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

Guido Matias Cortes*

University of Manchester

This Draft: January 20, 2014

Abstract

This paper presents a theoretical and empirical analysis of the effects of routine-biased technical change on occupational transition patterns and wage changes of individual workers using a general equilibrium model with endogenous sorting of workers into occupations. Consistent with the predictions of the model, data from the Panel Study of Income Dynamics shows (1) strong evidence of selection on ability in the occupational mobility patterns of routine workers, (2) a significant fall in the wage premium in routine occupations, (3) faster wage growth over long run horizons for workers switching out of routine jobs relative to those who stay.

JEL Codes: J24, J31, J62.

Keywords: Labor Market Polarization; Technological Change; Routinization; Occupational Mobility; Tasks; Panel Data.

*Department of Economics, University of Manchester, Arthur Lewis Building, Oxford Road, Manchester, UK M13 9PL. E-mail: matias.cortes@manchester.ac.uk. 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 Jaewon Jung, Jean Mercenier, Vadim Marmer, Henry Siu, and with participants at the CEA Conference (2011), the SOLE Conference (2012), and at seminars at UBC, SFU, Bank of Canada, Université de Montréal, UCL, Carleton, SOFI, University of Manchester, University of Queensland, University of Adelaide, Banco Central de Costa Rica and Humboldt University Berlin. 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 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 evidence on: (i) the micro-level dynamics underlying the aggregate patterns of employment and wage polarization, (ii) the way in which particular subsets of workers have been impacted by routinization, and (iii) the changes that have occurred over time in the 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, but only recently has technological change been linked to occupations and their task content through theories of routine-biased technical change (RBTC).[2] Empirical studies of the effects of RBTC for the United States have so far relied on repeated

[1] The polarization phenomenon has also been documented for European countries; see Dustmann, Ludsteck, and Schönberg (2009) and Goos, Manning, and Salomons (2009).

[2] The earlier literature thought of technological change as being skill-biased, in the sense that it disproportionately favored high-skill workers, and generally made no distinction between skills and tasks. See, for example, Katz and Murphy (1992), Juhn, Murphy, and Pierce (1993), Berman, Bound, and Machin (1998) and Krusell, Ohanian, Ríos-Rull, and Violante (2000).

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. It has been well documented that over the past three decades middle-wage occupations (such as blue-collar and clerical jobs, which have a high content of routine tasks) have had falling employment shares. Meanwhile, employment shares have been increasing both in low-wage occupations (mainly personal services, which have a high content of non-routine manual tasks), and in high-wage occupations (professional and managerial jobs, with a high content of non-routine cognitive tasks).[3] 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 United States. 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 providing information on their occupational mobility patterns and the wage changes they experience both in the short- and long-run.[4]

The empirical strategy followed in this paper also makes it possible to study the changes over time in the occupation wage premia in the United States. In contrast to the focus in the earlier skill-biased technical change literature on the evolution of the skill premium, changes in occupational wage premia implied by RBTC have not received much attention. This paper fills this gap in the literature, and in the process 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 based on observable and unobservable individual characteristics.[5]

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. This individual-level literature has been expanding in recent years, focusing both on the rates of occupational mobility and on the implications of occupational transitions for individuals' human capital and wages.

Kambourov and Manovskii (2008) and Moscarini and Thomsson (2007) document a rise

[3]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.

[4]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.

[5]Although many empirical studies include occupation dummies when estimating wage regressions, concerns about the effects of endogenous selection into occupations are rarely addressed.

in the rates of occupational mobility in the United States between the early 1970s and the mid-1990s. Meanwhile, Groes, Kircher, and Manovskii (2010), using Danish administrative data, study which workers are most likely to leave an occupation, and analyze what type of new occupations they tend to switch to. They find a U-shaped pattern for occupational mobility, with workers at the extremes of the wage distribution within an occupation being more likely to switch occupations than those in the middle. They also find that the relatively high (low) ability workers are more likely to switch to occupations with higher (lower) average wages.

Meanwhile, in terms of the wage costs associated with occupational switches, Kambourov and Manovskii (2009b) and Sullivan (2010) find that an important component of human capital is occupation-specific, and is lost when a worker switches occupations. Meanwhile Gathmann and Schönberg (2010), Poletaev and Robinson (2008) and Robinson (2011) provide a more nuanced view, suggesting that human capital has an important *task-specific* component, and the human capital loss experienced by occupational switchers depends on the level of dissimilarity in the task requirements across the occupations that he is switching between.

This paper contributes to this strand of the literature by focusing specifically on transitions out of a rapidly declining occupational category, and considering both the short and long run wage effects of these transitions. Moreover, the framework presented in this paper helps interpret many of the findings from this individual-level literature within the broader context of technological change and labor market polarization.

The paper begins by describing a model that features an occupational sorting mechanism which 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 (2012), the model economy is composed of three distinct occupations (non-routine manual, routine, and non-routine cognitive) and a continuum of workers differentiated according to their skill level.[6] 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).[7] 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

[6]The setup in Acemoglu and Autor (2011) instead features a continuum of tasks and three distinct skill groups. Section 2 discusses the reasons why the Jung and Mercenier (2012) setup is preferred. See also Costinot and Vogel (2010) for a model with a continuum of skills *and* a continuum of tasks.

[7]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.

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. These model predictions can also be derived (in expectations) from a more general setting with two-dimensional skills.[8]

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.[9]

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 the wage equation are that: (i) unobservable skills and their return 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. The empirical specification can allow for variation over time in observable skills or in the return to education, as well as for costs to occupational mobility due to the loss of occupation or task-specific human capital.

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.

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

[9]Full details of the occupations included in each of the categories are given in Appendix C, where I also discuss the robustness of the results to an alternative occupation classification based directly on task data.

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 is not explained by changes in the return to education, or by lower returns to occupational tenure in routine jobs.

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 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). The results are robust to accounting for susbsequent occupational switches and attrition.

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

2 Model

This section sketches the key elements of a theoretical model of occupational sorting based on Jung and Mercenier (2012), and discusses the predicted effects of routine-biased technical change (RBTC) on individual-level patterns, namely wage changes and occupational switches. The full model is presented in Appendix A.

There is a single representative household composed of a continuum of workers, who differ in terms of their skill levels. There is perfect information, and workers sort endogenously into one of three occupations.[10] The three occupations are labeled as non-routine manual (M),

[10]This contrasts with Acemoglu and Autor (2011), who consider a setting with a continuum of tasks and three skill groups. The main advantage of this alternative setup 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). Another advantage 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), which can be done by relying on broad occupation codes, which differ

routine (R) and non-routine cognitive (C).

Occupational sorting is driven by comparative advantage as in Gibbons, Katz, Lemieux, and Parent (2005). Specifically, workers of higher skill levels are assumed to be more productive at all tasks, but particularly so at more complex tasks (where non-routine cognitive tasks are assumed to be the most complex and non-routine manual the least complex). Letting z denote the individual's skill level and $\varphi_j(z)$ the productivity (in terms of supplied efficiency units) of a worker of skill z performing task $j \in \{M, R, C\}$, this assumption is formalized as:

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

Potential wages for each worker in each occupation are the product of the competitively determined wage per efficiency unit in that occupation, denoted λ_j, and the number of efficiency units supplied by the worker. That is, $w_j(z) = \lambda_j \varphi_j(z)$, where $w_j(z)$ is the potential wage in occupation $j \in \{M, R, C\}$ for an individual of skill level z.

In equilibrium, there will be two endogenously determined skill thresholds z_0 and z_1, such that the least skilled workers will find it optimal to select into the non-routine manual occupation; the middle-skill workers into the routine occupation; and the most skilled workers into the non-routine cognitive occupation. The cutoffs z_0 and z_1 are determined in equilibrium so that the marginal workers have no incentives to relocate between tasks.

The equilibrium relationship between skills, occupational choices and wages is depicted in Panel A of Figure 1, under the assumption that productivity is log-linear in skills. The three lines depict potential wages in each of the three occupations. The slope of the potential wage curve is lowest in the non-routine manual occupation, and highest in the non-routine cognitive one, reflecting the assumption that productivity increases fastest with skills in the non-routine cognitive occupation.

The intercepts of the three curves correspond to the wage per efficiency unit in each of the three occupations. Intuitively, if the wages per efficiency unit were the same for all three tasks (i.e. $\lambda_C = \lambda_R = \lambda_M$), all workers would want to sort into the non-routine cognitive occupation (where they are all most productive). However, it can be shown that in equilibrium demand for all tasks is positive; therefore it must be the case that in equilibrium λ_C is relatively low, while λ_M must be relatively high. The low λ_C makes it optimal only for the most skilled workers to select into the non-routine cognitive occupation (where they are much more productive), while the high λ_M attracts the least skilled workers to the non-routine manual occupation (as their extra productivity in the other tasks is relatively small).[11] The equilibrium distribution implies that real wages will be on average lowest among non-routine manual workers, and highest among non-routine cognitive workers, which is consistent with the data. Note also

sharply in terms of their task content – although admittedly some specific occupations may be difficult to classify in an obvious manner.

