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Guido Matias Cortes

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Abstract

Using a general equilibrium model with endogenous sorting of workers into occupations based on comparative advantage, this paper derives the effects of routine-biased technical change on occupational transition patterns and wage changes of individual workers. These predictions are then tested using data from the Panel Study of Income Dynamics (PSID) from 1976 to 2007. Consistent with the predictions of the model, occupational mobility patterns of routine workers show strong evidence of selection on ability. Workers of relatively high (low) ability are more likely to switch to non-routine cognitive (non-routine manual) occupations. Also consistent with the predictions of the model, there has been a significant increase over time in the relative wage premium in non-routine occupations. Workers staying in routine jobs therefore perform significantly worse in terms of wage growth than workers in any other type of occupation. Over long run horizons, switchers from routine to non-routine jobs also experience significantly faster wage growth than those who remain in the routine occupations.

*Department of Economics, University of Manchester, Arthur Lewis Building, Oxford Road, Manchester, UK M13 9PL. E-mail: gmcortes@alumni.ubc.ca. I am grateful to Nicole Fortin, Giovanni Gallipoli, David Green and Thomas Lemieux for their support and guidance. This paper also benefited from discussions with Uta Schönberg, Henry Siu, Vadim Marmer, Jean Mercenier, and with participants at the UBC Empirical Lunch, the CEA Conference (2011), the SOLE Conference (2012), and at seminars at SFU, Bank of Canada, Université de Montréal, UCL, Carleton, SOFI, University of Manchester, University of Queensland, University of Adelaide and Banco Central de Costa Rica. Financial support from CLSRN is gratefully acknowledged.

1 Introduction

Since the late 1980s, the labor market in the United States and other developed countries has become increasingly polarized. The share of employment in high-skill, high-wage occupations and in low-skill, low-wage occupations has grown relative to the share in occupations in the middle of the distribution. At the same time, wages have grown faster at the top and the bottom of the distribution than in the middle sections (Acemoglu and Autor, 2011).[1] Pioneering work by Autor, Levy, and Murnane (2003), Autor, Katz, and Kearney (2006) and Goos and Manning (2007) has linked the polarization phenomenon to the occupational structure of the economy, and in particular to the task content of different occupations. Workers in the middle of the wage distribution tend to be concentrated in occupations with a high content of routine tasks, as measured by information in the Dictionary of Occupational Titles (DOT). At the same time, technological changes occurring since the 1980s have resulted in the creation of capital, such as machines and computers, that can perform mainly routine tasks and can therefore substitute for workers in occupations with high routine task content. This hypothesis has become known as 'routinization', or routine-biased technical change (RBTC).

In this paper, I investigate the implications of routine-biased technical change within the context of a general equilibrium model with endogenous sorting of workers into occupations based on comparative advantage. The novel aspect of the paper is the focus on the individual-level predictions in terms of occupational switching patterns and wage changes. The paper's main contributions are to formalize these individual-level predictions within this type of model, and to test them using data from the Panel Study of Income Dynamics (PSID) from 1976 to 2007. To the best of my knowledge, the paper is the first to directly use individual-level panel data to study the labor market experience of routine workers in the U.S. over the past three decades, thus shedding light on what has happened to these workers over time. The approach taken in this paper provides micro-level evidence on the dynamics underlying the aggregate patterns of employment and wage polarization, on the way in which particular subsets of workers have been impacted by routinization, and on the changes over time in occupational wage premia once selection into occupations has been accounted for.

Technology has long been considered as a potential driver of changes in the economy's employment and wage structure. A large literature has thought of technological change as being skill-biased, in the sense that it has disproportionately favored high-skill workers (Juhn, Murphy, and Pierce (1993), Murphy and Welch (1993), Katz and Autor (1999), Berman, Bound,

[1]The polarization phenomenon has also been documented for European countries; see Dustmann, Ludsteck, and Schönberg (2009) and Goos, Manning, and Salomons (2009). See also Gregory and Vella (1995) for earlier work on the disappearance of middle-wage occupations in Australia over the period 1976-1990. Employment share polarization has also been documented at a sub-national level for the state of California in Milkman and Dwyer (2002). Their work also highlights differences in the patterns observed across metropolitan areas within the state.

and Machin (1998)).[2] In line with what Acemoglu and Autor (2011) call the 'canonical' model of the labor market, this literature mostly considers two types of workers (high and low skilled) performing distinct and imperfectly substitutable tasks. Empirically, the focus of this literature has been on the evolution of the college wage premium (with college education used as a proxy for skills), and the extent to which it is explained by technology through changes in the relative demand of college and non-college workers (Goldin and Katz (2008), Katz and Murphy (1992), Boudarbat, Riddell, and Lemieux (2010)), or by the intensity of capital use through capital-skill complementarities (Krusell, Ohanian, Ríos-Rull, and Violante, 2000).

The role of occupations in these types of studies was limited, as there was generally no distinction made between skills and tasks.[3] Recent theories of 'routinization' or routine-biased technical change (RBTC) have brought occupations and their task content to the forefront.[4] Empirical studies of the effects of RBTC for the United States have relied on repeated cross-sectional data, such as the Census or the Current Population Survey (CPS) (e.g. Autor, Katz, and Kearney (2008)), and have studied the effects of technological change on the wage structure of the economy, through changes in the occupational composition of employment.[5] Less is known about the ways in which specific subsets of workers have been impacted by RBTC. Autor and Dorn (2009) provide some insight on this by using data at the local labor market level. They study changes in employment shares across occupations for particular demographic groups, exploiting heterogeneities in the degree of initial specialization in routine-intensive occupations across commuting zones in the U.S. In this paper I go a step further by using individual-level panel data in order to directly study the labor market experience of routine workers, thus shedding light on their occupational mobility patterns and the wage changes they experience both in the short- and in the long-run.[6]

The occupational sorting mechanism featured in the model used in this paper follows Gibbons, Katz, Lemieux, and Parent (2005): workers select into occupations based on their comparative advantage. Unlike Acemoglu and Autor (2011), and following Jung and Mercenier (2010), the model economy is composed of three distinct occupations (non-routine man-

[2] See Lemieux (2008) for a survey on the evolving nature of wage inequality and the different theories that have been suggested since the 1990s. Another major potential driving force behind changes in the labor market is international trade. For recent work within this strand of the literature, see Autor et al. (2012).

[3] For example, Berman, Bound, and Machin (1998) and Berman, Bound, and Griliches (1994) use two broad occupational categories (production and non-production) as a proxy for skill groups.

[4] In addition to the routine content of occupations, their offshorability has also been argued to play an important role in the polarization of the labor market, as many middle-wage occupations also display task characteristics which make them more easily offshorable (Grossman and Rossi-Hansberg (2008), Firpo, Fortin, and Lemieux (2011)). Changes in the industrial composition, on the other hand, do not explain the changes in the employment structure: Acemoglu and Autor (2011) find that the shift against middle-skilled and favoring high- and low-skilled occupational categories occurs mainly within industries.

[5] Some attention has also been paid to changes in mean wages across occupations. For example, Krueger (1993) finds that occupations that have a larger increase in the share of workers using computers between 1984 and 1989 had a higher increase in mean log hourly earnings.

[6] A common assumption has been that most routine workers have been displaced into low-skill jobs (e.g. Acemoglu and Autor (2011), p.64), but there has been little evidence put forth to support this claim.

ual, routine, and non-routine cognitive) and a continuum of workers differentiated according to their skill level.[7] Capital is modeled as suggested by Autor, Levy, and Murnane (2003): it enters the production function as a substitute for labor working in routine tasks, and a complement for workers in non-routine cognitive tasks.

I derive the model's predictions for the effects of routine-biased technical change (RBTC) on individual workers. RBTC is modeled as an exogenous increase in the use of physical capital (due, for example, to a fall in the cost of computing power).[8] The model makes the following predictions: RBTC induces workers at the bottom of the ability distribution within routine occupations to switch to non-routine manual jobs, while inducing those at the top to switch to non-routine cognitive jobs. The model also makes predictions in terms of the changes in occupational wage premia: The wage premium in routine occupations is predicted to fall relative to that in the two non-routine occupations. For this reason, workers staying in routine jobs experience a fall in wages, relative to those staying in either non-routine manual or non-routine cognitive jobs. At the same time, the model predicts that switchers must do at least as well as stayers in terms of wage growth. The model and its predictions can be generalized (in expectations) to a setting with two-dimensional skills.[9]

To test the predictions of the model for individual workers, the paper uses data from the Panel Study of Income Dynamics (PSID). The PSID tracks individuals over time, making it possible to document the likelihood of transitions between different types of jobs, and to analyze the wage profiles for workers with different labor market experiences. Occupations are grouped into the three categories used in the model through an aggregation of 3-digit occupation codes: all service occupations are categorized as non-routine manual; sales and clerical occupations, craftsmen, foremen, operatives and laborers are categorized as routine; and professional and managerial occupations are categorized as non-routine cognitive.[10]

The empirical strategy involves the estimation of a wage equation that is obtained directly from the model. An individual worker's potential wage in each occupation consists of an occupation-specific premium (common to all workers in the same occupation in a given year), as well as an occupation-specific return to the worker's skills. Empirically, skills are allowed to contain both observable and unobservable components. Workers select into the occupation where their potential wage is highest. The key identifying assumptions for the estimation of

[7]The Acemoglu and Autor (2011) model instead features a continuum of tasks and three distinct skill groups. See also Costinot and Vogel (2010) for a model with a continuum of skills *and* a continuum of tasks.

[8]This is the view of capital that has been suggested in the literature as an explanation for employment and wage polarization (Acemoglu and Autor, 2011). See Nordhaus (2007) for evidence on the fall in the cost of computing power, and Bartel et al. (2007) on firm-level evidence on the effects of IT adoption on firms' skill requirements and human resource practices.

[9]This extension is presented in Appendix B. See also Yamaguchi (2012) for a model with two-dimensional skills.

[10]Full details of the occupations included in each of the categories are given in Appendix Table 11. Section 7.3 discusses the robustness of the results to an alternative occupation classification based directly on task data.

the wage equation are that: (i) unobservable skills are time-invariant, (ii) workers have full information about their skills, and (iii) any idiosyncratic temporary shocks to individual wages are independent of sectoral choice. Under these assumptions, estimating a wage equation with *occupation spell* fixed effects (i.e. interactions of individual fixed effects with occupation dummies) controls for the self-selection of workers into occupations based on unobserved ability, and allows for the consistent estimation of the changes over time in the occupation wage premia. The estimated occupation spell fixed effects themselves are also informative, as they can be used to rank workers according to ability *within* occupation-year cells.[11]

In contrast to the focus in the skill-biased technical change literature on the changes over time in the skill wage premium, changes in occupational wage premia (implied by models of RBTC such as the one used in this paper) have not received much attention in the literature. Gibbons, Katz, Lemieux, and Parent (2005) estimate the levels of occupational wage premia, but not their changes over time. Many empirical studies include occupation dummies when estimating wage regressions, but few include occupation-year dummies within a framework that allows for their consistent estimation.[12] The results in this paper provide information on the ways in which occupational wage premia have changed in the U.S. since the mid-1970s. The empirical strategy also provides a methodological contribution by outlining a method for the unbiased and consistent estimation of changes over time in occupational wage premia after controlling for selection into occupations.

The results indicate that there is strong evidence of selection on ability for workers switching out of routine jobs: Low ability routine workers are more likely to switch to non-routine manual jobs, while high ability routine workers are more likely to switch to non-routine cognitive jobs. This is fully consistent with the predictions of the model.

In terms of wage growth, I find that workers staying in routine jobs perform significantly worse than workers staying in any other type of occupation. The wage premium for routine occupations is estimated to have fallen by 17% from 1976 to the mid-2000s, relative to the wage premium for non-routine manual occupations. Meanwhile, over the same time period, the wage premium for non-routine cognitive occupations is estimated to have risen by 25% relative to the wage premium for non-routine manual occupations. The fall in the wage premium in routine occupations cannot be explained by changes in the return to education.

There are also significant differences in wage growth between routine workers who stay in routine jobs and those who switch to other occupations: Workers switching to non-routine

[11] The empirical strategy may be extended to allow for changes over time in the return to education and the empirical results are robust to this extension. See Section 7.2.

[12] For example, Cragg and Epelbaum (1996) estimate changes over time in the occupational premia in Mexico, but their estimation strategy does not take into account that selection into occupations may be correlated with workers' unobservable characteristics. They find that high paying occupations experienced high growth in their wage premia over the period 1987-1993, explaining close to half of the growing wage dispersion in Mexico, while low-skill occupations experienced rapid employment growth but sluggish wage growth. They link their findings to the elasticity of labor supply for workers of different skill levels.

manual jobs have significantly lower wage growth than stayers over short run horizons (around 14% lower over a two-year period), but subsequently recover from these losses and have significantly faster wage growth than stayers in the long run (5 to 12% higher over a 10-year period). Meanwhile, those who switch to non-routine cognitive occupations have significantly higher wage growth than stayers over all time horizons (6 to 12% higher over a two-year period; 14 to 16% higher over a 10-year period). All results are robust to allowing for time-varying skills (proxied by age).

The focus on the individual-level effects of RBTC helps bridge a gap between the aggregate-level literature on polarization and the individual-level literature on occupational mobility and its associated wage changes. Kambourov and Manovskii (2009) argue that an important component of human capital is occupation-specific, and is lost when a worker switches occupations.[13] Meanwhile Gathmann and Schonberg (2010) and Poletaev and Robinson (2008) provide evidence that human capital has an important task-specific component. Kambourov and Manovskii (2008) document an increase in occupational mobility in the United States between 1968 and 1997.[14] Groes, Kircher, and Manovskii (2009), using Danish administrative data, find a U-shaped pattern for occupational mobility (workers at the extremes of the wage distribution within an occupation are more likely to switch occupations than those in the middle), consistent with what I find in this paper. The framework presented in this paper helps interpret many of the findings from this literature within the broader context of technological change and labor market polarization. Routine-biased technical change is theoretically consistent as the driving force behind increasing occupational mobility, selection on ability among occupational switchers, and changes in occupation wage premia over time.

The rest of the paper is organized as follows. Section 2 describes the theoretical framework. Section 3 derives the model's predictions for the effects of routine-biased technical change. Section 4 describes the data and the occupational categories. Section 5 describes the empirical strategy. Section 6 presents the empirical results testing the predicted effects of RBTC using PSID data. Section 7 presents robustness checks on the main results of the paper, and Section 8 concludes.

2 Model

The model features an economy where workers sort into occupations based on comparative advantage as in Gibbons, Katz, Lemieux, and Parent (2005).[15] There is perfect information. Following Jung and Mercenier (2010) there is a continuum of workers who are differentiated

[13] See also Sullivan (2010) for evidence on the varying degrees of importance of occupation- and industry-specific human capital across different 1-digit occupations. His analysis uses data from the 1979 Cohort of the National Longitudinal Survey of Youth (NLSY).

[14] See also Moscarini and Thomsson (2007).

[15] Acemoglu and Autor (2011) call this type of model a Ricardian model of the labor market.

by their skill level, and three occupations.[16] Capital enters the production function as a substitute for routine tasks and a complement for non-routine cognitive tasks. Technical change is driven by increases in capital utilization (due, for example, to a fall in the cost of computing power), and is therefore routine-biased. Appendix B extends the model to allow for two-dimensional skill endowments (cognitive and manual) and describes the conditions under which the predictions of the basic model are still valid in expectations in that richer model. Note that the exposition of the model in this section follows Jung and Mercenier (2010).

2.1 Household Preferences

There is a single representative household composed of a continuum of workers. The household has Cobb-Douglas preferences over two consumption goods, Y_1 and Y_2. For reasons that will become clear later, Y_1 may be thought of as a service good, and Y_2 as a manufactured good. The household's utility function is given by:

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

where $0 < \beta < 1$. Maximizing utility subject to the budget constraint $I = p_1 Y_1 + p_2 Y_2$ (where I stands for total income) yields the following demand system:

$$p_1 Y_1 = (1-\beta) I \tag{2}$$

$$p_2 Y_2 = \beta I \tag{3}$$

2.2 Firms

Both industries Y_1 and Y_2 are perfectly competitive. Y_1, the service good, is produced by labor performing non-routine manual tasks (which, in practice, are mostly service occupations). Y_2, the manufactured good, requires the combination of two different tasks: routine and non-routine cognitive. Routine tasks may be performed either by labor or by physical capital (machines, computers), while non-routine cognitive tasks may be performed only by labor.

