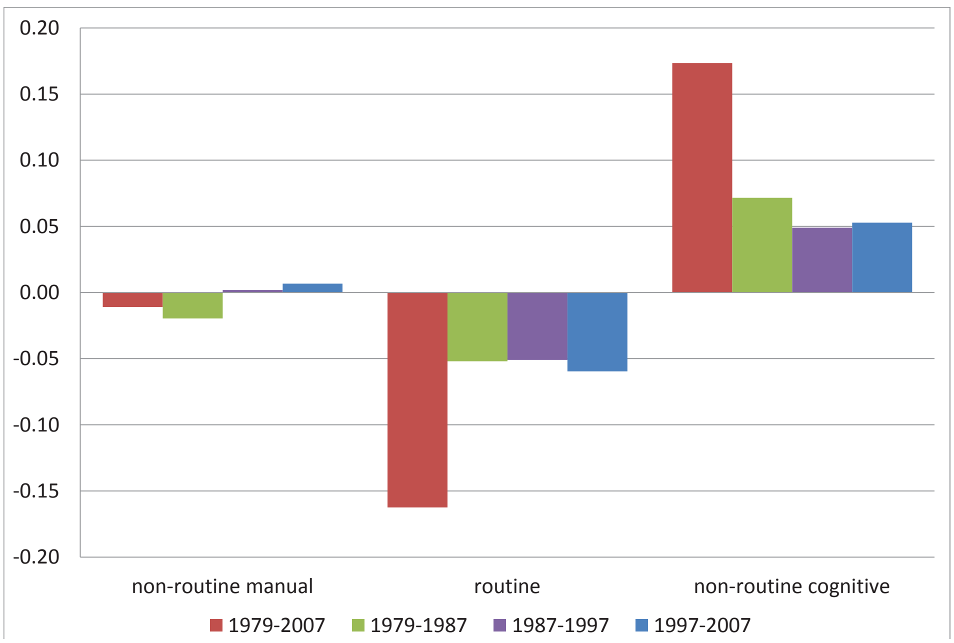
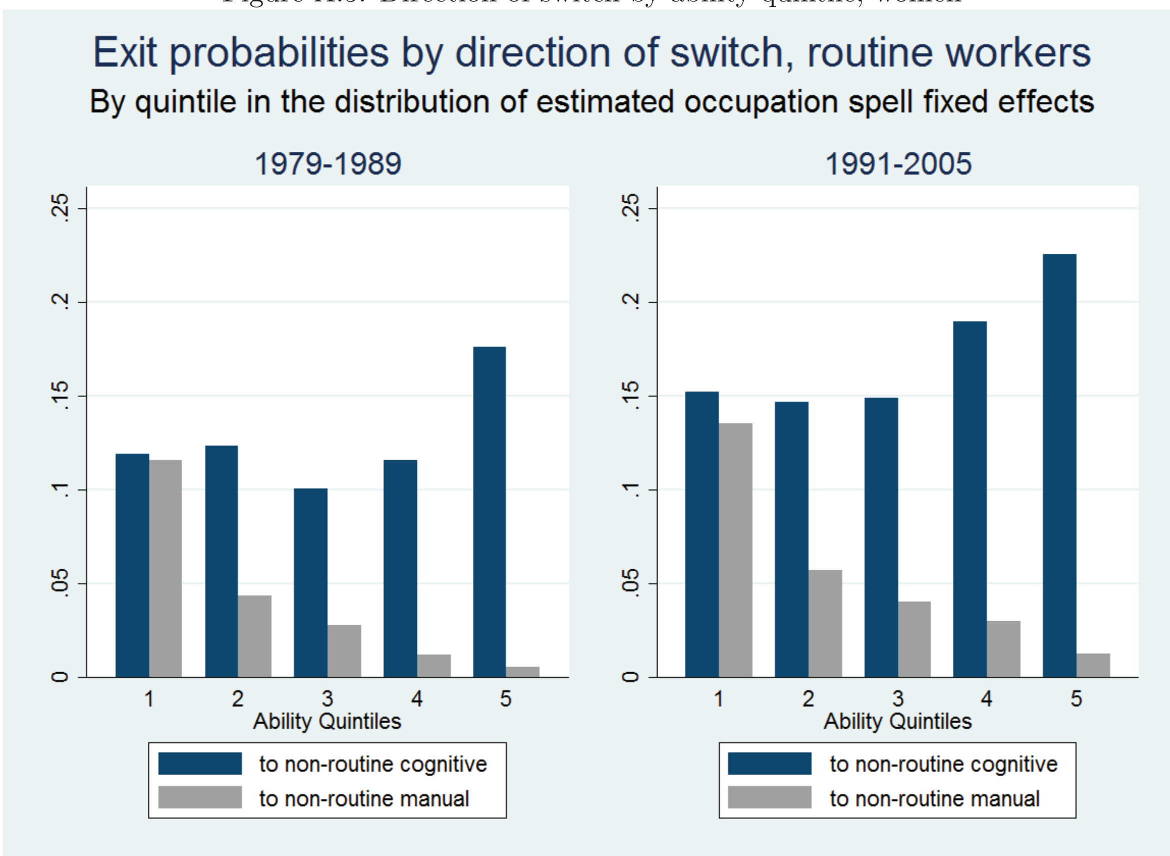