[11] Note that Gibbons et al. (2005) find empirical evidence for this type of sorting pattern.

that an individual worker's wage depends both on his skill level, and on the type of task he performs.

On the production side of the model, there are two consumption goods that use the different tasks as inputs. The representative household has Cobb-Douglas preferences over the two goods. The first good is a 'service good' which is produced using only labor performing non-routine manual tasks. The second is a 'manufactured good' which has a production function that features complementarities between routine and non-routine cognitive task services. Routine task services are supplied by labor and by physical capital (machines, computers), while non-routine cognitive tasks are performed only by labor. Thus, capital enters the production function as a complement for workers performing non-routine cognitive tasks, and as a substitute for workers performing routine tasks.[12] Capital is exogenous and assumed to be available at no cost.

Technical change is modeled as an exogenous increase in the capital stock. This shock reduces the relative demand for labor performing routine tasks and is therefore referred to as 'routine-biased' technical change (RBTC).[13] The effects of RBTC on the equilibrium of the model are illustrated in Panel B of Figure 1. Consider first the effect of an increase in the capital stock on the wages per efficiency unit in each occupation. The immediate effect of the shock is to increase the relative demand for non-routine cognitive tasks within the manufacturing sector due to the complementarities between routine and non-routine cognitive task services. This increases the wage per efficiency unit in those occupations relative to routine ones. Meanwhile, there is an increase in household income which increases the demand for the the service good. This pushes up the wage per efficiency unit in the non-routine manual occupation relative to the wages per efficiency unit in the other occupations.[14] It can be shown formally that the net general equilibrium effect is an increase in the wage per efficiency unit in the non-routine cognitive occupation and a decrease in the routine one.

The figure also shows the implications in terms of the occupational composition of employment. The increased demand for non-routine workers causes an expansion of both types of non-routine employment and a contraction of routine employment. This is the essence of job polarization.

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

[13] This differs from Jung and Mercenier (2012), who define RBTC as an increase in κ_R as well as a simultaneous increase in the slope of $\varphi_R(z)$. I define it only as an increase in κ_R in order to be consistent with previous literature on routinization, which has 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. Changing only one parameter also eases the interpretation of the results.

[14] The wage per efficiency unit in the non-routine manual sector is shown in the Appendix to be equal to the price of the service good, which is the numeraire. Therefore, the wage per efficiency unit for this task must be equal to 1 in any equilibrium, and its relative increase is manifested as a relative decline in the wages per efficiency unit in the other tasks.

We can also determine *who* switches out of routine jobs. As the skill cutoff between routine and non-routine cognitive tasks falls, the highest ability routine workers will be the ones who find it optimal to switch to non-routine cognitive jobs (due to comparative advantage). Meanwhile, the increase in the skill cutoff between non-routine manual and routine tasks implies that it is the lowest ability routine workers who find it optimal to switch to non-routine manual tasks.

Finally, consider the total wage changes for workers of different ability levels. Workers who do not find it optimal to switch occupations simply experience a wage change equal to the change in the wages per efficiency unit in their optimal occupation. Workers switching out of routine jobs must do at least as well as those who stay, as they could have chosen to stay in the routine occupation but find it optimal not to do so.

To summarize, the general equilibrium effects of RBTC are: (i) workers at the bottom of the ability distribution within routine occupations switch to non-routine manual jobs, workers at the top of the ability distribution within routine occupations switch to non-routine cognitive jobs, and no switching is induced for non-routine workers (either manual or cognitive), (ii) workers staying in routine jobs experience a fall in real wages relative to those staying in other jobs, and workers staying in non-routine cognitive jobs experience an increase in real wages relative to those staying in other jobs, and (iii) workers who switch from routine to non-routine jobs (either cognitive or manual) experience an increase in real wages relative to those who stay in the routine occupation.[15]

The theoretical model sketched above assumes that workers' skills are one-dimensional. The simple intuition obtained from this model can also be derived (in expectations) from a richer model where workers have two-dimensional skill endowments (cognitive and manual). Appendix B describes the conditions under which this is the case. The model also assumes that workers' skills are fixed over their lifetime, a common assumption in polarization models (e.g. Acemoglu and Autor (2011), Autor and Dorn (2013), Boehm (2013)). Heterogeneities across age groups could be introduced by allowing for changes over the life cycle in worker skills or in worker productivities in the different occupations. Conditional on the wages per efficiency unit in each occupation, occupational choice in this model depends only on skills. In this sense the model is similar to Kambourov and Manovskii (2009a) and Alvarez and Shimer (2011), while differing from models where occupational choice is driven also by uncertainty or idiosyncratic match qualities, such as Neal (1999) or Groes, Kircher, and Manovskii (2010).[16]

Another abstraction made by the model is that it assumes that there is no cost to switching occupations. Intuitively, if we allowed for a positive cost for switches into non-routine cognitive occupations (for example because of educational requirements) then the RBTC shock would

[15] Formal proofs for all of these implications are provided in Appendix A.

[16] Allowing for uncertainty or shocks to match quality within the context of a model of RBTC would be an interesting extension for future work.

induce fewer workers to switch to this occupation, and those who do switch would be a more positively selected subset. Depending on how this cost is modeled, it would also have implications for the equilibrium conditions of the model. Switching costs are discussed further in the context of the empirical implementation in Section 6.4. Finally, note that the model equates occupations and tasks, thus abstracting from the fact that occupations comprise multiple tasks, and that the task content within occupations may be changing over time (e.g., Autor et al. (2003) and Spitz-Oener (2006)). This abstraction is useful given that the relative ranking of occupations in terms of their task intensity tends to remain stable over time and that this paper focuses on the patterns across (rather than within) occupations.[17]

3 Empirical Implementation

This section describes the empirical strategy used to test the predicted effects of RBTC on individual workers derived in Section 2, and discusses identification issues.

From the model, the potential wage for an individual of skill level z_i in occupation j consists of an occupation wage premium λ_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:

$$\ln \varphi_j(z_i) = z_i a_j \tag{1}$$

where a_j may be interpreted as an occupation-specific return to skills. Following the assumptions on comparative advantage from the model, assume that these occupation-specific returns are highest in the non-routine cognitive occupation and lowest in the non-routine manual one. That is:

$$a_M < a_R < a_C$$

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

$$\ln w_{ijt} = \theta_{jt} + z_i a_j \tag{2}$$

[17] Analyzing the within-occupation wage effects of changes in the demand for routine tasks is left as an interesting avenue for future research.

where i denotes the individual, j denotes the occupation, t denotes the time period, and $\theta_{jt} \equiv \ln \lambda_{jt}$ 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:

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt} z_i a_j + \mu_{it} \tag{3}$$

where D_{ijt} is an occupation selection indicator which equals one if person i selects into occupation $j \in \{M, R, C\}$ 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). Thus, we have that in Equation (3): $E(\mu_{it}|\boldsymbol{D}_{ij}, z_i, \boldsymbol{\theta}_j) = 0$. This assumption rules out dynamic effects such as workers learning about their ability over time. Note, however, that Gibbons et al. (2005) find in their empirical analysis that introducing learning does not substantially change their estimates of the occupation wage premia once comparative advantage is accounted for, so this need not be a major concern. The assumption also rules out that different types of switches may have different costs (e.g. because of differences in task distances across occupations, as in Gathmann and Schönberg (2010) or Poletaev and Robinson (2008)) or that switching may be more costly for workers with higher levels of occupational tenure (because of the importance of occupation-specific human capital, as in Kambourov and Manovskii (2009b)). These restrictions will be relaxed later on.

Given that I am not interested in identifying a_j (the occupation-specific return to skills), I rewrite Equation (3) as:

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}\gamma_{ij} + \mu_{it} \tag{4}$$

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 (4) 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 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 (4) are orthogonal to the mean-zero error term μ_{it} and the coefficients are consistently estimated.[18]

In the empirical estimation, θ_{jt} is captured with interactions of occupation and year dummies. The omitted category in all years is the non-routine manual occupation (which is consistent with the model where $\theta_M = 0$ in any equilibrium), and all wages are relative to this normalization. To capture changes over time that affect all occupations (including non-routine manual), and to ensure that the normalization of $\theta_{M,t}$ 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 $\theta_{R,t}$ and $\theta_{C,t}$ 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 $\theta_{R,t}$ and $\theta_{C,t}$ to zero for a base year.[19] This identification argument implies that $\widehat{\theta}_{R,t}$ and $\widehat{\theta}_{C,t}$ 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.[20]

The estimation procedure also makes it possible to generate estimated occupation spell

[18] 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.