[16] This contrasts with Acemoglu and Autor (2011), who consider a continuum of tasks and three skill groups. One advantage of the Jung and Mercenier (2010) setup is that it does not require the definition of arbitrary distinctions between low-, middle- and high-skill workers. Boundaries only need to be defined between occupations (non-routine manual, routine, and non-routine cognitive). These distinctions can be made by relying on broad occupation codes, which differ sharply in terms of their task content (although the classification may still be subject to criticism, as some particular occupations may be hard to classify in an obvious manner). Another advantage of the setup used here is that it allows each individual worker's wage to depend both on their skill level *and* the task they perform (which as will be shown later, is empirically relevant). In Acemoglu and Autor (2011), all workers of a given skill receive the same wage, regardless of the task they are employed in.

Specifically, let the production function for the Y_2-good be:

$$Y_2 = \min\{\kappa_{rt} rt, cog\} \tag{4}$$

where κ_{rt} are exogenously determined routine task services provided by machines (capital), rt are total routine task services provided by workers, and cog are total non-routine cognitive task services provided by workers. Thus, capital is a substitute for labor providing routine tasks, while it is a complement for labor providing non-routine cognitive tasks.[17] rt and cog are endogenous and their determination will be described in detail below.

The assumptions of perfect substitutability between capital and routine workers, and perfect complementarity between capital and non-routine cognitive workers, although admittedly extreme, capture the role of capital in a simple and tractable way, and allow the derivation of strong and clear predictions from the model on the effects of routine-biased technical change (as will be discussed in Section 3).[18]

The marginal cost of labor (the wage per efficiency unit) for each task will be determined in equilibrium and is denoted C_{man}, C_{rt} and C_{cog}, for non-routine manual, routine, and non-routine cognitive tasks, respectively.

2.3 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 (man), routine (rt), or non-routine cognitive (cog).

Let $\varphi_j(z)$ denote the productivity (in terms of supplied efficiency units) of a worker of skill z performing task $j \in man, rt, cog$. $\varphi_j(z)$ is continuous and increasing in z so that a higher skilled worker is more productive than a less skilled one when performing the same task (absolute advantage). It is also assumed that more skilled workers 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:

$$0 < \frac{d\ln\varphi_{man}(z)}{dz} < \frac{d\ln\varphi_{rt}(z)}{dz} < \frac{d\ln\varphi_{cog}(z)}{dz} \tag{5}$$

Assume $\varphi_j(z_{min}) = 1$ for $j \in man, rt, cog$.

[17] See Autor et al. (2003) and Acemoglu and Autor (2011) for a discussion of why computers may be thought of as substitutes for routine workers and complements for non-routine workers.

[18] Autor et al. (2003) use a Cobb-Douglas specification to capture the complementarity between routine and non-routine tasks, with computers being perfect substitutes for workers in providing routine tasks.

2.4 Worker Sorting and Wages

Workers will choose which task to perform based on the 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:

$$w_j(z) = C_j \varphi_j(z) \tag{6}$$

where $w_j(z)$ is the potential wage in occupation $j \in man, rt, cog$ for an individual of skill level z.

In equilibrium, workers will sort between the three types of jobs according to their respective comparative advantage (given by Equation (5)). In particular, there will be 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, that is, those with $z \in [z_{min}, z_0)$ will find it optimal to select into the non-routine manual occupation, producing good Y_1; the medium-skill workers, that is, those with $z \in [z_0, z_1)$, will find it optimal to perform the routine task within the Y_2-sector; and the most skilled workers, i.e. those with $z \in [z_1, z_{max}]$, will find it optimal to work in non-routine cognitive jobs also within the Y_2-sector.

Wages will therefore satisfy:

$$w(z) = \begin{cases} C_{man}\varphi_{man}(z) & \text{for } z_{min} \leq z < z_0 \\ C_{rt}\varphi_{rt}(z) & \text{for } z_0 \leq z < z_1 \\ C_{cog}\varphi_{cog}(z) & \text{for } z_1 \leq z \leq z_{max} \end{cases}$$

In equilibrium, the cutoffs z_0 and z_1 are determined so that the marginal workers have no incentives to relocate between tasks. That is, the marginal worker would receive the same wage performing either task. Formally, this means:

$$C_{man}\varphi_{man}(z_0) = C_{rt}\varphi_{rt}(z_0) \tag{7}$$

$$C_{rt}\varphi_{rt}(z_1) = C_{cog}\varphi_{cog}(z_1) \tag{8}$$

According to the way in which the tasks have been labeled, this equilibrium distribution implies that mean real wages will be lowest for non-routine manual workers, and highest for non-routine cognitive workers, which is consistent with the data (as will be shown in the empirical section). Note also that an individual worker's wage depends both on his skill level, and on the type of task he performs.

2.5 Equilibrium

The equilibrium skill thresholds z_0 and z_1 determine the employment in each of the occupation types, and the output of each of the goods Y_1 and Y_2. For the Y_1-good, the market-clearing condition is:

$$\int_{z_{min}}^{z_0} \varphi_{man}(z)dG(z) = Y_1 \tag{9}$$

For the Y_2-sector, from equation (4), total input of routine and non-routine cognitive task services must be equal in equilibrium. That is:

$$\kappa_{rt} \int_{z_0}^{z_1} \varphi_{rt}(z)dG(z) = \int_{z_1}^{z_{max}} \varphi_{cog}(z)dG(z) \tag{10}$$

Recall that κ_{rt} accounts for the (exogenous) contribution of capital to the provision of routine tasks.

The market-clearing condition for the Y_2-good can be written either in terms of the total input of routine task services, or the total input of non-routine cognitive task services. In terms of the latter, it is as follows:

$$\int_{z_1}^{z_{max}} \varphi_{cog}(z)dG(z) = Y_2 \tag{11}$$

Marginal cost pricing holds in the Y_1-sector, so that:

$$p_1 = C_{man} \tag{12}$$

Finally, the household's income is given by:

$$I = C_{man} \int_{z_{min}}^{z_0} \varphi_{man}(z)dG(z) + C_{rt}\kappa_{rt} \int_{z_0}^{z_1} \varphi_{rt}(z)dG(z) + C_{cog} \int_{z_1}^{z_{max}} \varphi_{cog}(z)dG(z) \tag{13}$$

Let the Y_1 good be the numeraire, so $p_1 = 1$.

Equations (2), (3), (7), (8), (9), (10), (11), (12), and (13) along with the choice of numeraire determine the equilibrium levels of the endogenous variables C_{man}, C_{rt}, C_{cog}, z_0, z_1, Y_1, Y_2, p_1, p_2, I.

3 Effects of Routine-Biased Technical Change

In this section, I analyze the effects of routinization-biased technical change (RBTC) on the endogenous variables of the model. The analysis extends Jung and Mercenier (2010) 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. Unlike Jung and Mercenier (2010), who define RBTC as an increase in κ_{rt} as well as a simultaneous increase in the slope of $\varphi_{rt}(z)$, I define RBTC as an increase in κ_{rt} only.

I do this for two reasons. First, routinization theories have thought of capital as changing marginal productivities of workers performing different tasks due to the substitutabilities and complementarities embedded in the production function (Autor et al., 2003), rather than through changes in the supply of efficiency units of particular worker types. Although this extra channel might be worth exploring in future work, by changing only κ_{rt} I can study the implications of standard routinization theories within the context of the model considered in this paper. This ensures comparability with the predictions derived from other models in the literature, in particular, Acemoglu and Autor (2011).[19] Second, by changing only one parameter, the general equilibrium effects of that specific change may be isolated and formalized. This also eases the interpretation of the results, as all of the implied effects may be attributed to the change in one particular parameter.

3.1 Switching Patterns Induced by RBTC

First, consider a comparative statics analysis of the effects of a change in κ_{rt} on the ability cutoffs z_0 and z_1. This will tell us what kind of occupational switching is induced by RBTC, and which workers switch to which occupations.

Define:

$$\begin{aligned} man(z_0) &\equiv \int_{z_{min}}^{z_0} \varphi_{man}(z)dG(z) && (14)\\ rt(z_0,z_1) &\equiv \int_{z_0}^{z_1} \varphi_{rt}(z)dG(z) && (15)\\ cog(z_1) &\equiv \int_{z_1}^{z_{max}} \varphi_{cog}(z)dG(z) && (16) \end{aligned}$$

These are the equilibrium total labor services in non-routine manual, routine, and non-routine cognitive tasks, respectively.

Using the normalization $p_1 = 1$, and combining equations (2), (9)-(12), and (13) we can get to the following two-equation system, with two unknowns z_0 and z_1:

$$\begin{aligned} man(z_0) &= \frac{1-\beta}{\beta}\left[\frac{\varphi_{man}(z_0)}{\varphi_{rt}(z_0)}\left(1+\frac{\varphi_{rt}(z_1)}{\varphi_{cog}(z_1)}\right)\right] cog(z_1) && (17)\\ \kappa_{rt}rt(z_0,z_1) &= cog(z_1) && (18) \end{aligned}$$

[19] Jung and Mercenier (2010) are interested in distinguishing between the effects of RBTC and the effects of globalization, and for that purpose, changing the slope of $\varphi_{rt}(z)$ as a consequence of RBTC is important.

Take logs of these equations to get:

$$\begin{aligned} \ln man(z_0) &= \ln\left(\frac{1-\beta}{\beta}\right) + \alpha_0(z_0) + \tilde{\alpha}_1(z_1) + \ln cog(z_1) && (19) \\ \ln \kappa_{rt} + \ln rt(z_0, z_1) &= \ln cog(z_1) && (20) \end{aligned}$$

where the following definitions have been used: $\alpha_0(z_0) \equiv \ln\left[\varphi_{man}(z_0)/\varphi_{rt}(z_0)\right]$, and $\tilde{\alpha}_1(z_1) \equiv \ln\left[1 + \varphi_{rt}(z_1)/\varphi_{cog}(z_1)\right]$.

Take total derivatives of equations (19) and (20) to get:

$$\begin{pmatrix} \alpha_0'(z_0) - \frac{man'(z_0)}{man(z_0)} & \tilde{\alpha}_1'(z_1) + \frac{cog'(z_1)}{cog(z_1)} \\ -\frac{rt_0(z_0,z_1)}{rt(z_0,z_1)} & \frac{cog'(z_1)}{cog(z_1)} - \frac{rt_1(z_0,z_1)}{rt(z_0,z_1)} \end{pmatrix} \begin{pmatrix} dz_0 \\ dz_1 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix} d\ln \kappa_{rt} \qquad (21)$$

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:

$$\begin{aligned} \frac{dz_0}{d\ln\kappa_{rt}} &= \frac{-\tilde{\alpha}_1'(z_1) - \frac{cog'(z_1)}{cog(z_1)}}{\Delta} \quad > \quad 0 && (22) \\ \frac{dz_1}{d\ln\kappa_{rt}} &= \frac{\alpha_0'(z_0) - \frac{man'(z_0)}{man(z_0)}}{\Delta} \quad < \quad 0 && (23) \end{aligned}$$

where Δ is the determinant of the matrix on the left-hand-side of the system of Equation (21).

Proof: See Appendix A.1.

This proposition says that an increase in κ_{rt} (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_{rt} be z_0' and z_1'. An increase in κ_{rt} 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.

Intuitively, an increase in κ_{rt} means that physical capital produces a larger amount of routine task services. Because of the technology in the Y_2-sector, physical capital and labor performing routine tasks are substitutes, while physical capital and labor performing non-routine cognitive tasks are complements. The increase in the provision of routine task services by computers induces the Y_2-sector firms to transfer workers from routine to non-routine cognitive tasks. The workers with the highest ability among the routine workers are the best suited for this switch.

With the increased household income, demand for the Y_1 good will increase as well, so the Y_1 firms will want to hire more workers to perform non-routine manual tasks. The workers with the lowest ability among the routine workers are the best suited for this switch.

3.2 Wage Changes Induced by RBTC

The model has predictions for wage changes, both for workers who switch occupations and for workers who stay in the same occupation. First, consider the changes induced by RBTC on the wage per efficiency unit C_j in each occupation. Because of marginal cost pricing $C_{man} = p_1$, and p_1 is normalized to 1 in any equilibrium, so C_{man} does not change. All of the wage changes should be interpreted as being relative to this normalization.

Using the comparative statics results on the effects of κ_{rt} on z_0 and z_1, along with equations (7) and (8), we have the following result:

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

$$\frac{d\ln C_{man}}{d\ln \kappa_{rt}} = 0 \qquad \frac{d\ln C_{rt}}{d\ln \kappa_{rt}} < 0 \qquad \frac{d\ln (C_{cog}/C_{rt})}{d\ln \kappa_{rt}} > 0$$

$$\frac{d\ln C_{cog}}{d\ln \kappa_{rt}} \gtreqless 0 \;\; \textit{if and only if} \;\; \alpha_1'(z_1)\left[\alpha_0'(z_0) - \frac{man'(z_0)}{man(z_0)}\right] \gtreqless \alpha_0'(z_0)\left[\tilde{\alpha}_1'(z_1) - \frac{cog'(z_1)}{cog(z_1)}\right]$$

Proof: See Appendix A.2.

Intuitively, from Equation (7), the wage per efficiency unit of routine workers relative to non-routine manual workers depends on their relative productivity at the ability cutoff z_0. Routine-biased technical change induces an increase in z_0. At a higher z, the productivity gap between routine and non-routine manual workers is greater, so the relative wage per efficiency unit of routine workers is lower.

Conversely, from Equation (8) the wage per efficiency unit of routine relative to non-routine cognitive workers depends on their relative productivity at the ability cutoff z_1. Routine-biased technical change induces a fall in z_1, reducing the productivity gap between routine and non-routine cognitive workers, and reducing the relative wage per efficiency unit of routine workers.

The change in the wage per efficiency unit of non-routine cognitive relative to non-routine manual workers, however, is ambiguous. The fall in z_1 tends to increase relative wages in non-routine cognitive, but the increase in z_0 works in the opposite direction. The net effect will depend on how responsive the productivity ratios are to z at the cutoff levels (given by $\alpha_0'(z_0)$ and $\alpha_1'(z_1)$) and on how much the supply of tasks change with a marginal change in the cutoffs (which in turn depends on the productivity functions and the probability density of skills at the cutoffs).[20]

The wage change induced by the shock to κ_{rt} on workers of different skill levels are described in the following proposition.

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

$$\frac{d\ln w(z)}{d\ln \kappa_{rt}} = \begin{cases} \frac{d\ln C_{man}}{d\ln \kappa_{rt}} & = 0 & \text{if } z_{min} \leq z < z_0 & man \to man \\ \frac{d\ln C_{man}}{d\ln \kappa_{rt}} + \ln C_{man} + \ln \varphi_{man}(z) - (\ln C_{rt} + \ln \varphi_{rt}(z)) & < 0 & \text{if } z_0 \leq z < z_0' & rt \to man \\ \frac{d\ln C_{rt}}{d\ln \kappa_{rt}} & < 0 & \text{if } z_0' \leq z < z_1' & rt \to rt \\ \frac{d\ln C_{cog}}{d\ln \kappa_{rt}} + \ln C_{cog} + \ln \varphi_{cog}(z) - (\ln C_{rt} + \ln \varphi_{rt}(z)) & \geq \frac{d\ln C_{rt}}{d\ln \kappa_{rt}} & \text{if } z_1' \leq z < z_1 & rt \to cog \\ \frac{d\ln C_{cog}}{d\ln \kappa_{rt}} & > \frac{d\ln C_{rt}}{d\ln \kappa_{rt}} & \text{if } z_1 \leq z \leq z_{max} & cog \to cog \end{cases}$$

Proof: See Appendix A.3.

For stayers, wage changes are given by the change in wages per efficiency unit in their particular occupation. This implies a fall in wages of stayers in routine occupations, relative to stayers in either of the non-routine occupations. Meanwhile, workers switching out of routine must do at least as well as stayers (as they always could have chosen to stay in the routine occupation).

Figure 1 graphically summarizes all the results on the effects of RBTC on the equilibrium

[20] This is analogous to the ambiguity in Acemoglu and Autor (2011) regarding the effect of RBTC on the wage of high skill workers relative to low skill workers.

skill cutoffs and wages for workers of different ability levels. The black lines in the Figure represent the original equilibrium, before the RBTC shock. The cutoff skill levels are given by z_0 and z_1. Workers with ability below z_0 optimally select into the non-routine manual occupation, those with ability above z_1 select into the non-routine cognitive occupation, and those with ability between z_0 and z_1 select into the routine occupation. Mean wages are highest in the non-routine cognitive occupation and lowest in the non-routine manual one.