Figure A.4: Changes in employment shares for women



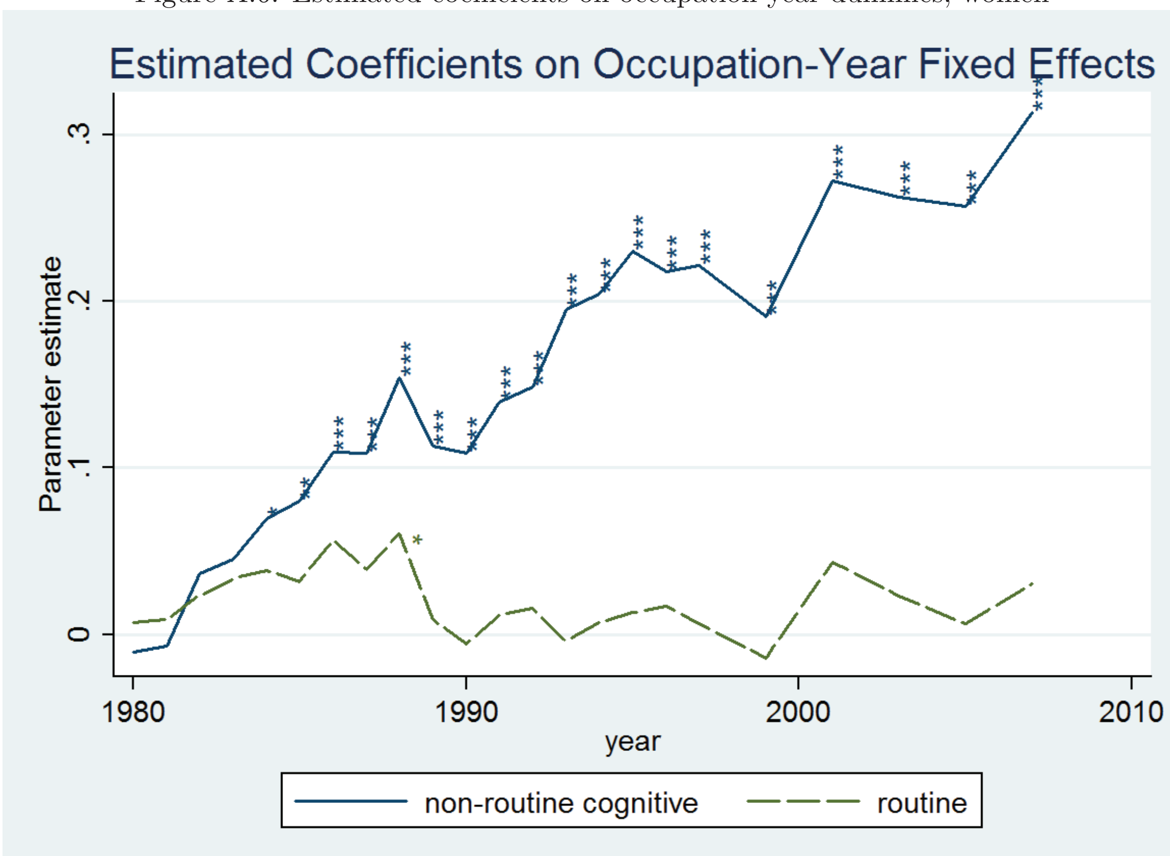
Note: Sample includes females (household heads or wives) aged 16 to 64 employed in non-agricultural, non-military jobs, who are part of the PSID's core sample and have non-missing wage data. See Data Section for details on the occupation classification.