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

[20] 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 (3) using a non-linear instrumental variables technique.

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 coefficient on skills is common for all workers who select 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 (4) in the data, I add an extra set of controls for marital status, unionization status, region of residence, and a dummy for whether the individual lives in a metropolitan area (SMSA). It is assumed that these variables are orthogonal to the 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.[21]

To summarize, the equation being estimated is:

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}\gamma_{ij} + \boldsymbol{Z'_{it}}\boldsymbol{\zeta} + \mu_{it} \tag{5}$$

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, and controls for marital status, unionization status, region of residence, and SMSA. In all the estimations, standard errors are clustered at the individual level.

Section 6 of the paper extends the empirical strategy to allow for time-varying observable skills (due to general human capital evolving over the life cycle), changes over time in the return to observable characteristics that affect ability (in particular changes in the return to education), and switching costs that depend either on individuals' occupational tenure or on task distances between occupations.

4 Data

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.[22] The PSID has

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

[22] 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.`

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.[23]

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. The most recent data used in the paper are for 2007.[24]

The sample is limited to male household heads, aged 16 to 64, employed in non-agricultural, non-military jobs, who are part of the core PSID sample ('SRC'). The over-sample of low-income households (SEO sample) and the Immigrant samples added in the 1990s are excluded from the analysis.[25] I focus mainly on employed workers; transitions out of employment are considered in Section 6.5.[26]

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:** 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 by workers in that occupation, as explained in Acemoglu and Autor (2011) and supported by data from the Dictionary of Occupational Titles. More details on the specific occupations and occupation codes included in each category are presented in Appendix C, where I also describe an alternative classification procedure based directly on task data from the Dictionary of Occupational Titles to which the results are robust.

---

edu/.

[23] 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.

[24] 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.

[25] The results presented in the paper do not use sample weights due to the fact that these are missing (or equal to zero) for as many as 40% of the observations after 1994 (see also Gouskova et al. (2008)).

[26] The patterns for women are analyzed separately in Appendix E. Women are excluded from the main analysis due the fact that there may be other confounding factors affecting the occupational composition of employment for women over the past three decades.

Figure 2 plots the changes in employment shares for each of the broad occupation groups over the period 1976-2007. The pattern is broadly consistent with evidence based on Census data (Acemoglu and Autor, 2011). The cumulative long-run change shows a sharp decline in the share of employment in routine occupations, with compensating increases in both of the non-routine categories. The patterns differ across the three decades displayed in the Figure. The first one, 1976-1987, features a large decline in employment in routine occupations and a large increase in non-routine cognitive jobs. The following decade, 1987-1997, shows relatively little change in employment shares. In the final decade, 1997-2007, routine employment falls again, but during this period non-routine cognitive employment does not grow either; all of the compensating increase is in non-routine manual jobs.[27] It is worth emphasizing that there is no evidence of an *acceleration* over time in the decline of routine employment in this sample.[28] This implies that the timeframe available in the data does not readily lend itself for an analysis where the early years are considered as a 'control' period, i.e. a period when the forces of routine-biased technical change are not evident. Thus, rather than emphasizing an analysis across sub-periods, I will analyze the general patterns that are observed throughout the sample period as well as the year-by-year changes in occupation wage premia.[29]

Table 1 presents descriptive statistics for each of the broad occupation groups across the three sub-periods. Non-routine cognitive and routine occupations account for the majority (over 90%) of total employment. In accordance with the set-up in the model, routine jobs are middle-wage jobs: in all three sub-periods, mean real wages are highest in non-routine cognitive occupations and lowest in non-routine manual ones. Non-routine cognitive jobs have a much higher share of college educated workers, and a much lower rate of unionization than the other occupations. Note however that the ranking of wages across the three occupation groups is not driven by the composition of workers along observable characteristics: routine occupations are also in the middle of the distribution in terms of residual wages.[30] Appendix Figure A.8 provides additional evidence on the extent of overlap in the distribution of wages across the three occupation groups. Although there is overlap in these distributions, particularly between routine and non-routine manual jobs, the differences in mean wages across the three occupations are not driven by outliers.

The data used for the estimation of Equation (5) includes a total of 50,028 (unweighted) observations, or 1,853 observations on average per year, for a total of 5,934 individuals. There

[27] See Beaudry et al. (2013), who argue that the demand for cognitive tasks underwent a reversal around the year 2000.

[28] Note that the data in Acemoglu and Autor (2011) shows a secular decline in the share of routine employment for males, without a particular acceleration at any point in time.

[29] As I will show in Section 5.2.1, the results on the changes in the occupation wage premia also support the idea that polarization has been an ongoing process since at least the early 1980s, making it impossible to split the sample period into a pre-polarization and a post-polarization era, given the data availability.

[30] Residual wages are obtained from a regression of log real wages on age, age squared, and dummies for education, union status, marital status, race, urban area, region and year.

are a total of 8,451 occupation spells, for an average of 1.4 spells per workers. The average occupation spell consists of 5.9 observations (not necessarily consecutive years).

Before proceeding to the results of the estimation, and in order to further motivate the focus of the paper on the patterns for employed workers, I take advantage of the panel structure of the data to provide some insight into the dynamics underlying the disappearance of routine jobs. The observed decline in the share of routine employment over time could be driven not only by occupational switching of employed workers, but also by increased exit rates towards non-employment among routine workers (e.g. due to retirement or disability) or reduced rates of entry from non-employment into routine occupations (e.g. due to changes in the occupational choices of new entrants to the labor market).

As shown in Appendix D, throughout the sample period there are net outflows in the PSID data from routine towards non-routine occupations among workers who remain in the employment sample. Moreover, the results of a simple decomposition exercise show that the fall in the routine employment share is almost entirely driven by net outflows of employed workers towards other occupations, rather than entry and exit from the employment pool. Net entry from non-employment in fact tends to increase rather than decrease the routine employment share. This justifies the focus of this paper on the occupational switching patterns and associated wage changes for employed workers.

5 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 workers' switching patterns according to their estimated ability. Then I discuss results regarding the wage changes for workers with different occupational trajectories.

5.1 Switching Patterns

I begin by testing the model prediction 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. Note that the results in this section are closely linked to the occupational switching patterns analyzed in Groes, Kircher, and Manovskii (2010). This link will be discussed in more detail after presenting the results.

As mentioned above, I rank routine workers in a given year according to their position in the distribution of estimated occupation spell fixed effects ($\widehat{\gamma}_{ij}$) from Equation (5). Recall that γ_{ij} is monotonically increasing in underlying ability z. Therefore, I refer to the quintiles of estimated occupation spell fixed effects within an occupation-year as ability quintiles. Strictly, the one-dimensional theoretical model implies that there should be no overlap across occupation groups in the distributions of these fixed effects. Appendix Figure A.8 shows that, although we do see a certain amount of overlap in the data (which could be rationalized under the two-dimensional skills assumption described in Appendix B), the ranking implied by the model is preserved both in the initial and the later years.

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

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. This difference is statistically significant. 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 significantly more likely to switch than those in the middle.[31]

Next, I consider the direction of the switches occurring at each quintile of the ability distribution. The results are plotted in the bottom panels of Figure 3. Switchers from all quintiles are more likely to go to non-routine cognitive jobs than to non-routine manual ones. This would be expected even if the direction of switch were random, as the non-routine cognitive occupation is much larger in terms of employment than the non-routine manual one. However, there is a clear pattern of selection according to ability quintiles. Consistent with the prediction of the model, the probability of switching to non-routine manual jobs is decreasing in ability, while the probability of switching to non-routine cognitive jobs is increasing in ability.[32] The differences in switching probabilities across quintiles are statistically significant during both sub-periods, with routine workers from the top quintile being significantly more likely to go to non-routine cognitive occupations than those in the middle of the distribution, and routine workers from the bottom quintile being significantly more likely to switch to non-routine manual occupations than those in the middle.

[31] I test the statistical significance of the differences in switching probabilities across quintiles by estimating a linear probability model where the dependent variable is a dummy equal to 1 if the worker switches occupations and the regressors are a set of ability quintile dummies. To account for the fact that these are generated regressors, the standard errors are adjusted through a bootstrap procedure that performs 100 replications on randomly drawn sets of 5,934 clusters of individuals (the total number available in the sample). For each randomly drawn sample, Equation (5) 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.