The effects of RBTC are depicted with the blue lines. From Proposition 2, the sign of the change in C_{cog} is ambiguous (although its change, if any, is greater than the change in C_{rt}). The graph is for the case where C_{cog} increases (which will prove to be empirically relevant). When the RBTC shock hits, C_{rt} falls, and workers with ability between z_0 and z_0' find it optimal to switch to non-routine manual jobs, while workers with ability between z_1' and z_1 find it optimal to switch to non-routine cognitive jobs. Stayers in routine jobs experience the largest fall in wages, given by the change in C_{rt}.

3.3 Summary of the Predictions of the Model

The general equilibrium effects of a positive shock to $\ln \kappa_{rt}$ are as follows:

1. Switching patterns:
   (a) The workers at the bottom of the ability distribution within routine occupations switch to non-routine manual jobs.
   (b) The workers at the top of the ability distribution within routine occupations switch to non-routine cognitive jobs.
   (c) No switching is induced for non-routine workers (either manual or cognitive).
2. Wage changes:
   (a) Workers staying in routine jobs experience a fall in real wages, relative to those staying in non-routine manual jobs (because C_{rt} falls).
   (b) Workers staying in non-routine cognitive jobs experience an increase in real wages, relative to those staying in routine jobs (because C_{cog}/C_{rt} increases).
   (c) Workers who switch from routine to non-routine jobs (either cognitive or manual) experience an increase in real wages relative to those who stay in the routine occupation.

4 Data

In order to test the individual-level predictions of the model, I use data from the Panel Study of Income Dynamics (PSID) for the United States. The PSID is a longitudinal study of nearly 9,000 U.S. families. Following the same families since 1968, the PSID collects data on economic, health, and social behavior, including the occupational affiliation of the household head and wife, their wage on their main job at the time of the interview, and their total labor earnings in the previous calendar year.[21] The PSID has the advantage of providing information for individuals from many different cohorts over a wide range of years. Data is available at an annual frequency between 1968 and 1997, and bi-annually from 1997 onwards.[22]

The paper uses wages reported for the current job, as they can be directly linked to the occupation that the respondent is working in at the time of the interview. Data on wages for salaried workers is only available starting in 1976, so the analysis only uses data from that year onwards.[23] The most recent data used in the paper are for 2007.

The sample is limited to male household heads, aged 16 to 64, employed in non-agricultural, non-military jobs, and who are part of the "Survey Research Center" (SRC) sample. This is the main original sample from the PSID. The over-sample of low-income households (SEO sample) and the Immigrant samples added in the 1990s are excluded from the analysis.[24]

Throughout the paper occupations are classified into three broad groups, based on the categories used by Acemoglu and Autor (2011). The groups are as follows:

- **Non-routine cognitive:** Professional, technical, management, business and financial occupations.
- **Routine:**[25] Clerical, administrative support, sales workers, craftsmen, foremen, operatives, installation, maintenance and repair occupations, production and transportation occupations, laborers.
- **Non-routine manual:** Service workers.

The categorization is based on the aggregation of 3-digit occupational codes that map into these broader categories. Each group is labeled with the name of the main task performed

[21] The Panel Study of Income Dynamics is primarily sponsored by the National Science Foundation, the National Institute of Aging, and the National Institute of Child Health and Human Development and is conducted by the University of Michigan. PSID data is publicly available at `http://psidonline.isr.umich.edu/`.

[22] Comparing trends in cross-sectional inequality across the PSID and the CPS, Heathcote, Perri, and Violante (2010) find that the two datasets track each other quite well. The only striking discrepancy is the sharp increase in the variance of CPS households earnings in the 1970s, which is not observed in the PSID.

[23] Throughout the paper, nominal values are converted to 1979 dollars using the Consumer Price Index for All Urban Consumers from the Bureau of Labor Statistics.

[24] Women are excluded as there are many confounding factors in the changes in the occupational composition of employed women over the past three decades. The low-income over-samples is excluded in order to keep a sample that is representative of the entire population (at least in the early years). The immigrant sample is excluded as it is only available for some years and significantly changes the occupational composition of employment in the sample.

[25] I do not distinguish between routine cognitive and routine manual workers in order to ensure consistency with the occupational groupings used in the model. Note that because the sample used in this paper includes only men, the vast majority of routine workers are in routine manual occupations.

by workers in that occupation, as explained in Acemoglu and Autor (2011) and supported by data from the Dictionary of Occupational Titles.[26] More details on the specific occupations and occupation codes included in each category are presented in Appendix C. The Appendix also describes an alternative classification procedure based on task data from the Dictionary of Occupational Titles, to which the results are robust (see Section 7.3).

Table 1 presents descriptive statistics for each of the broad occupation groups. Non-routine cognitive and routine occupations account for the majority (93%) of total employment. Mean wages are highest in non-routine cognitive occupations and lowest in non-routine manual jobs. Non-routine cognitive jobs have a much higher share of college educated workers, and a much lower rate of unionization than the other occupations.[27] Figure 2 plots the long-run changes in employment shares for each of the broad occupation groups over the period 1968-2007. The pattern is broadly consistent with evidence based on Census data (Acemoglu and Autor, 2011): there is a sharp decline in the share of employment in routine occupations, with compensating share increases in both of the non-routine categories.

5 Empirical Implementation

In order to test the predictions summarized in subsection 3.3, I estimate a wage equation and rank individuals according to their estimated ability. This section describes the empirical methodology and discusses identification issues.

From the model (Equation (6)), the potential wage for an individual of skill level z_i in occupation j consists of an occupation wage premium (C_j), which is common to everyone in the occupation, and on the individual's occupation-specific productivity ($\varphi_j(z_i)$). Assume that productivity is log-linear in skills; that is:

$$\ln \varphi_j(z_i) = z_i a_j \tag{24}$$

where a_j may be interpreted as an occupation-specific return to skills. Following Equation (5), assume that these occupation-specific returns are highest in the non-routine cognitive occupation and lowest in the non-routine manual one. That is:

$$a_{man} < a_{rt} < a_{cog}$$

This assumption reflects the fact that skill premia vary across occupations (see Gibbons

[26] In a recent working paper, Lefter and Sand (2011) suggest that the occupational coding scheme plays an important role in the extent and timing of polarization. They find that using alternative coding methods affects the extent of wage growth in low-skill occupations, and weakens the contrast between the 1980s and the 1990s in employment growth patterns, relative to what is suggested by Autor et al. (2006).

[27] It is worth noting, however, that the ranking of wages across the three occupation groups is not driven by the composition of workers along observable characteristics, as the same ranking is observed for the residuals from a flexible wage regression using a large number of observable individual characteristics.

et al. (2005)), leading to workers of different abilities self-selecting into different occupations, as described in the model.

Using the assumed functional form for productivity, and allowing for variation over time in the occupation wage premium (e.g. because of RBTC), we have the following equation for the potential wage in occupation j for individual i of skill level z_i:

$$\ln w_{ijt} = \theta_{jt} + z_i a_j \tag{25}$$

where i denotes the individual, j denotes the occupation, t denotes the time period, and $\theta_{jt} \equiv \ln C_{jt}$ is the occupation wage premium in occupation j at time t. Note that I am assuming that individual skills are time-invariant. This assumption will be relaxed later on to allow for certain types of time-varying skills.

The wage observed by the econometrician for individual i in period t will depend on the occupation chosen by the individual, and will be given by:

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt} z_i a_j + \mu_{it} \tag{26}$$

where D_{ijt} is an occupation selection indicator which equals one if person i selects into occupation $j \in \{man, rt, cog\}$ at time t and equals zero otherwise. μ_{it} reflects classical measurement error, which is assumed to be independent of sector affiliation and therefore orthogonal to D_{ijt}. μ_{it} may also be interpreted as a temporary idiosyncratic shock that affects the wages of individual i in period t regardless of his occupational choice.

Without any restrictions to mobility, a worker will select into the occupation where he receives the highest wage. Given a fixed θ_{jt}, there will exist critical values of z_i that determine the efficient assignment of workers to occupations. Because z_i and a_j are not varying over time, and because μ_{it} is not occupation-specific, occupational mobility will be driven exclusively by changes over time in θ_{jt}.

In practice occupational mobility is not frictionless. One can think of a worker's occupational choice as being driven by z_i and θ_{jt}, as well as a noise component which is *uncorrelated* with wages. This noise component may be interpreted as a search friction, which does not affect a worker's potential wage in the different occupations, but restricts the worker from immediately selecting into his desired occupation each period. Put differently, the identifying assumption is that *conditional on the occupation fixed effects and on individual workers' skills*, selection into occupations is random (i.e. driven by a search friction that is orthogonal to skills or to any other wage determinants). Therefore, we have that in Equation (26): $E(\mu_{it}|\boldsymbol{D}_{ij}, z_i, \boldsymbol{\theta}_j) = 0$. An estimation procedure that controls for D_{ijt}, z_i and θ_{jt} would lead to consistent estimates.[28]

[28]See also Wooldridge (2002) on estimation of unbalanced panels with selection on time-invariant unobserv-

For the purposes of this paper, I am not interested in identifying a_j. Therefore, I can rewrite Equation (26) as:

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}\gamma_{ij} + \mu_{it} \tag{27}$$

where $\gamma_{ij} \equiv z_i a_j$. The term γ_{ij} is composed of an individual's time invariant skills and the occupation-specific returns to those skills. γ_{ij} varies for an individual across occupation spells, but stays constant whenever the individual stays in the same occupation. Equation (27) can be consistently estimated using fixed effects *at the occupation spell level for each individual* (that is, using a fixed effect for each individual in each occupation that they are observed in). The fixed effect effectively demeans wages for each individual within occupation spells, thus capturing the time invariant component within the spell, which is precisely the unobserved effect γ_{ij}. Recall that once z_i (through the fixed effect γ_{ij}) and θ_{jt} are controlled for, selection into occupations is random (depends only on the search friction). Therefore, the regressors in Equation (27) are orthogonal to the mean-zero error term μ_{it} and the coefficients are consistently estimated.[29] [30]

In the empirical estimation, θ_{jt} may be captured with interactions of occupations and year dummies. The omitted category in all years will be the non-routine manual occupation (which is consistent with the model where $\theta_{man} = 0$ in any equilibrium), and all wages will be relative to this normalization. To capture changes over time that affect all occupations (including non-routine manual), and to ensure that the normalization of $\theta_{man,t}$ to zero in all years is appropriate, the estimation includes a set of aggregate year effects that are assumed to be common to all workers, regardless of their occupation or their skill level. The estimates of $\theta_{rt,t}$ and $\theta_{cog,t}$ will reflect changes in the occupation wage premium over time, due to RBTC or other shocks, relative to the base occupation. Because of the inclusion of the occupation spell fixed effects, the occupation-time fixed effects are identified only from variation over time within occupation spells. Therefore, it is necessary to normalize $\theta_{rt,t}$ and $\theta_{cog,t}$ to zero for a

ables.

[29]Note that although z_i includes only individual skills, in practice, the occupation spell fixed effect will capture the wage effects of *all* time-invariant characteristics of the individual that impact wages within the occupation spell, regardless of whether they reflect individual skills or other factors such as discrimination.

[30]Spell fixed effects are often used in analyses with matched employer-employee data where an outcome variables of interest is assumed to be affected by an unobserved individual component, as well as an unobserved firm component. If the objective is not to estimate the effects of any individual-specific or firm-specific variables, but rather some other time-varying variable of interest, a spell fixed effect can be used to account for all observed and unobserved time-invariant components within a job spell, and to consistently estimate the coefficient on the variable of interest. Andrews et al. (2006) describe the method. For applications, see Martins and Opromolla (2009) and Schank et al. (2007) in the context of the effect of a firm's exporter status on wages, Hummels et al. (2011) on the effects of offshoring and Gürtzgen (2009) on the relationship between firm profitability and wages. See also Harris and Sass (2010) for the use of a teacher-school 'spell' fixed effect to identify the impacts of teacher training on student achievement.

base year.[31] This identification argument implies that $\widehat{\theta}_{rt,t}$ and $\widehat{\theta}_{cog,t}$ should be interpreted as estimating a double difference: Rather than identifying the *level* of the occupation wage premia, they identify their *changes* over time relative to the base year, and relative to the analogous change experienced by the base occupation (non-routine manual). As the purpose of this paper is to analyze changes over time in occupational wage premia, rather than their level, these are in fact the parameters of interest.[32]

The estimation procedure also makes it possible to generate estimated occupation spell fixed effects $\widehat{\gamma}_{ij}$. They will be an estimator of the return to time-invariant skills for individual *i conditional on selecting into occupation j*. Because γ_{ij} is monotonically increasing in skill within the occupation (the coefficients on skills is common for all workers who selected into the occupation), the ranking of workers according to this measure corresponds to their ranking according to their underlying ability. In order to test the model's implications regarding switching patterns, I am only interested in a worker's relative ability *within an occupation* in a given year, so having an estimator with which I can rank workers conditional on having selected into an occupation is sufficient for my purposes.

When estimating Equation (27) in the data, I add an extra set of controls for marital status, unionization status, region, and a dummy for whether the individual lives in a metropolitan area (SMSA). It is assumed that these variables are orthogonal to measurement error μ_{it}, and that their return is not occupation- or skill-specific. Their inclusion will therefore not affect the consistency of the estimated coefficients.[33]

To summarize, the equation being estimated is:

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}\gamma_{ij} + \boldsymbol{Z'_{it}}\boldsymbol{\zeta} + \mu_{it} \tag{28}$$

where θ_{jt} are occupation-time fixed effects, γ_{ij} are occupation spell fixed effects for each individual, and $\boldsymbol{Z_{it}}$ includes year fixed effects, marital status, unionization status, region, and SMSA. In all the estimations, standard errors are clustered at the individual level.

The empirical strategy may be extended to allow for time-varying observable skills (Section 7.1), as well as for changes over time in the return to observable characteristics that affect ability such as education (Section 7.2).

[31] I do the normalization for the initial year, 1976.

[32] Gibbons et al. (2005) analyze differences in the levels of occupational wage premia and occupational returns to skills. They estimate a quasi-differenced version of Equation (26) using a non-linear instrumental variables technique.

[33] It is left as future work to relax this assumption in order to allow, for example, variation in the union premium across occupations.

6 Results: Effects of Routine-Biased Technical Change

In this section I test the predictions of the model using the PSID data. First I present results on worker's switching patterns according to their estimated ability. Then I discuss results regarding the wage changes for workers with different occupational trajectories.

6.1 Switching Patterns

I begin by testing the model's implications regarding occupational switching patterns. The model predicts that RBTC induces workers at the bottom of the ability distribution within routine occupations to switch to non-routine manual jobs, and workers at the top of the distribution to switch to non-routine cognitive jobs. As discussed above, I rank routine workers according to their position in the distribution of estimated log productivity in a given year (where estimated log productivity is equal to $\widehat{\gamma}_{ij}$, the estimated occupation spell fixed effect from Equation (28)). Recall that γ_{ij} is monotonically increasing in underlying ability z. Therefore, I refer to the quintiles of estimated log productivity within an occupation-year as ability quintiles.

I analyze the exit rates among workers in different quintiles of the ability distribution. Figure 3 plots the probability of switching at each ability quintile for two different sub-samples: 1977-1989 and 1991-2005. The fraction of switchers is calculated over a two year period; that is, each bar in the graph indicates the fraction of workers from ability quintile q who switch out of routine occupations between period t and period $t + 2$. Only odd years are used to generate the graph. These restrictions are imposed in order to ensure comparability with the period from 1997 onwards, when the PSID became bi-annual. The fraction of switchers is calculated over the total number of workers from each quintile who have valid occupation reports in years t and $t + 2$.

The Figure shows that workers at the top of the ability distribution are more likely to switch out of routine jobs than workers of lower ability in both sub-periods. After 1991, the probability of switching increases for all ability quintiles, but particularly for the lower ability workers. This leads to a U-shaped pattern in the probability of switching after 1991, with workers at the top and the bottom of the ability distribution being more likely to switch than those in the middle.

Table 2 confirms that the differences across quintiles are statistically significant. The Table presents the results from a linear probability model, where the dependent variable is a dummy equal to 1 if the worker switches occupations. The regressors are a set of ability quintile dummies, with the omitted category being the middle quintile. To account for the fact that these are generated regressors, the standard errors are adjusted through a bootstrap procedure.[34] Column (1) shows that before the 1990s, workers from the top ability quintile

[34] In particular, I implement a bootstrapping procedure that performs 100 replications on randomly drawn

are 8.8% more likely to switch out of routine jobs than are workers in the middle of the ability distribution. From Column (2), after 1991, both workers at the bottom and the top of the distribution are significantly more likely to switch than those in the middle.[35]

Next, I consider the direction of the switches occurring at each quintile of the ability distribution. The results are plotted in Figure 4. Switchers from all quintiles are more likely to go to non-routine cognitive jobs than to non-routine manual jobs. This would be expected even if the direction of switch were random, as the non-routine cognitive occupation is much larger in terms of employment than the non-routine manual one. However, there is a clear patter of selection according to ability quintiles. Consistent with the prediction of the model, the probability of switching to non-routine manual jobs is decreasing in ability, while the probability of switching to non-routine cognitive jobs is increasing in ability.[36]

After 1990, the probability of switching to both types of non-routine occupations increases, with the probability of switching to non-routine cognitive increasing more than the probability of switching to non-routine manual. This is documented in Table 3. The unconditional probability of switching to non-routine cognitive is 10.4% before 1991, and 13.4% afterwards, while the corresponding figures for non-routine manual are 1.9% and 3.0%.