Figure A.5: Direction of switch by ability quintile, women



Note: Sample includes workers in routine occupations, and plots their probability of switching to the different non-routine occupations between years t and $t+2$, according to their ability quintile.

Figure A.6: Estimated coefficients on occupation-year dummies, women



Note: The figure shows the estimates of the time-varying occupation fixed effects $\widehat{\theta}_{rt}$ and $\widehat{\theta}_{cog}$ obtained from the wage equation (5) using the sample of women from 1979-2007. Stars denote the level at which the estimated coefficients are significantly different from zero.

Figure A.7: Within-occupation wage inequality over time

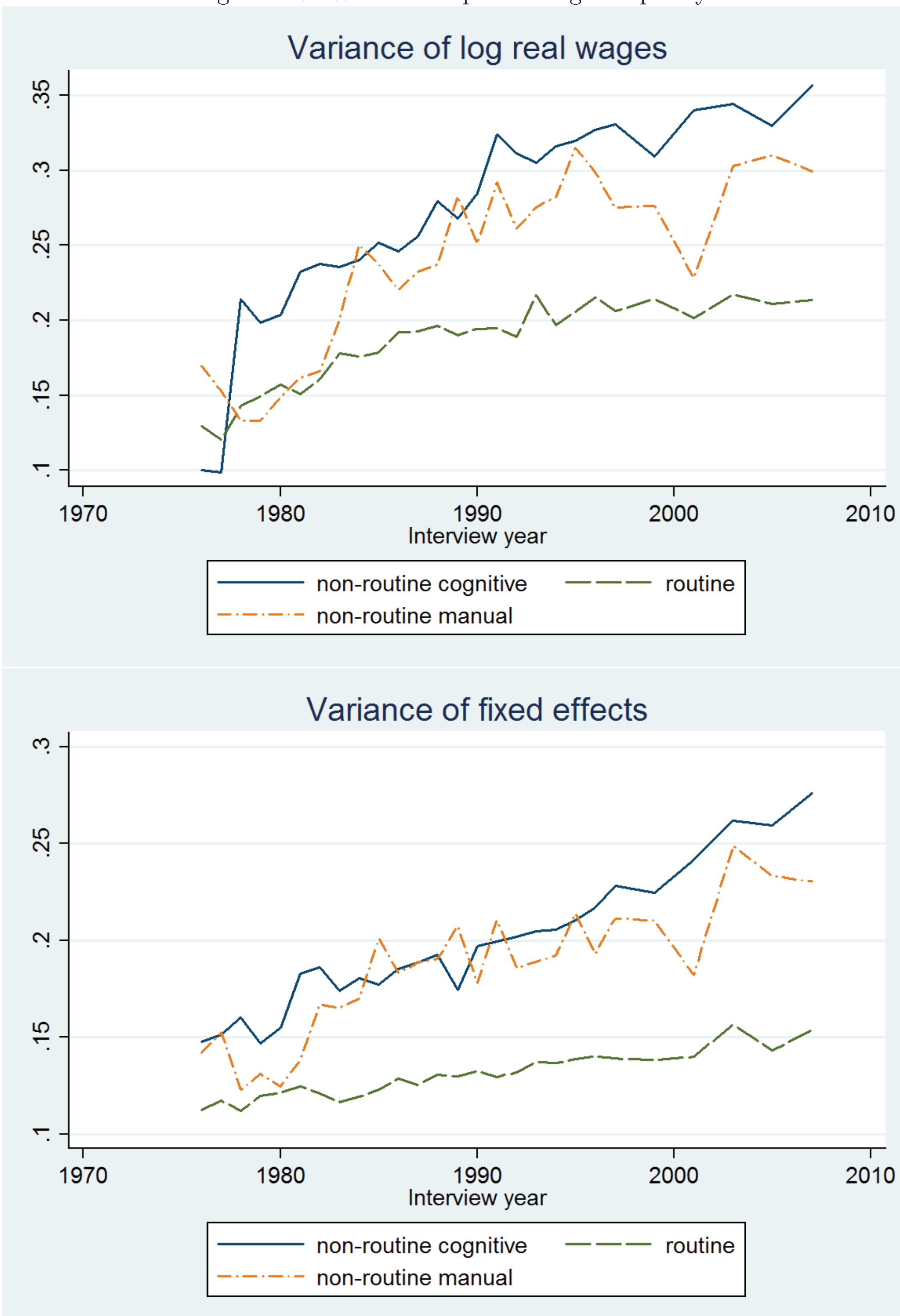
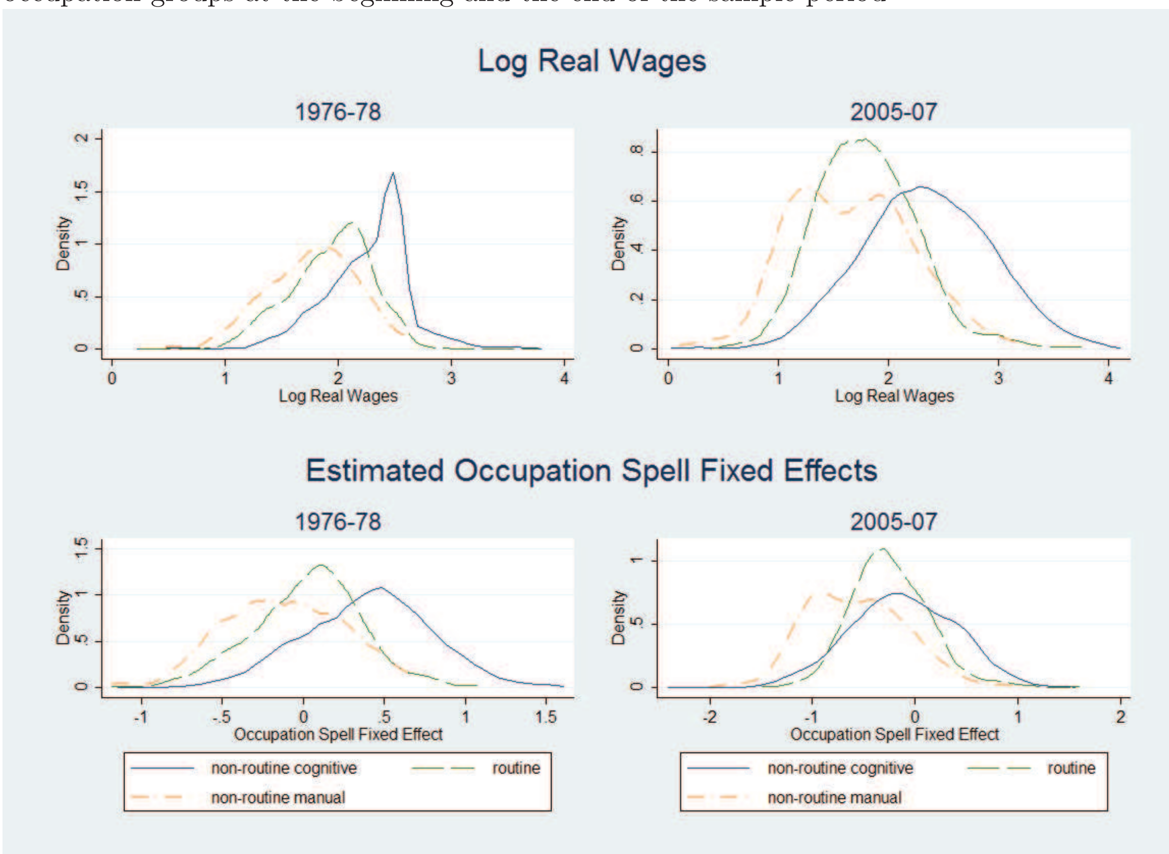


Figure A.8: Distribution of wages and occupation spell fixed effects in each of the broad occupation groups at the beginning and the end of the sample period



Note: Observations with real hourly wages below $1.1 or above $54.6 1979 dollars excluded.