[32] The U-shape in the probability of switching, and the patterns in the direction of switching are also observed in the PSID data when using raw or residual wages.

Note that 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 (from 10.4% before 1991 to 13.4% afterwards) than the probability of switching to non-routine manual (which increases from 1.9% to 3.0%).

These results for routine workers can be contrasted with the switching patterns for workers in non-routine occupations. As mentioned earlier, the data shows that there are net outflows over time from routine occupations, so the volume of switches from non-routine into routine occupations is lower than in the opposite direction. However, it is still interesting to investigate the patterns of switching across ability quintiles in the non-routine occupations. These are presented graphically in Figure 4. Interestingly, among non-routine workers we do not observe the U-shaped mobility pattern that is observed for routine workers; instead it is only the low ability workers who are disproportionately likely to switch occupations. For both non-routine cognitive and non-routine manual workers, these low ability switchers have relatively high probabilities of going into routine jobs.

U-shaped patterns of occupational mobility have been documented by Groes et al. (2010) using Danish administrative data and a much finer disaggregation of occupations. They find that high wage earners within an occupation tend to switch to occupations with higher average wages, while low wage earners tend to switch to occupations with lower average wages. They explain these patterns within the context of a model of information frictions, where workers learn about their ability level over time. They also find that in occupations with declining productivity (defined empirically as occupations with relatively low wage growth for stayers), it is the higher paid workers that are more likely to leave. This contrasts with the evidence presented here that both workers at the top and the bottom of the distribution within routine occupations are disproportionately likely to leave.[33] Although I am not able to rule out that part of the switching pattern is driven by learning, the interpretation that technological change is important in driving this pattern is consistent also with the fact that there are net outflows from routine occupations among switchers (something that would not be expected if switching were driven solely by learning) and with the wage evidence discussed below.

5.2 Wage Changes

I now turn to an analysis of 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 2 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,

[33] The extension of the Groes et al. (2010) model that allows for changing occupational sizes does admit this outcome as a theoretical possibility. The contrasting empirical results might be explained by the differences in the level of aggregation of the occupational categories.

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.

5.2.1 Wage changes for occupation stayers

Consider first the wage changes for workers who do not switch occupations. From Proposition 3, the wage changes for stayers are given by the changes in λ_j for their respective occupation. Empirically, from the estimation of Equation (5), the estimated occupation-time fixed effects ($\widehat{\theta}_{jt}$) will track changes in λ_j over time. The Proposition implies that θ_R should fall over time, while θ_C should increase over time (relative to the omitted category). Figure 5 plots the estimates of $\widehat{\theta}_R$ and $\widehat{\theta}_C$.

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. Note that all of the coefficients for the later periods are significantly different from zero. This means that the data agree with the predictions of the model for the changes in occupation wage premia: The wage premium falls significantly for routine occupations, relative to either of the non-routine categories, and the wage premium increases significantly for non-routine cognitive occupations, relative to the other occupation categories. 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.[34] Simple wage regressions similar to the ones presented in Table 2 but using only the sample of workers who do not switch occupations also provide evidence of significantly slower wage growth for stayers in routine occupations. Sections 6.1 through 6.4 confirm the robustness of this result to a number of additional controls, including time varying skills and heterogeneous tenure profiles across occupations.

5.2.2 Wage growth according to direction of switch

Next I study the wage changes for routine workers who follow different switching patterns. Table 3 presents the results of a number of wage regression where the sample is restricted to

[34] Changes in the college wage premium will be discussed in further detail in Section 6.2.

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

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 jobs 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. This result is not driven by changes in the composition of the workers included in the different regressions, as will be discussed below.

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

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 jobs 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 (although not significantly different).

One potential concern with the results in Table 3 is that non-random attrition, in terms of which switchers and stayers are still observed at the longer time horizons, may be biasing the results. To address this concern, I run the regressions for changes in log real wages from Table 3 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 4 and are very similar to the results in the previous table. Therefore, the results 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. Overall, 8% of workers who are observed in a routine job in period t switch to a non-routine occupation (either cognitive or manual) between t and $t+2$ and remain in their new occupation in $t+4$. Meanwhile, 5% of routine workers at time t switch to a non-routine occupation between t and $t+2$ and return to a routine job in $t+4$.[35]

To explore whether subsequent switching patterns might be a concern, I repeat the analysis from Table 3 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.[36] The results are presented in Columns (4) and (5) of Table 4 and confirm the main findings: Switchers to non-routine cognitive jobs 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 are not driven by subsequent occupational transitions.

The findings presented so far on the wage growth of workers switching out of routine jobs are consistent with the theoretical predictions of the model of RBTC. However, one potential concern is the possibility that occupational switching may simply reflect career progression. It might be the case that, regardless of the type of transition made, workers who switch occupations experience faster wage growth than stayers in the long run. To rule out this concern, Table 5 replicates the analysis from Table 3 for the sample of *non-routine* workers (non-routine cognitive workers in Panel A and non-routine manual workers in Panel B). The regressions include only workers who are still in their period t occupation in the final year over which the wage change is taken (as in Columns (4) and (5) of Table 4). The results show that there is no evidence that switching occupations is generally beneficial. In fact, switchers out of non-routine cognitive occupations suffer wage losses over all horizons considered, regardless of the direction of switch. Switchers out of non-routine manual occupations do tend to enjoy faster wage growth than stayers, particularly when switching to non-routine cognitive occupations. Note however that the long-run (10-year) difference in wage growth between non-routine manual workers who remain in their occupation group and those who switch to

[35] Appendix Table A.5 presents additional descriptive evidence on occupational cycles in the PSID data.

[36] Note that this does not condition on the full occupational history, only on the $t+2$ and either $t+4$ or $t+10$ occupation.

routine occupations is small and statistically insignificant.

6 Robustness Checks and Additional Evidence

This section presents a set of robustness checks on the empirical specification of the paper, as well as additional evidence on transitions to unemployment and out of the labor force.

6.1 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 (1) 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:

$$\ln \varphi_j(\boldsymbol{z_{it}}) = X_{it}\beta_j + \eta_i b_j \tag{6}$$

Following the assumptions on comprative advantage from the model, assume that $\ln \varphi_j(\boldsymbol{z_{it}})$ is increasing in both of its arguments. That is:

$$\beta_M < \beta_R < \beta_C$$
$$b_M < b_R < b_C$$

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

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}X_{it}\beta_j + \sum_j D_{ijt}\eta_i b_j + \mu_{it} \tag{7}$$

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 (5), I rewrite Equation (7) as:

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}X_{it}\beta_j + \sum_j D_{ijt}\gamma_{ij} + \boldsymbol{Z'_{it}\zeta} + \mu_{it} \tag{8}$$

Assuming that all unobservable skills are time-invariant, Equation (8) 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.[37] I estimate Equation (8) including a set of dummies for 10-year age bins interacted with occupation dummies.[38] The resulting estimated occupation-year fixed effects are presented in the top left panel of Figure 6. The fall in the occupation wage premium in routine jobs remains significant and is very close in magnitude to that in Figure 5.

6.2 Changing Returns to Education

The empirical strategy may also be extended to allow for changes over time in the *return* to observable characteristics that affect ability. Specifically, it has been widely documented that the college premium has experienced important changes 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 (6) all individual skills are fixed, but the return to certain kinds of (observable) skills is allowed to vary over time. That is, rewrite Equation (6) as:

$$\ln \varphi_{jt}(\boldsymbol{z_i}) = X_i \beta_{jt} + \eta_i b_j \tag{9}$$

where now X_i reflects education and η_i captures all other individual skills.[39] Following the assumptions on comparative advantage from the model, assume that, for all t:

$$\beta_{M,t} < \beta_{R,t} < \beta_{C,t}$$
$$b_M < b_R < b_C$$

The maintained assumption is that b_j, the return to all skills other than education, 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:

$$\ln w_{ijt} = \theta_{jt} + X_i \beta_j + X_i \beta_t + \eta_i b_j + \boldsymbol{Z'_{it}} \boldsymbol{\zeta} + \mu_{it} \tag{10}$$

where μ_{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

[37] Note that X_{it} may only include time-varying variables that reflect *general* and not occupation-specific ability, as this setup assumes that X_{it} is fully transferable between occupations (although its return varies across occupations). Occupation-specific skills will be discussed below.

[38] The bins are for age below 25, 25-34, 35-44, 45-54, and 55 and over.