Table 4 confirms the statistical significance of the differences across quintiles in the direction of switch patterns observed in Figure 4.[37] Columns (1) and (2) are linear probability models for the probability of switching to non-routine cognitive occupations for the sub-periods 1977-1989 and 1990-2005, respectively. Columns (3) and (4) are analogous regressions for the probability of switching to non-routine manual. Workers in the middle of the ability distribution (third quintile) are the omitted category. Columns (1) and (2) show positive and significant coefficients on the dummies for quintile 5, meaning that high ability routine workers are significantly more likely to go to non-routine cognitive occupations than those in the middle of the distribution. Meanwhile, workers in the bottom quintile are signif-

sets of 6975 clusters of individuals (the total number available in the sample). For each randomly drawn sample, Equation (28) is estimated, then the estimated occupation spell fixed effects are used to rank routine workers into ability quintiles, and finally the linear probability model (with switching as the dependent variable) is estimated for these routine workers using ability quintile dummies as regressors. The standard errors presented in the Table are the bootstrapped standard errors based on these 100 replications.

[35]U-shapes in the patterns of occupational mobility have also been documented by Groes et al. (2009) using Danish administrative data. They explain these patterns within the context of a model of information frictions, where workers learn their ability level over time. This paper offers a complementary view on the reason for these U-shapes. As will be seen below, along with the U-shaped pattern of mobility observed in the PSID data, there have also been changes in the relative wage premia across occupations. Both phenomena can be explained simultaneously by the simple model of routine-biased technical change presented in this paper, while only the U-shapes are implied by the learning model in Groes et al. (2009). There is evidence, therefore, that technological change plays an important role in driving occupational mobility, although learning motives may certainly be contributing to the U-shaped patterns as well.

[36]The U-shape and the patterns in the direction of switching are also observed in the PSID data when using raw wages, or when using residuals from a flexible regression of wages on a large number of observable individual characteristics.

[37]The standard errors in Table 4 are obtained through the same bootstrap procedure as those in Table 2. See footnote 34.

icantly more likely to switch to non-routine manual occupations than those in the middle, as evidenced by the findings in Columns (3) and (4).

A common concern with datasets such as the PSID is the prevalence of coding error in the occupational affiliation data (see Kambourov and Manovskii (2004) and Kambourov and Manovskii (2008)). One might be concerned, for example, that the workers at the top and the bottom of the ability distribution within routine jobs might actually be non-routine workers who are miscoded, and thus that their transitions are spurious. To address this concern I analyze the data for the period up to 1980, when the occupational coding was done retrospectively and the prevalence of errors is thus far less severe (see Kambourov and Manovskii (2008) for full details on this argument). The results, using transitions over 1-year horizons, are shown in Figure 5. The patterns in the direction of switch are present even for this period, with high ability routine workers being more likely to switch to non-routine cognitive jobs, and low ability routine workers being relatively more likely to switch to non-routine manual jobs. The Figure confirms that the results are not driven by coding error. Overall, the findings on switching patterns support the predictions of the model.

6.2 Wage Changes

The next step is to explore the behavior of wages and wage changes. I begin with a simple motivating analysis to determine whether an individual's occupation at time t has explanatory power over his subsequent wage growth. Table 5 shows the results of a regression of individual wage growth between periods t and $t + j$ (where j ranges from 1 to 20 years) on dummies for the individual's occupation at time t. All regressions include year dummies. In all cases, workers in non-routine manual occupations in year t are the omitted category.

The Table shows that individuals who start a given period in a routine job have significantly lower wage growth over subsequent years than workers in non-routine occupations. This is true over time horizons as long as 20 years. For example, a worker holding a routine job in a given year can expect his real wages to grow on average 6.2% less over the subsequent four years than workers in other occupations, regardless of his future job transitions. The next sub-sections separately analyze the wage changes for stayers in routine jobs and for switchers, and take into account heterogeneities across individuals. This allows a comparison of the data with the predictions of the model.

6.2.1 Wage changes for occupation stayers

Consider first the wage changes for workers who do not switch occupations. Table 6 shows the results from running the same regressions as in Table 5, but now the sample includes only occupation stayers. In Column (1), stayers are defined as workers who are observed in the same broad occupation in years t and $t + 1$, while in the remaining columns they are defined as workers who are observed in the same broad occupation in years t and $t+2$ (even though the wage changes may be taken over horizons longer than two years). The last two columns split the sample into two different sub-periods, 1976-1989 and 1990-2005, and consider wage changes over two-year horizons within those sub-periods. In all cases, those workers who are classified as stayers in non-routine manual jobs are the omitted category.

The Table shows that those who stay in routine jobs have significantly lower wage growth than stayers in any of the other occupational categories. For example, a worker staying in a routine job over the course of two years has a wage growth that is 1.8% lower than that of a worker remaining in a non-routine manual job over the same time period. Note that the rate of wage growth for routine workers is also in all cases significantly lower than that of non-routine *cognitive* workers.

From Proposition 3, the wage changes for stayers are given by the changes in C_j for their respective occupation. Empirically, from the estimation of Equation (28), the estimated occupation-time fixed effects ($\widehat{\theta}_{jt}$) will track changes in C_j over time. The Proposition implies that θ_{rt} should fall over time (relative to the omitted category). The Proposition is ambiguous about the trend of θ_{cog} relative to the omitted category, but does predict that θ_{cog} increases relative to θ_{rt}. Figure 6 plots the estimates of $\widehat{\theta}_{rt}$ and $\widehat{\theta}_{cog}$.

The figure shows that from the early 1980s onwards, the estimated fixed effects for routine occupations have a clear downward trend. Meanwhile, the corresponding fixed effects for non-routine cognitive occupations show an upward trend, particularly from the 1990s onwards.[38] Note that all of the coefficients for the latter periods are significantly different from zero. This means that the data agree with the predictions of the model for wage stayers: Wages fall significantly for stayers in routine occupations, relative to stayers in either of the non-routine categories. The data also show a significant increase in the wage for stayers in non-routine cognitive relative to stayers in non-routine manual. Note also that the magnitude of the fall in the occupation wage premium for routine jobs is substantial. The fall from its peak in the early 1980s until the mid 2000s is similar in magnitude to the estimated rise in the college wage premium over that period.[39]

6.2.2 Wage growth according to direction of switch

Next I study the wage changes for routine workers who follow different switching patterns. Table 7 restricts the sample to routine workers only (both stayers and switchers). The dependent variable is the wage change, and the regressors are dummies for the direction of

[38]This is consistent with Acemoglu and Autor (2011), who talk about two different 'eras' in the changes in the distribution of wages: 1974-1988 and 1988-2008. During the first period, earnings increased monotonically with the percentile in the earnings distribution. During the second period, in contrast, growth of wages by percentiles is polarized, or U-shaped. The U-shape is more pronounced during the period 1988-1999. For employment shares, they also document a U-shaped pattern during the 1990s.

[39]Changes in the college wage premium will be discussed in further detail below in Section 7.2 and Figure 8.

occupational switching (either to non-routine cognitive or to non-routine manual). Staying in routine jobs is the omitted category. The estimated coefficients reflect the differential wage growth for each type of switcher, relative to the stayers. Column (1) defines switchers and stayers based on individuals' occupational codes in years t and $t+1$, while the remaining columns are based on the codes in years t and $t+2$.

Panel A uses changes in real wages, while Panel B uses changes in fitted model wages, that is, changes over time in $\widehat{\theta}_{jt}+\widehat{\gamma}_{ij}$. For reference purposes, Panel C reports the percentage of routine workers classified into each of the switching categories.

The Table shows significantly lower wage growth for switchers to non-routine manual over horizons up to two years, both for real and for fitted model wages. This negative differential, however, goes away when considering longer horizons (10 years), becoming positive and significant. For example, when using fitted model wages, workers switching from a routine job in year t to a non-routine manual job in year $t+2$ experience a wage change that is 14% lower than that experienced by stayers in routine jobs. By year $t+10$ however, the wage change for these workers is 5% above that of stayers.

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

Columns (5) and (6) in the Table show interesting differences between the periods before and after 1990. The wage gains for those who switch to non-routine cognitive are substantially larger after 1990 (18% above stayers in terms of fitted model wages after 1990, relative to 5% in the earlier period), while the wage cuts for those who switch to non-routine manual are somewhat smaller in magnitude (13% below stayers in terms of fitted model wages after 1990, relative to 15% in the earlier period).

One potential concern with the results in Table 7 is that the sample of workers included in each column varies according to the availability of the data, and this may be biasing the results. To address this concern, I run the regressions for changes in log real wages from Table 7 keeping the same set of workers over the different time horizons (that is, I only keep workers for which I have data at t, $t+2$, $t+4$ *and* $t+10$). The results are presented in Columns (1) through (3) in Table 8 and are very similar to the results in the previous Table. Therefore, the results in Table 7 are not driven by differential attrition across switchers and stayers.

So far the regressions presented have considered the implications of occupational switches in the *short-run* (between years t and $t+2$) on individual workers' wage changes *both in the short- and long-run* (between t and $t+2$, $t+4$ and $t+10$). An interesting question is whether the workers who switch out of routine occupations in the short run remain in their new occupation in future periods, or whether their subsequent switching patterns explain the long-run wage changes observed in the data. For example, if workers who switch to non-routine manual jobs in the short-run subsequently switch to other occupations in the long-run, this might be driving the finding that their wage growth is slower in the short run but faster in the long run. A full study of the occupational histories for different workers is beyond the scope of this paper (and would be difficult to perform using PSID data, given its small sample size). However, to explore whether subsequent switching patterns might be a concern, I repeat the analysis from Table 7, including only workers who are still observed in their $t+2$ occupation in subsequent years. That is, workers classified as stayers (switchers) will be those who stay in the routine occupation (switch to non-routine) between years t and $t+2$ *and* are still in the routine (non-routine) occupation in the longer run (i.e. in year $t+4$ or $t+10$). People who switch occupations between $t+2$ and the later years are dropped from the sample.[40] The results are presented in Columns (4) and (5) of Table 8 and confirm the main findings: Switchers to non-routine cognitive experience faster wage growth than stayers over a variety of time horizons. The same is true for the long-run wage performance of switchers to non-routine manual occupations. In short, the findings on wage changes for switchers provide support for the predictions of the model regarding the effects of RBTC.

7 Robustness Checks

This section presents a set of robustness checks on the empirical results of the paper.

7.1 Time-Varying Skills

The empirical strategy may be extended to allow for time-varying skills, under the maintained assumption that *unobservable* skills are time-invariant. To do this, Equation (24) can be modified to allow z_i to be a vector composed of two types of variables: a set of time-varying characteristics X_{it}, and a set of fixed characteristics η_i, each of which has an occupation-specific return which is fixed over time. That is:

$$\ln \varphi_j(\boldsymbol{z_{it}}) = X_{it}\beta_j + \eta_i b_j \tag{29}$$

Following Equation (5), assume that $\ln \varphi_j(\boldsymbol{z_{it}})$ is increasing in both of its arguments. That

[40]Note that this does not condition on the full occupational history, only on the $t+2$ and either $t+4$ or $t+10$ occupation. Note also that an important fraction of workers do in fact switch occupations between $t+2$ and the longer horizons, so the sample size for these regressions is smaller than in Table 7. For example, based on the sample in Table 7, of those switching from routine to non-routine cognitive between t and $t+2$, 38% switch again between $t+2$ and $t+4$ and 43% do so between $t+2$ and $t+10$ (mostly back to routine). Of those switching from routine to non-routine manual between t and $t+2$, 49% switch again between $t+2$ and $t+4$ and 62% do so between $t+2$ and $t+10$. Of those staying in routine between t and $t+2$, 10% switch between $t+2$ and $t+4$ and 19% switch between $t+2$ and $t+10$. This evidences a large degree of measured churning, even at the level of these very broad occupational categories. See also Kambourov and Manovskii (2008) for evidence of high mobility rates across 1-digit occupational categories.

is:

$$\beta_{man} < \beta_{rt} < \beta_{cog}$$
$$b_{man} < b_{rt} < b_{cog}$$

Observed wages for individual i in period t are then given by:

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}X_{it}\beta_j + \sum_j D_{ijt}\eta_i b_j + \mu_{it} \tag{30}$$

where, assuming (as before) that μ_{it} is independent of sector affiliation, one can now think of a worker's occupational choice as being driven by η_i, X_{it}, and θ_{jt}, as well as a noise component which is uncorrelated with wages (search friction). Thus, we have that: $E(\mu_{it}|\boldsymbol{D}_{ij}, \boldsymbol{X}_i, \eta_i, \boldsymbol{\theta}_j) = 0$. Following the same logic used to obtain Equation (28), I can rewrite Equation (30) as:

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}X_{it}\beta_j + \sum_j D_{ijt}\gamma_{ij} + \boldsymbol{Z'_{it}\zeta} + \mu_{it} \tag{31}$$

Assuming that all unobservable skills are time-invariant, Equation (31) can be empirically estimated using occupation-year and occupation spell fixed effects, as well as controls for (observable) time-varying skills and their occupation-specific returns. In practice, the strongest candidate variable to include in X_{it} is total work experience, which may be proxied by age.[41] I estimate Equation (31) including a set of dummies for 10-year age bins interacted with occupation dummies.[42] The resulting estimated occupation-year fixed effects are presented in Figure 7. The fall in the occupation wage premium in routine jobs remains significant and is very close in magnitude to that in Figure 6.

7.2 Changing Returns to Education

The empirical strategy may also be extended to allow changes over time in the *return* to observable characteristics that affect ability. Specifically, there is evidence that the college premium has changed over the past four decades in the United States (see for example Goldin and Katz (2008) and Acemoglu and Autor (2011)). To account for this, assume that, in Equation (29) all individual skills are fixed, but the return to certain kinds of (observable) skills is allowed to vary over time. That is, rewrite Equation (29) as:

[41] Note that X_{it} may only include time-varying variables that reflect *general* and not occupation-specific ability, as the framework assumes that X_{it} is fully transferable between occupations (although its return varies across occupations).

[42] The bins are for age below 25, 25-34, 35-44, 45-54, and 55 and over. Because the estimation includes both occupation spell and time fixed effects, and age increases linearly over time, it is not possible to control for age directly, but only through age bins.

$$\ln \varphi_{jt}(\boldsymbol{z_i}) = X_i\beta_{jt} + \eta_i b_j \tag{32}$$

Following Equation (5), assume that, for all t:

$$\beta_{man,t} < \beta_{rt,t} < \beta_{cog,t}$$
$$b_{man} < b_{rt} < b_{cog}$$

Think of X_i as education and η_i as all other individual skills.[43] The maintained assumption is that b_j, the return to all other skills, is not time-varying. For simplicity, assume that the time variation in the return to education is the same for all occupations; that is: $\beta_{jt} = \beta_j + \beta_t$. Then, the potential wages for individual i in occupation j at time t would be given by:

$$\ln w_{ijt} = \theta_{jt} + X_i\beta_j + X_i\beta_t + \eta_i b_j + \boldsymbol{Z'_{it}\zeta} + \epsilon_{it} \tag{33}$$

where ϵ_{it} is measurement error, which as before is orthogonal to education, ability and the wage premia, and is independent of sector affiliation. The following equation can be estimated using occupation spell fixed effects:

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + X_i\beta_t + \sum_j D_{ijt}\nu_{ij} + \boldsymbol{Z'_{it}\zeta} + \epsilon_{it} \tag{34}$$

where ν_{ij} are the occupation spell fixed effects, and they are such that $\nu_{ij} \equiv X_i\beta_j + \eta_i b_j$. The estimated occupation spell fixed effects and the estimated occupation wage premia will now be purged of the time-varying return to education. The occupation spell fixed effect will now only include the return to education in the base year, and the return to unobserved ability. Rankings on ability can now be constructed based on $X_i\widehat{\beta}_t + \widehat{\nu}_{ij}$.