[39] The PSID does not ask individuals their education level every year. I assign each individual their highest reported education level across all survey years.

using occupation spell fixed effects:

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + X_i\beta_t + \sum_j D_{ijt}\nu_{ij} + \boldsymbol{Z'_{it}\zeta} + \mu_{it} \tag{11}$$

where $\nu_{ij} \equiv X_i\beta_j + \eta_i b_j$. 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 education groups: high school dropouts, high school graduates, some college, and college graduates. The estimation results confirm 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. The new estimated occupation-year fixed effects are plotted in the top right panel of Figure 6. 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 5. 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.[40]

6.3 Occupation-Specific Tenure Profiles

As discussed in Section 3, identification of the occupation fixed effects $\boldsymbol{\theta}_t$ is obtained from variation over time within individuals' occupation spells. One concern with these estimates might be the existence of heterogeneous returns to occupational tenure (or occupation-specific human capital) in the different occupation categories. Kambourov and Manovskii (2009b) have shown that returns to occupation-specific human capital are substantial, and the evidence in Sullivan (2010) suggests that there is heterogeneity in the returns across one-digit occupations. A flat tenure profile in routine occupations and a positively-sloped profile in non-routine occupations, for example, could account for the finding that occupation fixed effects in routine jobs are falling over time. To rule this out, I modify the empirical setup as follows:[41] Suppose that wages are determined as in Equation (5), but there is also a return to the individual's occupational tenure, that is:

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}z_i a_j + \sum_j D_{ijt}F_j(Ten_{ijt}) + \boldsymbol{Z'_{it}\zeta} + \mu_{it} \tag{12}$$

[40] The differences across ability quintiles in the probability of switching and in the direction of the switches are also robust to using $X_i\widehat{\beta}_t + \widehat{\nu}_{ij}$ as the proxy for ability.

[41] Note that adding tenure to the theoretical model from Section 2 adds dynamic considerations that would change the way in which the occupation wage premia are determined. These theoretical considerations are left for future work.

where Ten_{ijt} is individual i's tenure in occupation j at time t, and $F_j(.)$ is a non-linear function which captures the occupation-specific returns to tenure. Suppose that an individual loses all of his occupation-specific human capital if he switches occupations.[42]

An individual's occupational choice at time t will depend, as before, on their skill level z_i and the occupation wage premia $\boldsymbol{\theta}_t$. Their choice will also depend on their tenure in their current occupation Ten_{ijt} and may depend on their expectations about future $\boldsymbol{\theta}$'s. For the estimation, it would only be a concern if the choice D_{ijt} were correlated with μ_{it}. Because of the maintained assumption that μ_{it} is a wage shock to individual i regardless of their occupational choice, this will still not influence D_{ijt}. Therefore, we have that $E(\mu_{it}|\boldsymbol{D}_{ij}, \boldsymbol{\theta}_j, z_i, \boldsymbol{Ten}_{ij}, \boldsymbol{Z}_i) = 0$. Intuitively, current and future (expected) occupation fixed effects will affect individuals' decisions, but they are orthogonal to μ_{it}. If expectations are common across all individuals, there will be skill cutoffs that determine sorting, but these skill cutoffs would differ for individuals with different levels of occupational tenure.

I follow the procedure in Kambourov and Manovskii (2009b) to construct occupational tenure and, as in their paper, use data from 1981 onwards for the wage equation estimation.[43] I use a quadratic function of occupational tenure, interacted with occupation dummies to allow for different returns to tenure across the broad occupation categories.

The results from the estimation of Equation (12) do in fact imply that the return to tenure is lower in routine occupations than in non-routine ones. However, as shown in the bottom left panel of Figure 6, this lower return to tenure does not account for the estimated fall in the occupation wage premium in routine occupations. This fall remains robust to controlling for this heterogeneity in tenure profiles.

6.4 Switching Costs

In this section I extend the empirical specification to allow for costs to switching between occupations due to loss of occupation-specific or task-specific human capital (Kambourov and Manovskii (2009b), Gathmann and Schönberg (2010), Poletaev and Robinson (2008)). If switching costs are introduced, the occupational choices at time t and the wages at time t will depend on the occupational choice at time $t-1$, and this may be biasing the estimated occupation fixed effects. In particular, let wages be given by:

[42] This implies that even if the workers returns to his original occupation at a later date he starts off again with no occupation-specific human capital. This is the same assumption as in Kambourov and Manovskii (2009b).

[43] See Appendix A of Kambourov and Manovskii (2009b) for details on the construction of occupational tenure. I consider an occupation switch to occur if an individual's current broad occupation is different from his most recent previous occupation report, without conditioning on an employer or position switch.

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt} z_i a_j + \sum_j D_{ijt}\left(1 - D_{ijt-1}\right)\phi\left(\boldsymbol{D_{it}}, \boldsymbol{D_{it-1}}\right) + \boldsymbol{Z'_{it}\zeta} + \mu_{it} \quad (13)$$

where $\phi(.)$ is a function which reflects the transition cost. It impacts the wages of worker i in occupation j in period t if and only if $D_{ijt} \neq D_{ijt-1}$. This cost is a function of the worker's occupational choices in t and $t-1$, and is allowed to vary across occupation pairs due to factors such as task distance (Gathmann and Schönberg, 2010). Empirically, I control for $\phi\left(\boldsymbol{D_{it}}, \boldsymbol{D_{it-1}}\right)$ with a set of dummy variables for transitions between all possible occupation pairs, interacted with a dummy which is equal to 1 if the individual's occupation in period t is different from his occupation in $t-1$.

For this estimation I can only use individuals who are also observed in the previous period; therefore, I estimate Equation (13) using odd years only and using workers for whom I have occupation data two years before period t. The results for the estimated changes in the occupation wage premia (relative to 1977) are presented in the bottom right panel of Figure 6. They confirm the robustness of the finding that the occupation wage premium in routine jobs has been falling since the early 1980s.

6.5 Transitions to Unemployment and Out of the Labor Force

Although the model presented in this paper features full employment, unemployment is another potential consequence of RBTC for routine workers. Thus, in this section I analyze the patterns in the transitions out of employment for workers in different occupation groups. Table 6 presents the results from estimating a linear probability model, where in Columns (1) through (3) the dependent variable is the probability of switching to unemployment two years ahead, and in Columns (4) through (6) the dependent variable is the probability of exiting the labor force two years ahead. All regressions include year dummies, and some include controls for individuals' demographic characteristics, as indicated in the table.[44]

The results indicate that, up until 1991, non-routine cognitive workers are significantly less likely to become unemployed relative to non-routine manual workers (the omitted category). After that year, the probability of becoming unemployed is approximately the same for the two types of non-routine workers. Routine workers meanwhile have a slightly lower (although statistically insignificant) probability of becoming unemployed relative to non-routine manual workers before 1991. In the period after 1991, routine workers are approximately 1 percentage point more likely to become unemployed relative to non-routine manual workers.

Meanwhile, the results in Columns (4) through (6) show that the probability of exiting

[44]Specifically, a quartic in age and dummies for education, union status, marital status, race, SMSA and region of residence.

the labor force is significantly lower for non-routine cognitive workers relative to those in non-routine manual jobs throughout the entire sample period. The same is true for routine workers, whose probabilities of transitioning from employment to labor force non-participation are, all else equal, very similar to those of non-routine cognitive workers.

In short, these results suggest that since the 1990s, the probability of becoming unemployed has become slightly higher for routine workers compared to observationally equivalent workers in non-routine occupations. This could be interpreted as another effect of RBTC, in addition to the occupational mobility and wage effects discussed above. Meanwhile, there is no evidence in this sample that routine workers are disproportionately likely to exit the labor force.

7 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 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, changes in the return to education or differences in the return to tenure across occupations. 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. This is driven by the increase over time in the occupation wage premium in non-routine manual jobs relative to routine jobs. Workers who switch from routine to non-routine cognitive jobs have significantly higher wage growth than stayers over a variety of time horizons.

These results highlight the fact that, conditional on remaining employed, the workers who are hardest hit in the long run by the effects of technological change are those who stay in routine jobs rather than those who switch occupations. Meanwhile, there is evidence that since the 1990s the probability of becoming unemployed is slightly higher for routine workers relative to non-routine workers with the same demographic characteristics. There is no evidence of differences in the rates at which observationally equivalent workers in different occupations leave the labor force.[45]

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 (2012), 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.

Although the evidence on occupational mobility is consistent with the predicted effects of RBTC in the model, it cannot easily be ruled out that these switching patterns may be driven by learning as in Groes et al. (2010). However, the findings on the changes over time in the occupation wage premia provide much stronger evidence for RBTC, as these changes would not be expected in a model that only features learning. The changes in the occupation wage premia are robust to controlling for life-cycle patterns and for changes in the return to education. It is also noteworthy that the results suggest that RBTC has been an ongoing process since the early 1980s, so any analysis that seeks to analyze the effects of RBTC by performing comparisons across time would require data from earlier years in order to accurately capture the period before the onset of RBTC.

One shortcoming of the model is that its simple static framework is unable to account for the fact that workers switching from routine to non-routine manual occupations experience an initial wage loss relative to stayers, which is only reversed in the long run.[46] This could be addressed by adding occupation-specific skills to the model, which 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. Incorporating this type of dynamic considerations into a model that features shocks to demand for different tasks would be an interesting avenue for future research.

[45] Interestingly, the evidence for women (presented in Appendix E) is more mixed: Although the wage premium in routine occupations has fallen relative to non-routine cognitive jobs, it has not done so relative to non-routine manual ones.

[46] Another shortcoming of the model is that it predicts that switchers to non-routine manual jobs should be at the top of the wage distribution in their new occupation, but this is not confirmed in the data; see Appendix F.

References

Acemoglu, D. and D. Autor (2011), "Skills, tasks and technologies: Implications for employment and earnings." *Handbook of Labor Economics*, 4, 1043–1171.

Alvarez, Fernando and Robert Shimer (2011), "Search and rest unemployment." *Econometrica*, 79, 75–122.

Autor, D. and D. Dorn (2009), "This job is "getting old": Measuring changes in job opportunities using occupational age structure." *American Economic Review*, 99, 45–51.

Autor, David H. and David Dorn (2013), "The growth of low skill service jobs and the polarization of the U.S. labor market." *American Economic Review*, 103, 1553–1597.

Autor, D.H., L.F. Katz, and M.S. Kearney (2006), "The Polarization of the US Labor Market." *The American Economic Review*, 96, 189–194.

Autor, D.H., L.F. Katz, and M.S. Kearney (2008), "Trends in US wage inequality: revising the revisionists." *The Review of Economics and Statistics*, 90, 300–323.

Autor, D.H., F. Levy, and R.J. Murnane (2003), "The Skill Content of Recent Technological Change: An empirical exploration." *Quarterly Journal of Economics*, 118, 1279–1333.

Bartel, A., C. Ichniowski, and K. Shaw (2007), "How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills." *The Quarterly Journal of Economics*, 122, 1721–1758.

Beaudry, Paul, David A Green, and Benjamin M Sand (2013), "The great reversal in the demand for skill and cognitive tasks." *National Bureau of Economic Research Working Paper*.

Berman, E., J. Bound, and S. Machin (1998), "Implications of skill-biased technological change: International evidence." *Quarterly Journal of Economics*, 113, 1245–1279.

Boehm, Michael (2013), "The wage effects of job polarization: Evidence from the allocation of talents." *Working Paper*.

Costinot, A. and J. Vogel (2010), "Matching and inequality in the world economy." *Journal of Political Economy*, 118, 747–786.

Dustmann, C., J. Ludsteck, and U. Schönberg (2009), "Revisiting the German Wage Structure." *Quarterly Journal of Economics*, 124, 843–881.

Firpo, S., N. Fortin, and T. Lemieux (2011), "Occupational tasks and changes in the wage structure." *University of British Columbia Working Paper*.

Gathmann, C. and U. Schönberg (2010), "How General is Human Capital? A Task-Based Approach." *Journal of Labor Economics*, 28, 1–49.

Gibbons, R., L. Katz, T. Lemieux, and D. Parent (2005), "Comparative advantage, learning, and sectoral wage determination." *Journal of Labor Economics*, 23, 681–724.

Goldin, C.D. and L.F. Katz (2008), "Long-run changes in the wage structure: Narrowing, widening, polarizing." *Brookings Papers on Economic Activity*, 2007, 135–165.

Goos, M. and A. Manning (2007), "Lousy and lovely jobs: The rising polarization of work in Britain." *The Review of Economics and Statistics*, 89, 118–133.

Goos, M., A. Manning, and A. Salomons (2009), "Job polarization in Europe." *American Economic Review*, 99, 58–63.

Gouskova, Elena, Steven Heeringa, Katherine McGonagle, Robert Schoeni, and Frank Stafford (2008), "Panel Study of Income Dynamics Revised Longitudinal Weights 1993–2005." *Panel Study of Income Dynamics Technical Paper Series, University of Michigan*.

Groes, F., P. Kircher, and I. Manovskii (2010), "The U-Shapes of Occupational Mobility." *University of Pennsylvania mimeo*.

Grossman, G.M. and E. Rossi-Hansberg (2008), "Trading tasks: A simple theory of offshoring." *The American Economic Review*, 98, 1978–1997.

Heathcote, J., F. Perri, and G.L. Violante (2010), "Unequal we stand: An empirical analysis of economic inequality in the United States, 1967-2006." *Review of Economic Dynamics*, 13, 15–51.

ICPSR, 1981 (1981), *Dictionary of Occupational Titles (DOT): Part I - Current Population Survey, April 1971, Augmented with DOT Characteristics, and Part II - Fourth Edition Dictionary of DOT Scores for 1970 Census Categories [Computer File]. Study Nr. 07845.* National Academy of Sciences - Committee on Occupational Classification and Analysis, Washington DC: U.S. Department of Commerce, Bureau of the Census [Producer], Ann Arbor, MI: Inter-university Consortium for Political and Social Research [Distributor].

Juhn, C., K.M. Murphy, and B. Pierce (1993), "Wage inequality and the rise in returns to skill." *Journal of Political Economy*, 410–442.

Jung, J. and J. Mercenier (2012), "Routinization-biased technical change and globalization: A theoretical exploration of labor market polarization." *Working Paper, RWTH Aachen University*.

Kambourov, G. and I. Manovskii (2008), "Rising occupational and industry mobility in the United States: 1968-1997." *International Economic Review*, 49, 41–79.

Kambourov, G. and I. Manovskii (2009a), "Occupational mobility and wage inequality." *Review of Economic Studies*, 76, 731–759.

Kambourov, G. and I. Manovskii (2009b), "Occupational specificity of human capital." *International Economic Review*, 50, 63–115.

Katz, L.F. and K.M. Murphy (1992), "Changes in relative wages, 1963–1987: supply and demand factors." *The Quarterly Journal of Economics*, 107, 35.

King, Miriam, Steven Ruggles, Trent Alexander, Sarah Flood, Katie Genadek, Matthew B. Schroeder, Brandon Trampe, and Rebecca Vick (2010), "Integrated Public Use Microdata Series, Current Population Survey: Version 3.0. [Machine-readable database]." Technical report, University of Minnesota, Minneapolis, MN.

Krusell, P., L.E. Ohanian, J.V. Ríos-Rull, and G.L. Violante (2000), "Capital-skill complementarity and inequality: A macroeconomic analysis." *Econometrica*, 68, 1029–1053.

Moscarini, G. and K. Thomsson (2007), "Occupational and Job Mobility in the US." *Scandinavian Journal of Economics*, 109, 807–836.

Neal, Derek A (1999), "The complexity of job mobility among young men." *Journal of Labor Economics*, 17, 237–61.

Nordhaus, W.D. (2007), "Two centuries of productivity growth in computing." *Journal of Economic History*, 67, 128.

Poletaev, M. and C. Robinson (2008), "Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984-2000." *Journal of Labor Economics*, 26, 387–420.

Robinson, C. (2011), "Occupational mobility, occupation distance and specific human capital." *University of Western Ontario, CIBC Centre for Human Capital and Productivity Working Papers*.

Spitz-Oener, Alexandra (2006), "Technical change, job tasks, and rising educational demands: Looking outside the wage structure." *Journal of Labor Economics*, 24, 235–270.

Sullivan, P. (2010), "Empirical evidence on occupation and industry specific human capital." *Labour Economics*, 17, 567–580.

Yamaguchi, Shintaro (2012), "Tasks and heterogeneous human capital." *Journal of Labor Economics*, 30, pp. 1–53.