I classify individuals into four occupation groups: high school dropouts, high school graduates, some college, and college graduates. The estimation strategy allows identification of changes in the return to education relative to a base year, and relative to the analogous change experienced by an excluded education category. Figure 8 shows the estimated returns to education for high school dropouts, workers with some college education, and college graduates, relative to the base year (1976) and relative to the omitted education category (high school graduates). The Figure confirms the finding in the literature that there has been an important rise in the return to college degrees, particularly during the 1980s and up to the mid-1990s.

Table 9 shows the results for switching patterns according to ability quintiles, and confirms the findings from the main body of the paper: workers in the middle of the distribution are less

[43]Note that the PSID does not ask individuals their education level every year. Therefore, I assign each individual their highest reported education level in any survey year, making each individual's level of education fixed over time.

likely to switch than those at the extremes, and there is selection on ability in the direction of switching.[44]

Figure 9 plots the new estimated occupation-year fixed effects. Changing returns to education account for a sizable portion of the increase in the return to non-routine cognitive jobs that was observed in Figure 6. However, the pattern remains such that the wage premium in routine occupations experiences a substantial fall relative to the wage premium in either of the non-routine occupational categories. Finally, Table 10 confirms that the results in terms of wage changes for switchers presented for the baseline specification also go through when allowing for changing returns to education.

7.3 Alternative Classification of Occupations

Appendix C describes an alternative classification of occupations into the broad categories (non-routine manual, routine, non-routine cognitive) based directly on task information from the Dictionary of Occupational Titles, rather than a simple aggregation of 3-digit codes. The alternative classification procedure is related to Autor et al. (2003) and Autor and Dorn (2009), and is applicable to the data up to 2001. Figure 10 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 switch across ability quintiles remains robust. Meanwhile, Figure 11 shows the estimated changes in occupation wage premia from the estimation of Equation (28) 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.

8 Conclusions

This paper derives the individual-level effects of routinization-biased technical change in a model of occupational sorting, and provides empirical evidence on the labor market experience of workers holding routine jobs during the past three decades in the United States.

Consistent with the prediction of the model, the data show strong evidence of selection on ability in occupational mobility out of routine occupations: workers of relatively high ability are more likely to switch to non-routine cognitive jobs, and workers of relatively low ability are more likely to switch to non-routine manual ones. Interestingly, after the 1990s, the probability of switching to non-routine cognitive jobs increases more than the probability of switching to non-routine manual jobs for routine workers at all ability quintiles. This suggests

[44] The standard errors in Table 9 are obtained through the same bootstrap procedure as those in Table 2, except that now the first step that is bootstrapped is the estimation of Equation (34) instead of Equation (28), and ability rankings are built based on $X_i\widehat{\beta}_t + \widehat{\nu}_{ij}$. See footnote 34 for more details on the bootstrap procedure.

that there has not been a large displacement of middle-skill workers towards low-skill jobs in the 1990s or 2000s, as has been sometimes assumed.

In terms of wage growth, also consistent with the prediction of the model, workers staying in routine jobs perform significantly worse than workers staying in any other type of occupation. This is due to a substantial fall in the wage premium for routine occupations, which is not driven by changes in the composition of the workers in terms of their skill level, or by changes in the return to education. Meanwhile, switchers from routine to non-routine manual jobs suffer wage cuts relative to stayers over horizons of up to two years, but those wage cuts disappear over time. Workers who switch from routine to non-routine cognitive jobs have significantly higher wage growth than stayers over a variety of time horizons.

The results in the paper provide micro-level evidence for the dynamics underlying the aggregate patterns of changes in employment shares and mean wages across major occupation groups. The paper finds that a model of occupational sorting with routine-biased technical change is able to rationalize many of the individual-level facts concerning the labor market experience of routine workers in the United States in the past three decades. The fact that there is a continuum of skills and three occupations, as in Jung and Mercenier (2010), rather than a continuum of occupations and three skill groups, as in Acemoglu and Autor (2011), is crucial, as it allows for the (empirically relevant) differences in the wage changes for workers who switch occupations, relative to those who stay.

Thinking of occupational mobility and wage changes in the context of routine-biased technical change gives a new perspective on the findings in the literature on occupational mobility which uses individual-level data. For example, part of the increase in mobility found in Kambourov and Manovskii (2008), and part of the U-shaped pattern in occupational switching found in Groes et al. (2009) may be explained by routinization. In addition to this, routinization is also able to explain the observed changes over time in the wage premia across occupations.

In future work, it would be relevant to formally decompose the changing aggregate shares of employment of the three major occupation groups into changes in exit rates and changes in the patterns of occupational choice of new entrants to the labor market. This would shed light on the relative importance of occupational mobility and of changes in entry and exit patterns in explaining the process of employment polarization.

Another important avenue for future work would be to consider the implications of occupation-specific skills (Kambourov and Manovskii, 2009) within the context of the model discussed in this paper. Workers that have built more human capital specific to routine jobs (generally older workers) will have a lower incentive to switch out of those jobs, even if the prospective wage growth in their occupation is low, as they would face a large human capital loss from switching occupations. This consideration would be less important for younger workers. The ability cutoffs at which young and old routine workers decide to switch occupations, then, would not be the same.

Extending the model in this way would induce a dynamic aspect to workers' switching decisions. A worker with specific human capital who switches occupations would be trading off an initial loss of specific human capital against the opportunity to work in an occupation with a steeper wage profile. This type of consideration could explain the findings in this paper regarding the wage changes for switchers to non-routine manual occupations, who experience an initial wage cut but subsequently recover from it, due to the fact that wages in non-routine manual jobs are growing faster than they do in routine ones.

Appendix A Proposition Proofs

Appendix A.1 Proof of Proposition 1

First, consider the signs of the partial derivatives of Equations (14) to (16). Using the fundamental theorem of calculus, we have that:

$$man'(z_0) \equiv \frac{\partial man(z_0)}{\partial z_0} = \varphi_{man}(z_0)g(z_0) > 0 \tag{35}$$
$$rt_0(z_0, z_1) \equiv \frac{\partial rt(z_0, z_1)}{\partial z_0} = -\varphi_{rt}(z_0)g(z_0) < 0 \tag{36}$$
$$rt_1(z_0, z_1) \equiv \frac{\partial rt(z_0, z_1)}{\partial z_1} = \varphi_{rt}(z_1)g(z_1) > 0 \tag{37}$$
$$cog'(z_1) \equiv \frac{\partial cog(z_1)}{\partial z_1} = -\varphi_{cog}(z_1)g(z_1) < 0 \tag{38}$$

Intuitively, increases in z_0 (given z_1) increase the measure of workers performing non-routine manual tasks, and decrease the measure of workers performing routine tasks. Increases in z_1 (given z_0) increase the measure of workers performing routine tasks, and decrease the measure of workers performing non-routine cognitive tasks.

Meanwhile, based on the assumptions on absolute and comparative advantage across skill groups (Equation (5)), we have that α_0 and $\tilde{\alpha}_1$ are decreasing functions in their respective arguments. That is:

$$\alpha_0'(z_0) = \frac{d \ln \varphi_{man}}{dz_0} - \frac{d \ln \varphi_{rt}}{dz_0} < 0 \tag{39}$$
$$\tilde{\alpha}_1'(z_1) = \frac{\varphi_{rt}(z_1)}{\varphi_{cog}(z_1) + \varphi_{rt}(z_1)} \left[\frac{d \ln \varphi_{rt}}{dz_1} - \frac{d \ln \varphi_{cog}}{dz_1} \right] < 0 \tag{40}$$

It follows that $\Delta > 0$ and the signs of the general equilibrium effects of a change in $\ln \kappa_{rt}$ are as indicated in Proposition 1.

Appendix A.2 Proof of Proposition 2

C_{man} is constant, as it is equal to p_1 which is normalized to 1. So d $d \ln C_{man}/d \ln \kappa_{rt} = 0$.

From Equation (7),

$$\begin{aligned} \ln C_{rt} &= \ln \left(\frac{\varphi_{man}(z_0)}{\varphi_{rt}(z_0)} \right) + \ln C_{man} \\ &= \alpha_0(z_0) + \ln C_{man} \end{aligned}$$

So:

$$\frac{d\ln C_{rt}}{d\ln \kappa_{rt}} = \alpha_0'(z_0)\frac{dz_0}{d\ln \kappa_{rt}} + \frac{d\ln C_{man}}{d\ln \kappa_{rt}}$$
$$= \alpha_0'(z_0)\frac{dz_0}{d\ln \kappa_{rt}}$$

From Proposition 1 and its proof, $dz_0/d\ln\kappa_{rt} > 0$ and $\alpha_0'(z_0) < 0$. Therefore, $d\ln C_{rt}/d\ln\kappa_{rt} < 0$.

From Equation (8),

$$\ln C_{cog} = \ln\left(\frac{\varphi_{rt}(z_1)}{\varphi_{cog}(z_1)}\right) + \ln C_{rt}$$
$$= \alpha_1(z_1) + \ln C_{rt}$$

So:

$$\frac{d\ln C_{cog}}{d\ln \kappa_{rt}} = \alpha_1'(z_1)\frac{dz_1}{d\ln \kappa_{rt}} + \frac{d\ln C_{rt}}{d\ln \kappa_{rt}}$$

Given the assumptions on comparative advantage, $\alpha_1'(z_1) < 0$. From Proposition 1, $dz_1/d\ln\kappa_{rt} < 0$, so the first term is positive. However, $d\ln C_{man}/d\ln\kappa_{rt} < 0$, so the sign of $d\ln C_{cog}/d\ln\kappa_{rt}$ is ambiguous.

From Equation (8),

$$\ln\left(\frac{C_{cog}}{C_{rt}}\right) = \alpha_1(z_1)$$

So:

$$\frac{d\ln(C_{cog}/C_{rt})}{d\ln \kappa_{rt}} = \alpha_1'(z_1)\frac{dz_1}{d\ln \kappa_{rt}}$$

which is unambiguously positive and implies:

$$\frac{d\ln C_{cog}}{d\ln \kappa_{rt}} > \frac{d\ln C_{rt}}{d\ln \kappa_{rt}}$$

Appendix A.3 Proof of Proposition 3

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

$$\frac{d\ln w(z)}{d\ln \kappa_{rt}} = \frac{d\ln C_{j'}}{d\ln \kappa_{rt}} + \mathbb{1}(j \neq j'|z)\left[\ln C_{j'} - \ln C_j + \ln\varphi_{j'}(z) - \ln\varphi_j(z)\right] \tag{41}$$

where j denotes the occupation that a worker of skill level z optimally chooses before the change in κ_{rt}, 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_{rt} is equal to the change in the wage per efficiency unit C_j in their occupation.

For workers who do switch occupations, the wage change is equal to the change in $C_{j'}$ (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 defining the new cutoff skill levels (after the shock to κ_{rt}) as z'_0 and z'_1, we have that:

$$\mathbb{I}(j \neq j'|z) = \begin{cases} 0 & \text{if } z_{min} \leq z < z_0 \text{ or } z'_0 \leq z < z'_1 \text{ or } z_1 \leq z \leq z_{max} \\ 1 & \text{if } z_0 \leq z < z'_0 \text{ or } z'_1 \leq z < z_1 \end{cases}$$

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, $d \ln C_{man}/d \ln \kappa_{rt}$ is zero. Now, recall that before the shock to κ_{rt}, 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 C_{man} and C_{rt}, 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: $\ln C_{rt} + \ln \varphi_{rt}(z) > \ln C_{man} + \ln \varphi_{man}(z)$ 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.

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:

$$\begin{aligned} \frac{d \ln w(z'_1)}{d \ln \kappa_{rt}} &= \frac{d \ln C_{cog}}{d \ln \kappa_{rt}} + \ln C_{cog} + \ln \varphi_{cog}(z'_1) - \big(\ln C_{rt} + \ln \varphi_{rt}(z'_1)\big) \\ &= \frac{d \ln C_{rt}}{d \ln \kappa_{rt}} \\ &< 0 \end{aligned}$$

where the second line is the wage change if the worker had not switched occupations, which must be equal to the first line due to the indifference condition between switching and staying.

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 $\ln C_{cog} + \ln \varphi_{cog}(z_1) = \ln C_{rt} + \ln \varphi_{rt}(z_1)$. It follows then that:

$$\begin{aligned}
\frac{d \ln w(z_1)}{d \ln \kappa_{rt}} &= \frac{d \ln C_{cog}}{d\kappa_{rt}} + \ln C_{cog} + \ln \varphi_{cog}(z_1) - (\ln C_{rt} + \ln \varphi_{rt}(z_1)) \\
&= \frac{d \ln C_{cog}}{d \ln \kappa_{rt}} \\
&> \frac{d \ln C_{rt}}{d \ln \kappa_{rt}}
\end{aligned}$$

The wage change for workers of ability z_1 is unambiguously greater than the wage change for stayers in routine jobs. The conclusion is that, among the workers who switch to non-routine cognitive, the wage change is increasing in the worker's ability level, and their wage change is greater or equal to that experienced by workers staying in routine occupations.

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.

In particular, assume that workers are endowed with a certain level of cognitive skills z_i^{cog} and manual skills z_i^{man}. 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 $\{z_i^{cog}, z_i^{man}\}$ is given by:

$$\ln \varphi_j(z_i) = \begin{cases} b_{man}^{man} z_i^{man} & \text{in non-routine manual jobs} \\ b_{rt}^{man} z_i^{man} + b_{rt}^{cog} z_i^{cog} & \text{in routine jobs} \\ b_{cog}^{cog} z_i^{cog} & \text{in non-routine cognitive jobs} \end{cases}$$

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:

$$Cov\left\{w_{cog}(z_i^{man}, z_i^{cog}) - w_{rt}(z_i^{man}, z_i^{cog}), w_{rt}(z_i^{man}, z_i^{cog})\right\} > 0 \tag{42}$$

$$Cov\left\{w_{man}(z_i^{man}, z_i^{cog}) - w_{rt}(z_i^{man}, z_i^{cog}), w_{rt}(z_i^{man}, z_i^{cog})\right\} < 0 \tag{43}$$

where $w_j(z_i^{man}, z_i^{cog})$ are the wages received in occupation j by a worker of skills $\{z_i^{cog}, z_i^{man}\}$.

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, while the workers with relatively lower wages will in expectation be the ones with more to gain from switching to non-routine manual.

Assume that the endowments of the two types of skills are independently distributed in the population, so that $Cov(z_i^{man}, z_i^{cog}) = 0$. The variances of each of the two types of skills are denoted σ^2_{man} and σ^2_{cog}. Using these assumptions, along with the equation for log wages (6) and the assumption for $\ln \varphi_j(z_i)$, Equation (42) implies:

$$\begin{aligned} Cov\left\{\theta_{cog} - \theta_{rt} + (b^{cog}_{cog} - b^{cog}_{rt})z_i^{cog} - b^{man}_{rt} z_i^{man}, \theta_{rt} + b^{cog}_{rt} z_i^{cog} + b^{man}_{rt} z_i^{man}\right\} > 0 \\ (b^{cog}_{cog} - b^{cog}_{rt})b^{cog}_{rt}\sigma^2_{cog} - (b^{man}_{rt})^2\sigma^2_{man} > 0 \end{aligned}$$

That is:

$$(b^{cog}_{cog} - b^{cog}_{rt})b^{cog}_{rt}\sigma^2_{cog} > (b^{man}_{rt})^2\sigma^2_{man} \tag{44}$$

And Equation (43) implies:

$$\begin{aligned} Cov\left\{\theta_{man} - \theta_{rt} + (b^{man}_{man} - b^{man}_{rt})z_i^{man} - b^{cog}_{rt} z_i^{cog}, \theta_{rt} + b^{cog}_{rt} z_i^{cog} + b^{man}_{rt} z_i^{man}\right\} < 0 \\ (b^{man}_{man} - b^{man}_{rt})b^{man}_{rt}\sigma^2_{man} - (b^{cog}_{rt})^2\sigma^2_{cog} < 0 \end{aligned}$$

That is:

$$(b^{man}_{man} - b^{man}_{rt})b^{man}_{rt}\sigma^2_{man} < (b^{cog}_{rt})^2\sigma^2_{cog} \tag{45}$$

Equations (44) and (45) 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 $(b^{man}_{man} - b^{man}_{rt}) > 0$), as long as the variance of cognitive skills in the population is large enough relative to the variance of manual skills.

Appendix C Grouping of Occupation Codes

Table 11 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).

For the alternative classification of occupations used in Section 7.3, 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:

$$RTI_j = \frac{rt_j}{max\{nr\_cog_j, nr\_man_j\}} \tag{46}$$

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.[45] Among the remaining occupations, I generate an index of relative non-routine cognitive task intensity (CTI_j) as follows:

$$CTI_j = \frac{nr\_cog_j}{nr\_man_j} \tag{47}$$

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).

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

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Figure 1: Effects of routine-biased technical change on skill cutoffs and wages (case where C_{cog} increases relative to C_{man})

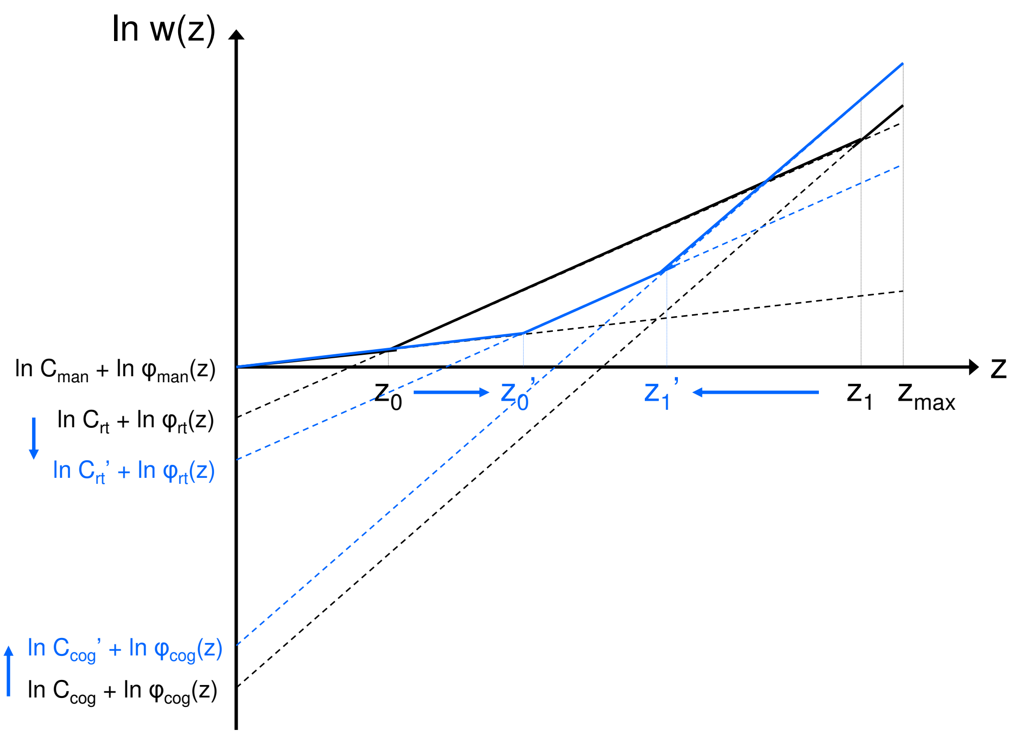
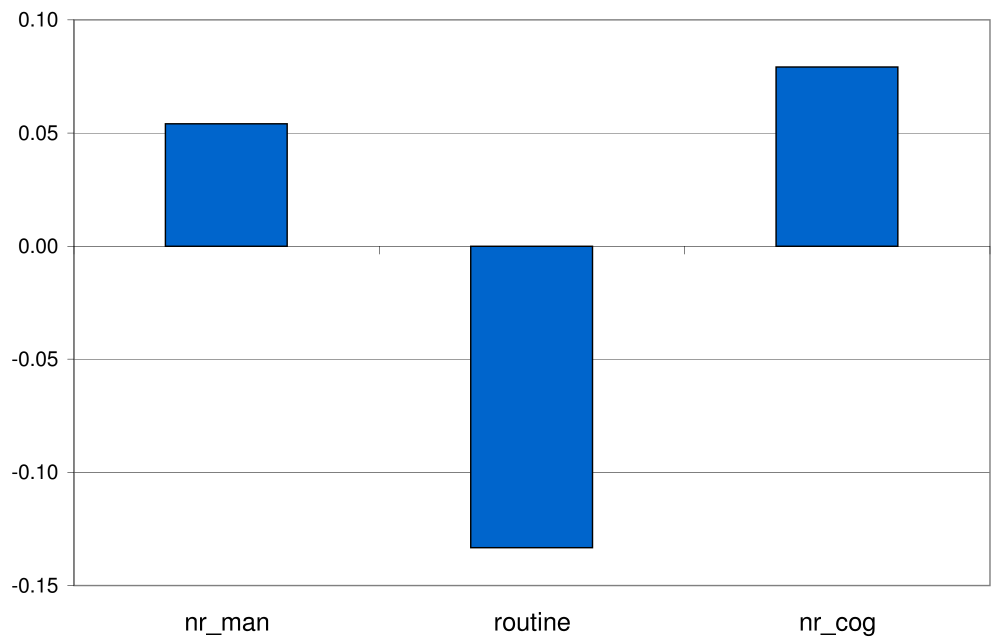
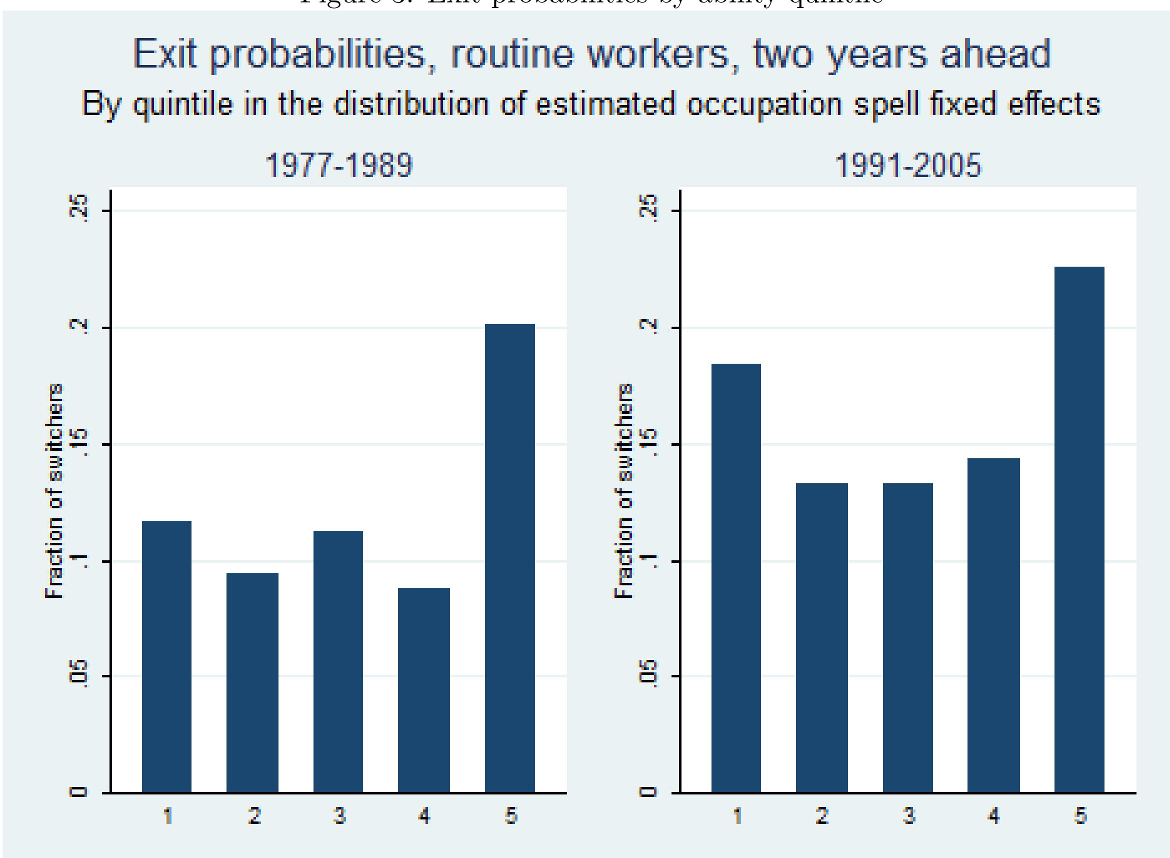


Figure 2: Changes in employment shares for broad occupation groups, men, PSID, 1968-2007



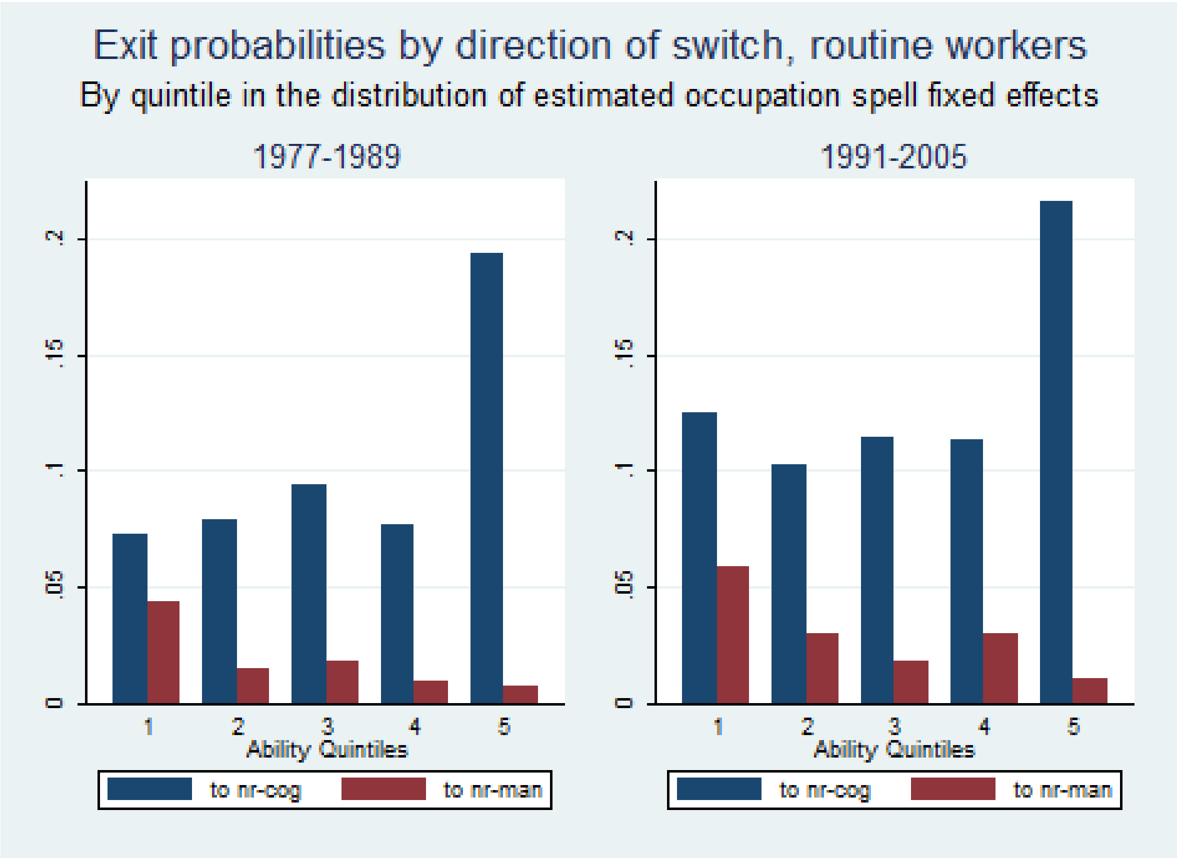
Note: Sample includes male household heads aged 16 to 64 employed in non-agricultural, non-military jobs, who are part of the PSID's core sample. nr_cog stand for non-routine cognitive; nr_man stands for non-routine manual. See Data Section for details on the occupation classification.

Figure 3: Exit probabilities by ability quintile



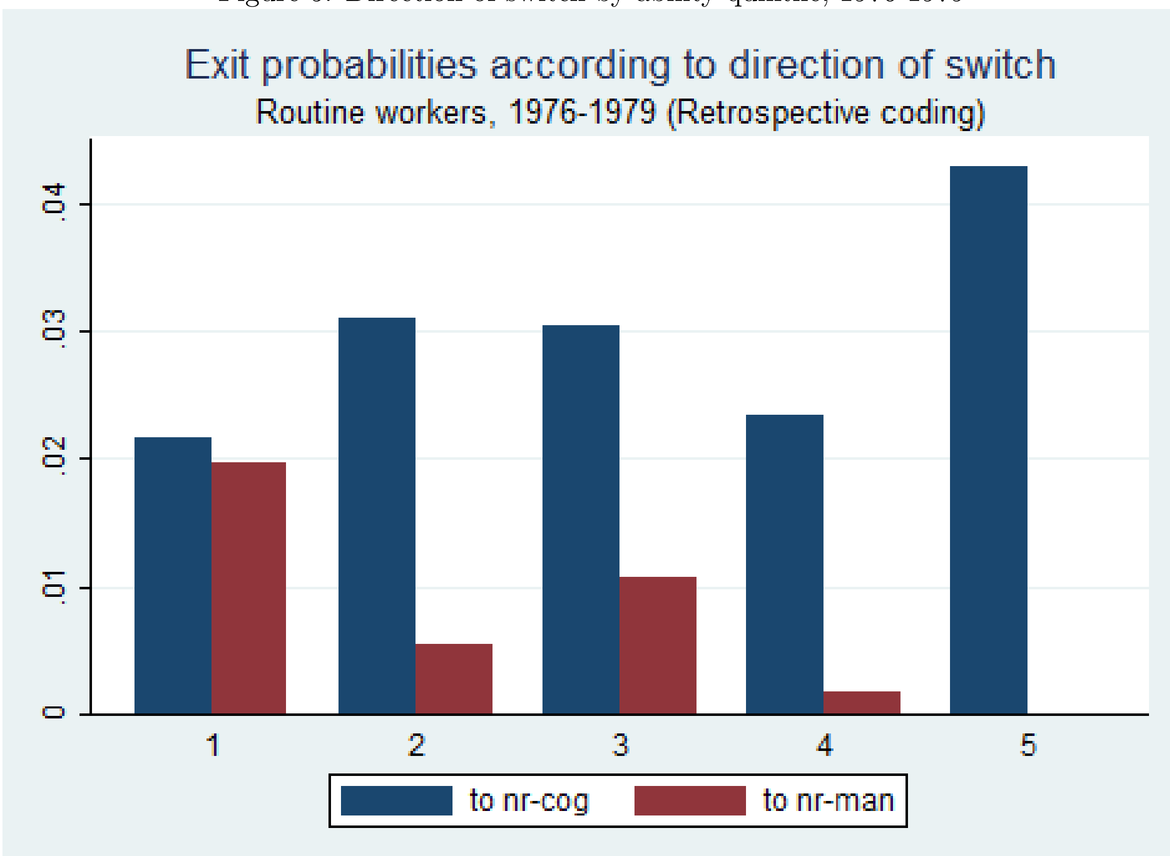
Note: Sample includes workers in routine occupations, and plots their probability of switching out of this type of occupation between years t and $t+2$, according to their ability quintile.

Figure 4: Direction of switch by ability quintile



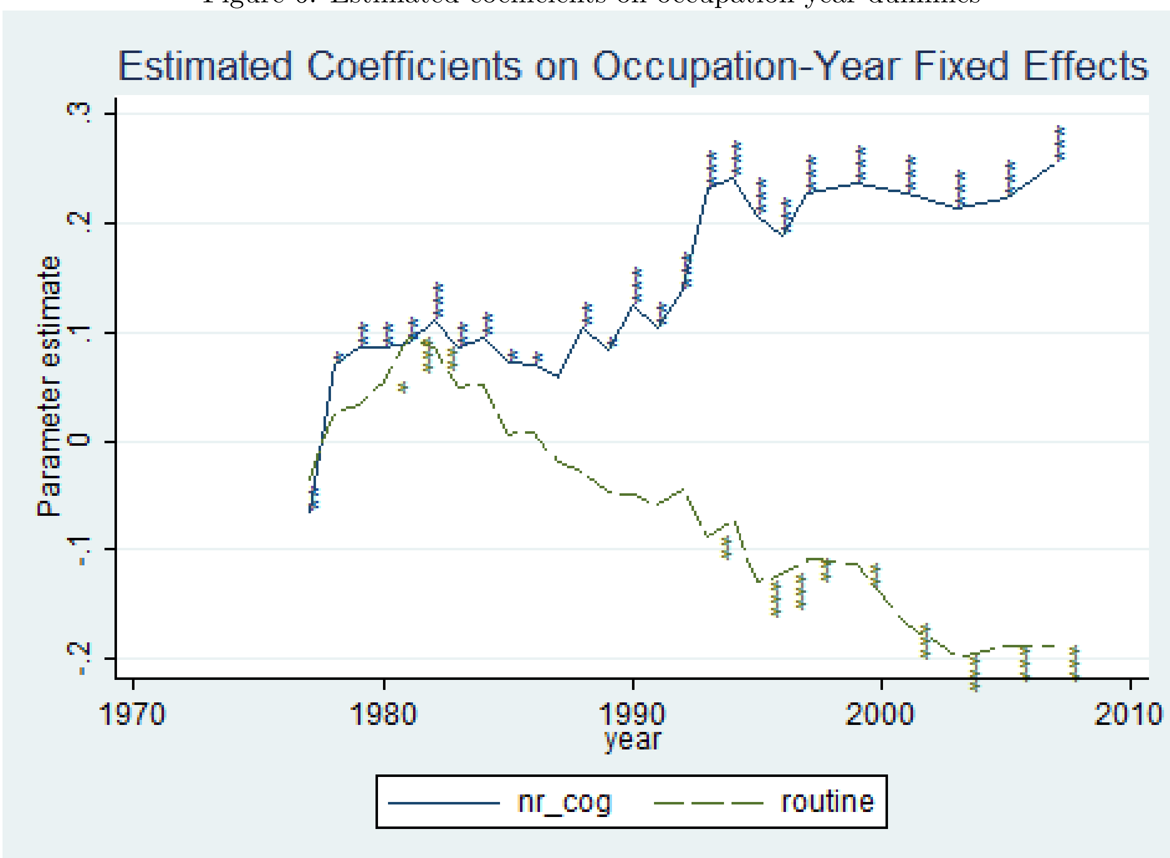
Note: Sample includes workers in routine occupations, and plots their probability of switching to the different non-routine occupations between years t and $t+2$, according to their ability quintile.