Table 1: Descriptive statistics

	Non-Routine Cognitive			Routine			Non-Routine Manual		
	1976-1986	1987-1996	1997-2007	1976-1986	1987-1996	1997-2007	1976-1986	1987-1996	1997-2007
Nr of Obs	6,741	8,561	6,129	9,102	9,747	7,012	944	1,249	1,284
Share	0.40	0.44	0.42	0.54	0.50	0.49	0.06	0.06	0.09
Nr of Indiv	1,380	1,818	2,119	1,933	2,340	2,665	300	430	619
Averages:									
Real Wages	10.47	11.82	13.78	7.07	6.78	7.30	5.65	5.82	6.27
Residual Wages	0.034	0.116	0.168	0.002	-0.070	-0.098	-0.256	-0.241	-0.254
Age	39.26	39.91	41.88	37.03	37.52	39.25	37.14	36.58	38.16
Fractions within the occupation group:									
Union	0.08	0.08	0.08	0.38	0.26	0.21	0.29	0.31	0.27
H.S. Dropout	0.03	0.01	0.01	0.22	0.14	0.10	0.13	0.10	0.08
H.S. Grad	0.15	0.15	0.16	0.49	0.54	0.52	0.42	0.44	0.42
Some Coll.	0.19	0.22	0.24	0.22	0.23	0.26	0.33	0.33	0.34
College	0.63	0.62	0.59	0.08	0.09	0.12	0.12	0.13	0.16
Task measures:									
Non-Routine Cognit.	6.08	6.01	5.95	1.81	1.82	1.88	1.31	1.32	1.21
Routine	3.17	2.99	2.95	4.81	4.70	4.46	2.35	2.30	2.31
Non-Routine Manual	0.72	0.76	0.78	1.89	1.86	1.82	2.47	2.32	2.31

Note: Sample includes male household heads aged 16 to 64 employed in non-agricultural, non-military jobs, who are part of the PSID's core sample and have non-missing wage data. Real wages are in 1979 dollars. Residual wages are obtained from a regression of log real wages on age, age squared, and dummies for education, union status, marital status, race, urban area, region and year. 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 (COC), rescaled to have a (potential) range from zero to 10, and attached to the occupation codes observed in the data at the individual level. 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 average task measures for the post-1997 period are for 1997-2001, as task measures at the 1970-COC level cannot be attached to PSID data from 2003 onwards (when occupations are coded in 2000 Census codes).

Table 2: 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)
non-routine cognitive	-.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
Nr of Indiv.	3855	4764	4129	2756	1848	1225
R^2	.014	.02	.026	.046	.065	.062

Note: 'non-routine cognitive' 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 3: Wage changes for routine workers, according to direction of switch

Panel A: Dependent variable is change in log real wages

	Change in log real wages between year t and year:					
	$t+1$	$t+2$	$t+4$	$t+10$	$t+2$	$t+2$
Period:	1976-1997	1976-2007	1976-2007	1976-2007	1977-1991	1991-2007
	(1)	(2)	(3)	(4)	(5)	(6)
to non-routine cognitive	.034 (.008)***	.059 (.008)***	.085 (.010)***	.163 (.019)***	.022 (.016)	.088 (.012)***
to non-routine manual	-.112 (.023)***	-.143 (.023)***	-.035 (.026)	.115 (.046)**	-.134 (.039)***	-.123 (.033)***
Const.	.037 (.007)***	.066 (.009)***	.016 (.011)	-.002 (.018)	.026 (.009)***	.041 (.010)***
Obs.	15800	18341	14278	7568	4754	6701
Nr of Indiv.	2655	3253	2701	1735	1609	2234
R^2	.013	.028	.033	.061	.019	.025

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

	Change in fitted model wages between year t and year:					
	$t+1$	$t+2$	$t+4$	$t+10$	$t+2$	$t+2$
Period:	1976-1997	1976-2007	1976-2007	1976-2007	1976-1991	1991-2007
	(1)	(2)	(3)	(4)	(5)	(6)
to non-routine cognitive	.086 (.010)***	.122 (.009)***	.098 (.008)***	.139 (.011)***	.051 (.014)***	.184 (.012)***
to non-routine manual	-.152 (.023)***	-.139 (.021)***	-.030 (.019)	.054 (.027)**	-.151 (.037)***	-.115 (.028)***
Const.	-.038 (.002)***	.026 (.003)***	.049 (.004)***	-.014 (.008)*	.067 (.003)***	-.034 (.004)***
Obs.	15800	18341	14278	7568	4754	6701
Nr of Indiv	2655	3253	2701	1735	1609	2234
R^2	.168	.174	.147	.09	.179	.221

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

	Fraction of routine workers in year t switching to non-routine jobs in year:					
	$t+1$	$t+2$	$t+2$	$t+2$	$t+2$	$t+2$
Period:	1976-1997	1976-2007	1976-2007	1976-2007	1977-1991	1991-2007
	(1)	(2)	(3)	(4)	(5)	(6)
to non-routine cognitive	8.07	10.95	11.26	11.47	9.82	13.10
to non-routine manual	1.51	2.18	1.92	1.88	1.83	2.75

Note: Workers who stay in routine occupations are the omitted category. All regressions include year dummies. The wage changes are taken over the time horizons indicated above each column (in years). For column (1), occupation transitions between years t and $t+1$ are considered. For column (2) onwards, occupation transitions between years t and $t+2$ are considered (even though the wage change may be taken over a longer horizon). Columns (5) and (6) use odd years only. Observations with log real hourly wages below 0.1 (\$1.1 1979 dollars) or above 4 (\$54.6 1979 dollars) excluded. Standard errors are clustered at the individual level.

Table 4: 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 non-routine cognitive	.045	.092	.170	.129	.282
	(.012)***	(.014)***	(.020)***	(.014)***	(.026)***
to non-routine manual	-.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
Nr of Indiv.	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). All three columns include the same set of individual workers. 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 5: Wage changes for non-routine workers, according to direction of switch

Panel A: Non-Routine Cognitive Workers

	Change in log real wages between year t and year:			
	$t+1$	$t+2$	$t+4$	$t+10$
	(1)	(2)	(3)	(4)
to routine	-.047	-.079	-.098	-.203
	(.010)***	(.009)***	(.015)***	(.028)***
to non-routine manual	-.068	-.090	-.038	-.185
	(.041)*	(.032)***	(.048)	(.107)*
Const.	-.013	.131	.071	.148
	(.010)	(.016)***	(.016)***	(.024)***
Obs.	13290	15855	11222	5690
Nr of Indiv.	1985	2558	2028	1245
R^2	.032	.039	.042	.051

Panel B: Non-Routine Manual Workers

	Change in log real wages between year t and year:			
	$t+1$	$t+2$	$t+4$	$t+10$
	(1)	(2)	(3)	(4)
to routine	.106	.065	.125	.018
	(.026)***	(.021)***	(.029)***	(.047)
to non-routine cognitive	.095	.154	.235	.489
	(.036)***	(.033)***	(.061)***	(.100)***
Const.	.076	.073	.021	.082
	(.027)***	(.033)**	(.035)	(.040)**
Obs.	1823	2327	1454	637
Nr of Indiv.	494	663	455	221
R^2	.047	.052	.114	.172

Note: Sample includes workers who are in non-routine occupations (non-routine cognitive in Panel A and non-routine manual in Panel B) in period t. 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. Only workers who are still in their destination occupation in the terminal year (over which the wage change is taken) are included in the sample. Workers who stay in their original occupation group are the omitted category. All regressions include year dummies. Observations with log real hourly wages below 0.1 ($1.1 1979 dollars) or above 4 ($54.6 1979 dollars) excluded. Standard errors are clustered at the individual level.

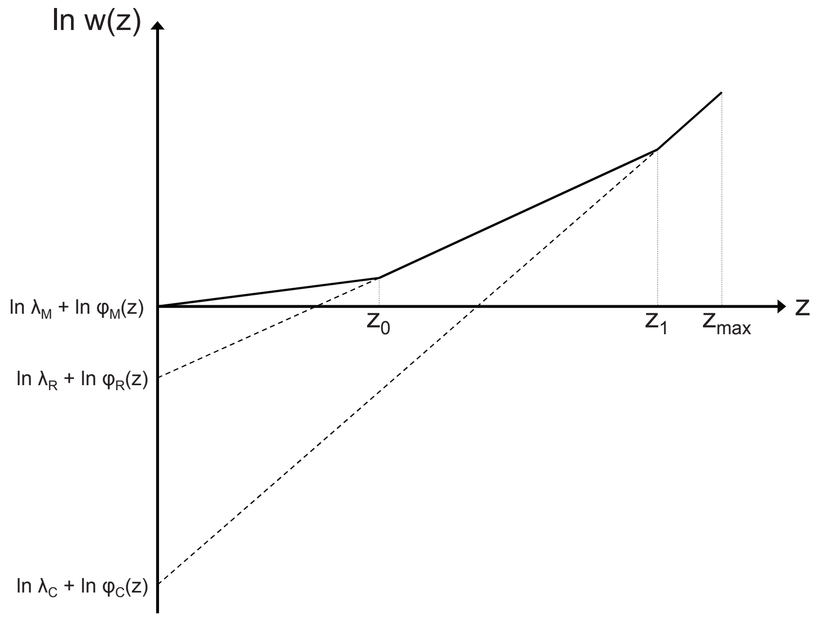
Table 6: Linear regressions for the probability of switching to unemployment or labor force non-participation two years ahead (odd years only, 1977-2005)