Figure 5: Direction of switch by ability quintile, 1976-1979



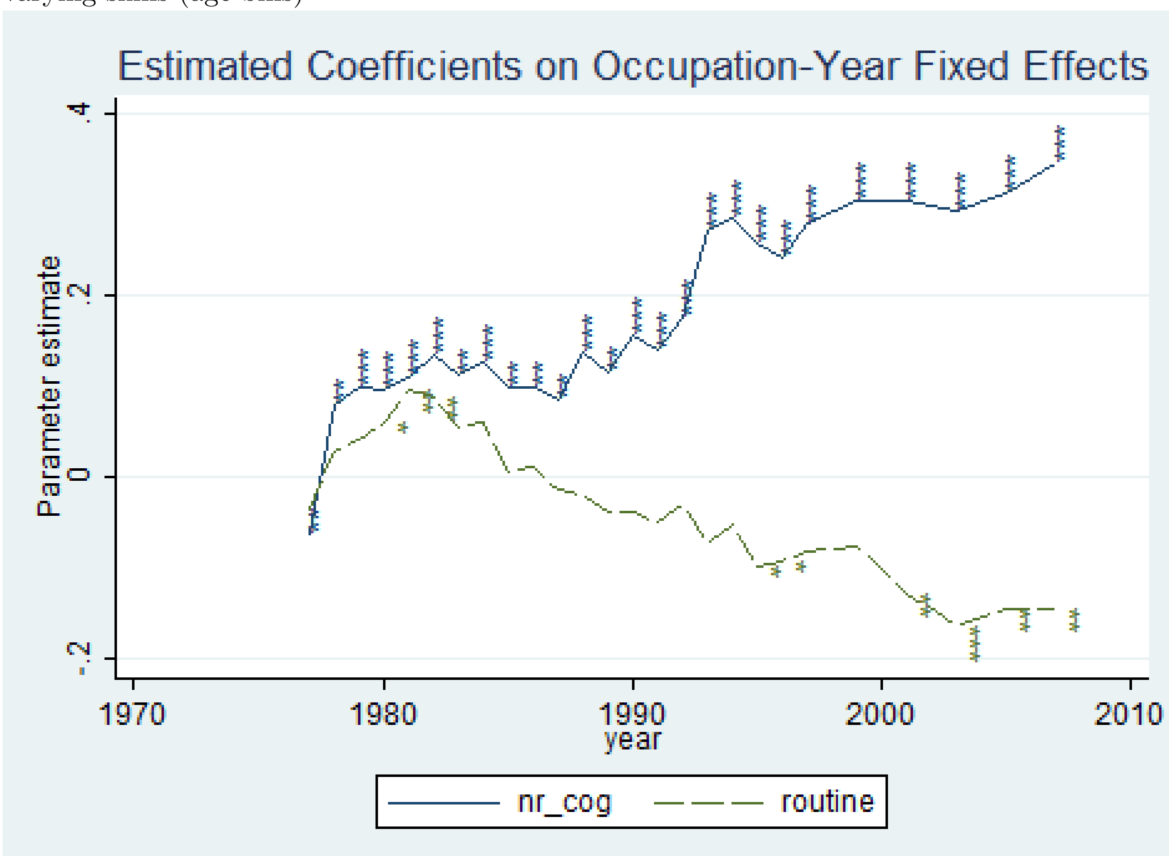
Note: Sample includes workers in routine occupations for the years 1976-1979, and plots their probability of switching to the different non-routine occupations between years t and $t+1$, according to their ability quintile.

Figure 6: Estimated coefficients on occupation-year dummies



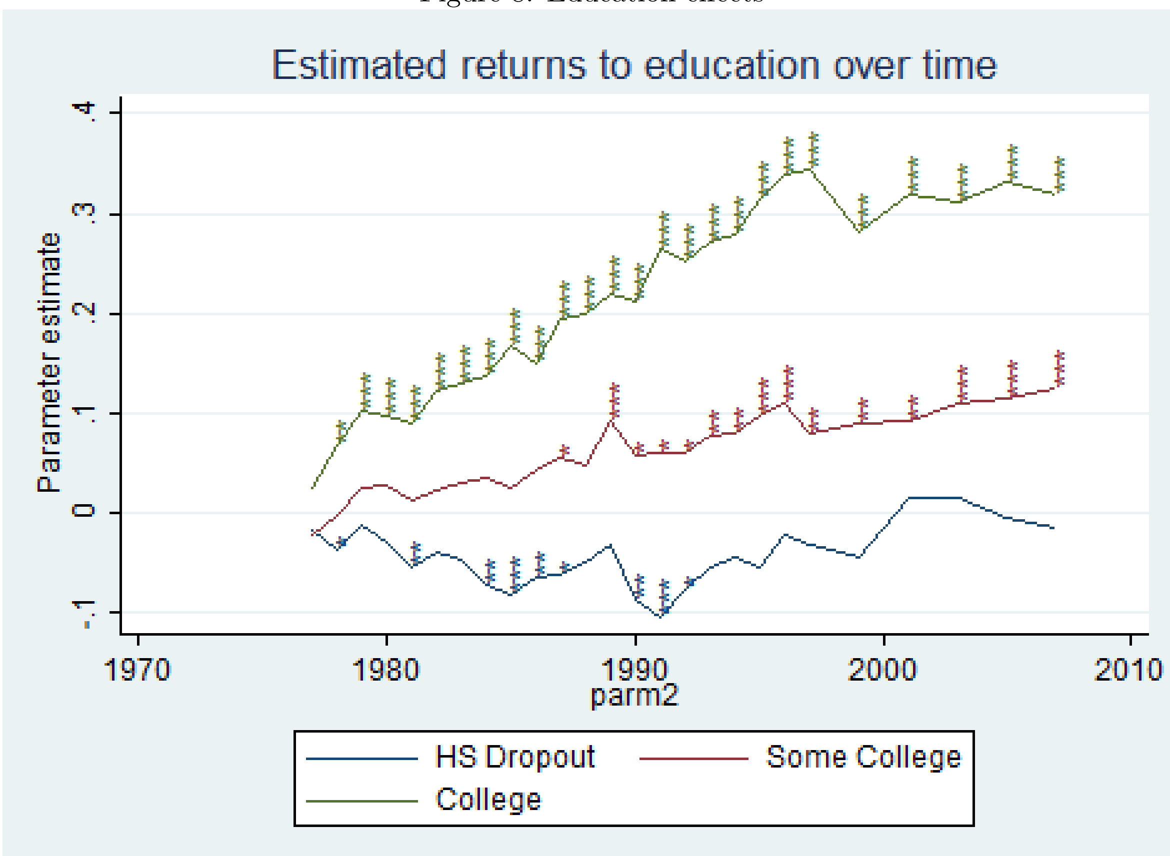
Note: The figure shows the estimates of $\widehat{\theta}_{rt}$ and $\widehat{\theta}_{cog}$ obtained from the wage equation (28). Stars denote the level at which the estimated coefficients are significantly different from zero.

Figure 7: Estimated coefficients on occupation-year dummies when controlling for time-varying skills (age bins)



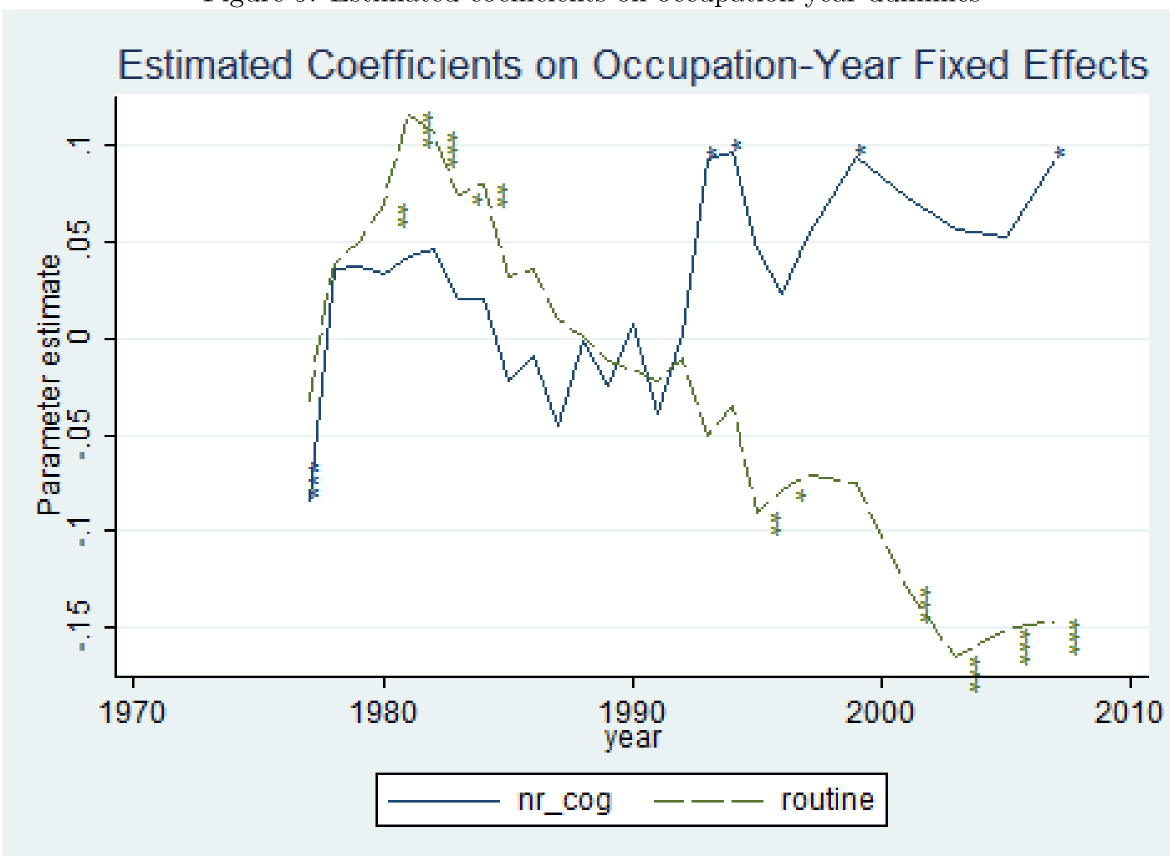
Note: The figure shows the estimates of $\widehat{\theta}_{rt}$ and $\widehat{\theta}_{cog}$ obtained from the wage equation (31). Stars denote the level at which the estimated coefficients are significantly different from zero.

Figure 8: Education effects



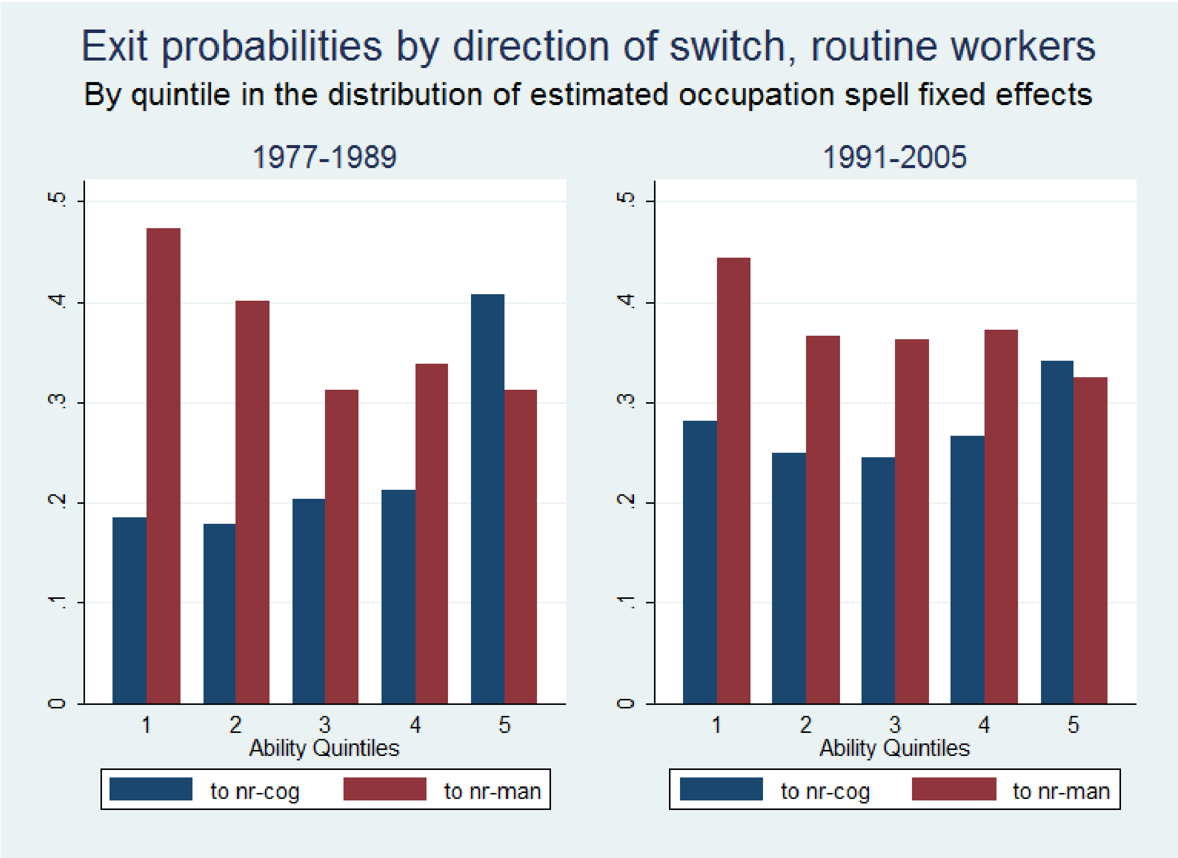
Note: Estimated coefficients are obtained from the estimation of the wage equation (34). Stars denote the level at which the estimated coefficients are significantly different from zero.

Figure 9: Estimated coefficients on occupation-year dummies



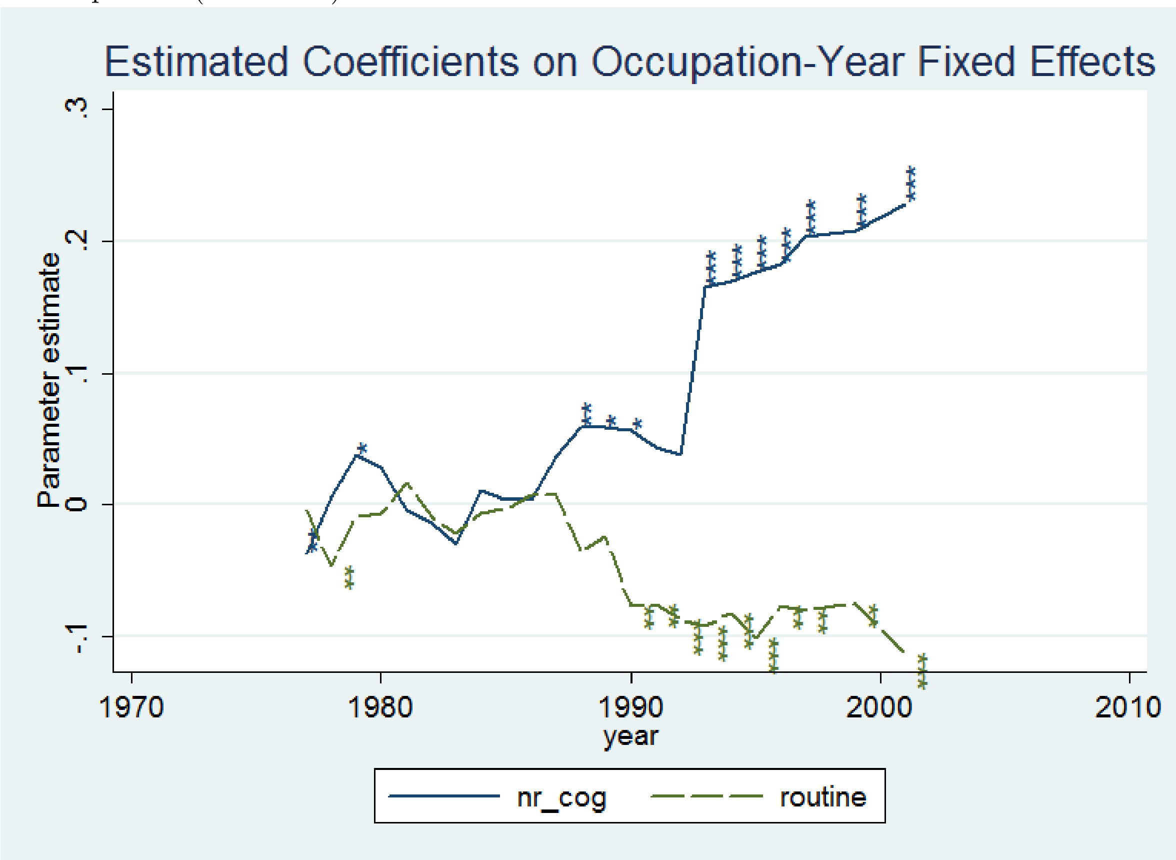
Note: The figure shows the estimates of $\widehat{\theta}_{rt}$ and $\widehat{\theta}_{cog}$ obtained from the wage equation (34). Stars denote the level at which the estimated coefficients are significantly different from zero.

Figure 10: 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.

Figure 11: Estimated coefficients on occupation-year dummies under alternative classification of occupations (1976-2001)



Note: The figure shows the estimates of $\widehat{\theta}_{rt}$ and $\widehat{\theta}_{cog}$ obtained from the wage equation (28) using the alternative classification of occupations into broad categories described in Appendix C. Stars denote the level at which the estimated coefficients are significantly different from zero.

Table 1: Descriptive statistics (1976-2007)

	nr_cog (Prof, Manag, Tech)	routine (Prodctn, Operators, Clerical)	nr_man (Service)
Nr of Obs	21,431	25,861	3,477
Share	0.42	0.51	0.07
Averages:			
Real Wages	11.96	7.02	5.94
Age	40.67	38.24	37.40
Fractions within the occupation group:			
Union	0.07	0.25	0.26
H.S. Dropout	0.02	0.15	0.11
H.S. Grad	0.16	0.50	0.42
Some Coll.	0.22	0.24	0.32
College	0.60	0.11	0.14
Task measures (1976-2001 averages):			
DOT Non-Routine Cognitive	6.01	1.82	1.30
DOT Routine	2.97	4.50	2.40
DOT Non-Routine Manual	0.74	1.89	2.28

Note: Real wages are in 1979 dollars. Sample includes male household heads aged 16 to 64 employed in non-agricultural, non-military jobs, who are part of the PSID's core sample. The task measures are from the Dictionary of Occupational Titles (DOT) 4th Edition, published in 1977 (ICPSR, 1981). DOT task measures are aggregated to 1970 Census Occupation Codes following Autor et al. (2003). Each DOT score is rescaled to have a (potential) range from zero to 10. Following Autor et al. (2003), Non-Routine Cognitive is the mean score for 'Mathematics' and 'Direction, control and planning'; Routine is the mean score for 'Dealing with set limits, tolerances and standards' and 'Finger dexterity'; and Non-Routine Manual is the score for 'Eye-hand-foot coordination'. The averages are for the period 1976-2001, as task measures at the 1970-COC level cannot be attached to PSID data from 2003 onwards (when occupations are coded in 2000 Census codes).

Table 2: Regressions of the probability of switching occupations two years ahead on dummies for ability quintiles (routine workers, odd years only)

	1977-1989	1991-2005
	(1)	(2)
q-1	.004	.052
	(.015)	(.015)***
q-2	-.018	.0002
	(.017)	(.014)
q-4	-.025	.011
	(.016)	(.017)
q-5	.088	.093
	(.018)***	(.016)***
Const.	.112	.132
	(.012)***	(.010)***
Obs.	5181	7512

Note: Sample includes workers in routine occupations. The dependent variable is a dummy equal to 1 if the worker is employed in a routine occupation in year t and in a non-routine occupation in year $t+2$. q-1 through q-5 represent dummies for the individual workers' estimated ability quintiles among routine workers in year t. q-1 represents the lowest ability workers and q-5 the highest ability workers. q-3 is the omitted category. Ability quintiles are built based on estimated individual-occupation fixed effects. Standard errors are bootstrapped using 100 replications based on 6975 clusters of individuals. See footnote 34 for details.

Table 3: Regressions of the probability of switching to particular occupations two years ahead for routine workers (odd years only, 1977-2005)

	P(nr_cog)	P(nr_man)
	(1)	(2)
Const.	.104	.019
	(.005)***	(.002)***
post91	.030	.011
	(.006)***	(.003)***
Obs.	12693	12693

Note: Sample includes workers in routine occupations in year t. In Column (1), the dependent variable is a dummy equal to 1 if the worker is employed in a non-routine cognitive occupation in year $t+2$. In Column (2), the dependent variable is a dummy equal to 1 if the worker is employed in a non-routine manual occupation in year $t+2$. post91 is a dummy for years from 1991 onwards.

Table 4: Regressions of the probability of switching to particular occupations two years ahead for routine workers (odd years only)

	P(nr_cog)	P(nr_cog)	P(nr_man)	P(nr_man)
Sub-period:	1977-1989	1990-2005	1977-1989	1990-2005
	(1)	(2)	(3)	(4)
q-1	-.022	.011	.026	.040
	(.014)	(.012)	(.007)***	(.009)***
q-2	-.015	-.011	-.002	.011
	(.017)	(.013)	(.006)	(.006)*
q-4	-.017	-.0008	-.008	.012
	(.015)	(.015)	(.005)	(.006)**
q-5	.099	.101	-.010	-.008
	(.018)***	(.015)***	(.005)**	(.005)*
Const.	.095	.114	.018	.018
	(.011)***	(.009)***	(.005)***	(.004)***
Obs.	5181	7512	5181	7512

Note: Sample includes workers in routine occupations in year t. In Columns (1) and (2), the dependent variable is a dummy equal to 1 if the worker is employed in a non-routine cognitive occupation in year $t+2$. In Columns (3) and (4), the dependent variable is a dummy equal to 1 if the worker is employed in a non-routine manual occupation in year $t+2$. q-1 through q-5 represent dummies for the individual workers' estimated ability quintiles among routine workers in year t (with q-1 representing the lowest ability workers and q-5 the highest). Workers in the middle of the ability distribution (q-3) are the omitted category. Ability quintiles are based on estimated individual-occupation fixed effects. Standard errors are bootstrapped using 100 replications based on 6975 clusters of individuals. See footnote 34 for details.

Table 5: Regression of changes in log real wages over different time horizons on dummies for initial occupation

	Change in log real wages between year t and year:					
	$t+1$	$t+2$	$t+4$	$t+10$	$t+15$	$t+20$
	(1)	(2)	(3)	(4)	(5)	(6)
nr-cog	-.016	-.017	-.013	.006	.013	.045
	(.006)***	(.006)***	(.010)	(.023)	(.034)	(.060)
routine	-.029	-.041	-.062	-.105	-.166	-.170
	(.006)***	(.006)***	(.009)***	(.022)***	(.032)***	(.059)***
Const.	.044	.121	.078	.103	.153	.216
	(.008)***	(.010)***	(.013)***	(.025)***	(.035)***	(.060)***
Obs.	31328	37114	30255	16072	8433	3752
# of Indiv.	3855	4764	4129	2756	1848	1225
R^2	.014	.02	.026	.046	.065	.062

Note: nr-cog is a dummy equal to 1 if the individual is employed in a non-routine cognitive occupation at time t. routine is a dummy equal to 1 if the individual is employed in a routine occupation at time t. Workers employed in a non-routine manual occupation at time t 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. Due to data constraints, Column (1) uses data only up to 1997.

Table 6: Regression of changes in log real wages over different time horizons on dummies for initial occupation for workers who do not switch occupations

	Change in log real wages between year t and year:					
	$t+1$	$t+2$	$t+4$	$t+10$	$t+2$	$t+2$
Period:	1976-1997	1976-2007	1976-2007	1976-2007	1976-1989	1990-2005
	(1)	(2)	(3)	(4)	(5)	(6)
nr-cog	.010	.019	.027	.060	.010	.027
	(.004)**	(.005)***	(.009)***	(.023)***	(.008)	(.006)***
routine	-.009	-.018	-.038	-.079	-.024	-.014
	(.004)**	(.005)***	(.008)***	(.022)***	(.007)***	(.006)**
Const.	.020	.094	.043	.069	.101	.115
	(.007)***	(.009)***	(.012)***	(.025)***	(.011)***	(.009)***
Obs.	28029	31930	25389	13439	15999	15931
# of Indiv.	3750	4518	3832	2540	2650	3538
R^2	.016	.026	.034	.057	.025	.022

Note: Workers staying in non-routine manual 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). The sample includes only occupational stayers. For column (1), stayers are defined as workers in the same broad occupation in years t and $t+1$. For column (2) onwards, stayers are defined as workers in the same broad occupation in years t and $t+2$ (even though the wage change may be taken over a longer horizon). 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 7: Wage changes for routine workers, according to direction of switch

Panel A: Dependent variable is change in log real wages

	Change in log real wages between year t and year:					
	$t+1$	$t+2$	$t+4$	$t+10$	$t+2$	$t+2$
Period:	1976-1997	1976-2007	1976-2007	1976-2007	1976-1989	1990-2007
	(1)	(2)	(3)	(4)	(5)	(6)
goto-nrcog	.034	.059	.085	.163	.024	.087
	(.008)***	(.008)***	(.010)***	(.019)***	(.013)*	(.011)***
goto-nrman	-.112	-.143	-.035	.115	-.162	-.128
	(.023)***	(.023)***	(.026)	(.046)**	(.033)***	(.031)***
Const.	.037	.066	.016	-.002	.067	.041
	(.007)***	(.009)***	(.011)	(.018)	(.009)***	(.010)***
Obs.	15800	18341	14278	7568	9364	8977
# of Indiv.	2655	3253	2701	1735	1810	2425
R^2	.013	.028	.033	.061	.025	.025

Panel B: Dependent variable is change in fitted model wages (in logs)

	Change in fitted model wages between year t and year:					
	$t+1$	$t+2$	$t+4$	$t+10$	$t+2$	$t+2$
Period:	1976-1997	1976-2007	1976-2007	1976-2007	1976-1989	1990-2005
	(1)	(2)	(3)	(4)	(5)	(6)
goto-nrcog	.086	.122	.098	.139	.050	.180
	(.010)***	(.009)***	(.008)***	(.011)***	(.012)***	(.011)***
goto-nrman	-.152	-.139	-.030	.054	-.151	-.128
	(.023)***	(.021)***	(.019)	(.027)**	(.032)***	(.027)***
Const.	-.038	.026	.049	-.014	.029	-.034
	(.002)***	(.003)***	(.004)***	(.008)*	(.002)***	(.004)***
Obs.	15800	18341	14278	7568	9364	8977
# of Indiv.	2655	3253	2701	1735	1810	2425
R^2	.168	.174	.147	.09	.158	.22

Panel C: Fraction of routine workers in each of the switching categories (%)

	Fraction of routine workers in year t switching to non-routine jobs in year:					
	$t+1$	$t+2$	$t+2$	$t+2$	$t+2$	$t+2$
Period:	1976-1997	1976-2007	1976-2007	1976-2007	1976-1989	1990-2005
	(1)	(2)	(3)	(4)	(5)	(6)
goto-nrcog	8.07	10.95	11.26	11.47	9.43	12.54
goto-nrman	1.51	2.18	1.92	1.88	1.83	2.55

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). 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 8: Robustness checks for the wage changes for routine workers, according to direction of switch

	Change in log real wages between year t and year:				
	$t+2$	$t+4$	$t+10$	$t+4$	$t+10$
	(1)	(2)	(3)	(4)	(5)
to nr-cog	.045	.092	.170	.129	.282
	(.012)***	(.014)***	(.020)***	(.014)***	(.026)***
to nr-man	-.124	.011	.112	-.083	.160
	(.038)***	(.035)	(.047)**	(.042)**	(.065)**
Const.	.095	.032	.016	.014	.013
	(.013)***	(.013)**	(.019)	(.011)	(.019)
Obs.	6553	6553	6553	12435	5953
e(N-clust)	1496	1496	1496	2515	1520
R^2	.033	.038	.061	.04	.095

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 columns (1) through (3), occupation transitions between years t and $t+2$ are considered (even though the wage change may be taken over a longer horizon). In columns (4) and (5), only workers who are still in their $t+2$ occupation in the terminal year ($t+4$ in column (4), $t+10$ in column (5)) are included in the sample. 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 9: Regressions of the probability of switching two years ahead for routine workers (odd years only, 1977-2005)

	P(sw)	P(nr_cog)	P(nr_man)
	(1)	(2)	(3)
q-1	.033	-.0009	.034
	(.012)***	(.010)	(.006)***
q-2	-.008	-.011	.003
	(.011)	(.010)	(.004)
q-4	-.001	-.004	.003
	(.011)	(.010)	(.004)
q-5	.091	.102	-.011
	(.013)***	(.013)***	(.003)***
Const.	.122	.102	.020
	(.008)***	(.007)***	(.003)***
Obs.	12530	12530	12530

Note: Sample includes workers in routine occupations in year t. In Column (1) the dependent variable is a dummy equal to 1 if the worker is employed in any non-routine occupation in year $t+2$. In Column (2) the dependent variable is a dummy equal to 1 if the worker is employed in a non-routine cognitive occupation in year $t+2$. In Column (3) the dependent variable is a dummy equal to 1 if the worker is employed in a non-routine manual occupation in year $t+2$. q-1 through q-5 represent dummies for the individual workers' estimated ability quintiles among routine workers in year t (with q-1 representing the lowest ability workers and q-5 the highest), obtained from the estimation of Equation (34). Workers in the middle of the ability distribution (q-3) are the omitted category. Standard errors are bootstrapped using 100 replications based on 6975 clusters of individuals. See footnotes 34 and 44 for details.

Table 10: Wage changes for routine workers, according to direction of switch

Panel A: Dependent variable is change in fitted model wages (in logs)

	Change in fitted model wages between year t and year:					
	$t+1$	$t+2$	$t+4$	$t+10$	$t+2$	$t+2$
Period:	1976-1997	1976-2007	1976-2007	1976-2007	1976-1989	1990-2005
	(1)	(2)	(3)	(4)	(5)	(6)
goto-nrcog	.089	.124	.100	.144	.069	.170
	(.010)***	(.009)***	(.008)***	(.011)***	(.012)***	(.011)***
goto-nrman	-.147	-.135	-.027	.062	-.146	-.126
	(.023)***	(.021)***	(.020)	(.028)**	(.032)***	(.027)***
Const.	-.042	.032	.068	.018	.034	-.023
	(.002)***	(.003)***	(.004)***	(.009)**	(.003)***	(.004)***
Obs.	15749	18188	14179	7548	9358	8830
# of Indiv.	2632	3181	2649	1722	1808	2355
R^2	.171	.178	.15	.091	.184	.198

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:	1976-1997	1976-2007	1976-2007	1976-2007	1976-1989	1990-2005
	(1)	(2)	(3)	(4)	(5)	(6)
goto-nrcog	8.05	10.83	11.15	11.43	9.44	12.31
goto-nrman	1.52	2.18	1.93	1.87	1.83	2.56

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). Standard errors are clustered at the individual level.

Table 11: Occupation code groupings

Task label	Occupations included	3-digit Census Codes 1970-COC	3-digit Census Codes 2000-COC
nr_cog	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
nr_man	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). nr_cog stands for non-routine cognitive and nr_man stands for non-routine manual. 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.