	P(Unemp)	P(Unemp)	P(Unemp)	P(NLF)	P(NLF)	P(NLF)
	(1)	(2)	(3)	(4)	(5)	(6)
non-routine cognitive	-.024	-.011	-.041	-.024	-.023	-.016
	(.005)***	(.005)**	(.010)***	(.005)***	(.005)***	(.008)*
routine	.002	.004	-.014	-.018	-.021	-.015
	(.005)	(.005)	(.010)	(.005)***	(.005)***	(.008)*
non-routine cognitive x post91			.046			-.011
			(.011)***			(.010)
routine x post91			.027			-.010
			(.011)**			(.010)
Const.	.034	.121	.138	.050	-.056	-.062
	(.006)***	(.025)***	(.027)***	(.007)***	(.026)**	(.026)**
Year Dummies	Y	Y	Y	Y	Y	Y
Demog. Controls	N	Y	Y	N	Y	Y
Obs.	31764	30972	30972	31764	30972	30972
Nr of Indiv.	5323	5127	5127	5323	5127	5127
R^2	.009	.017	.019	.002	.08	.08

Note: 'non-routine cognitive' 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. Standard errors are clustered at the individual level. All regressions include year dummies. Demographic controls are a quartic in age, and dummies for education, union status, marital status, race, urban area and region.

Figure 1: Equilibrium relationship between skills, occupational choices and wages, and effects of routine-biased technical change

Panel A: Model Equilibrium



Panel B: Effects of Routine-Biased Technical Change

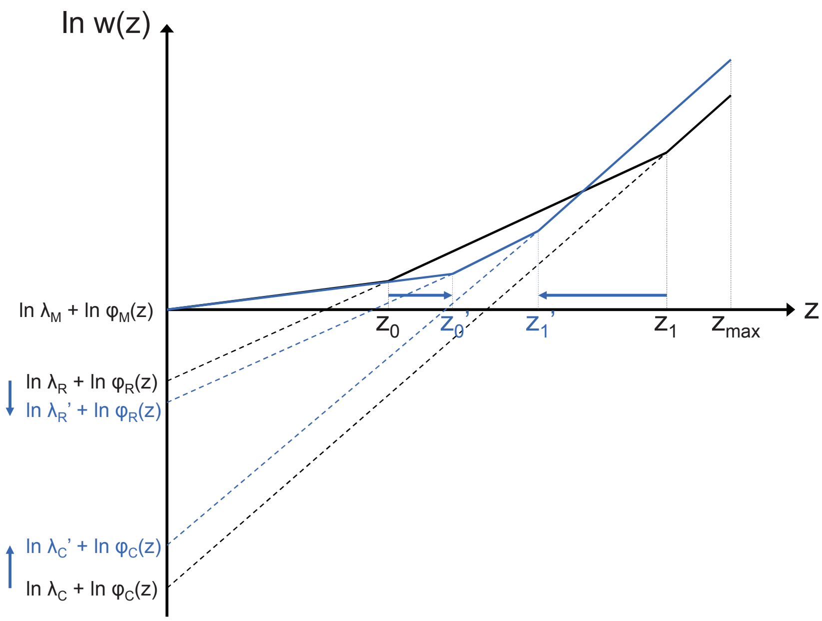
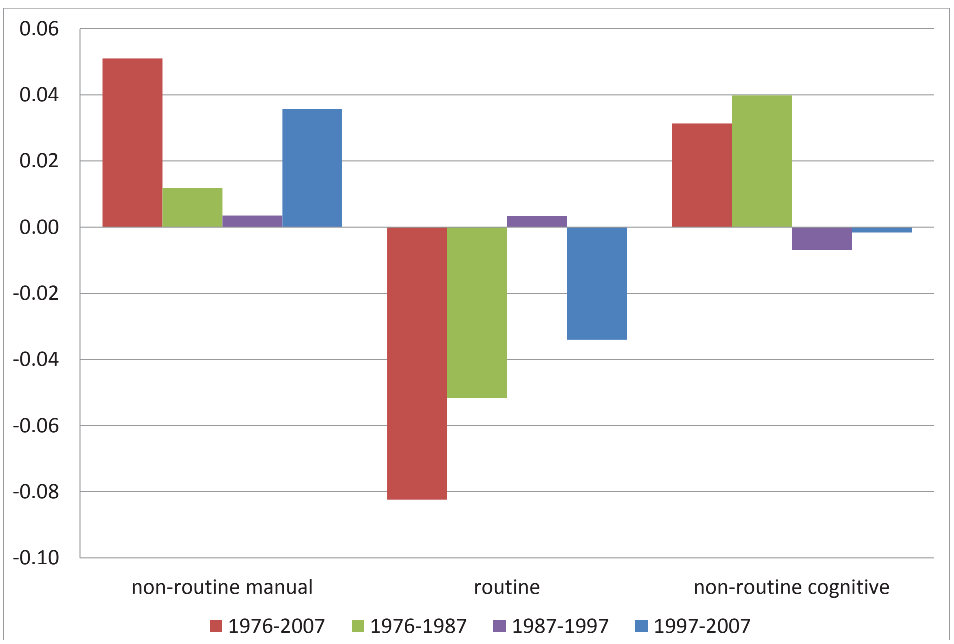
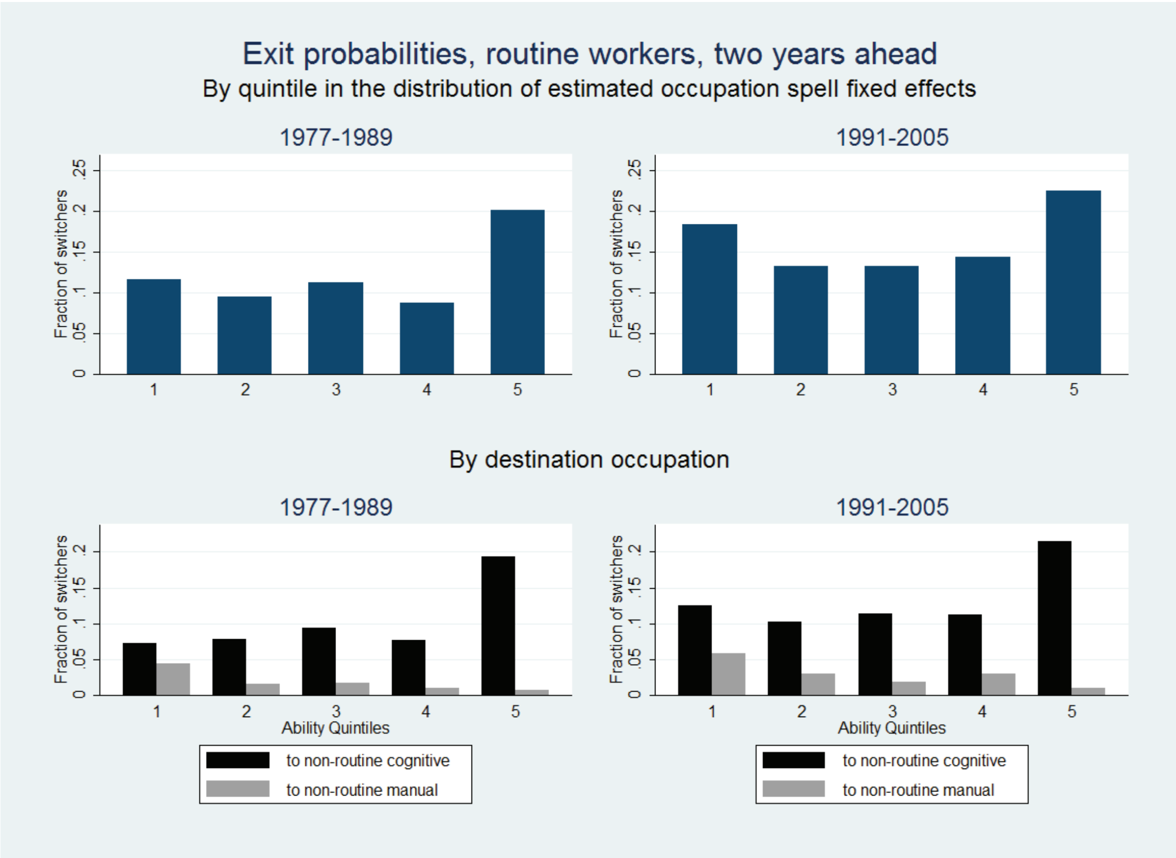


Figure 2: Changes in employment shares for broad occupation groups, men, PSID, 1976-2007



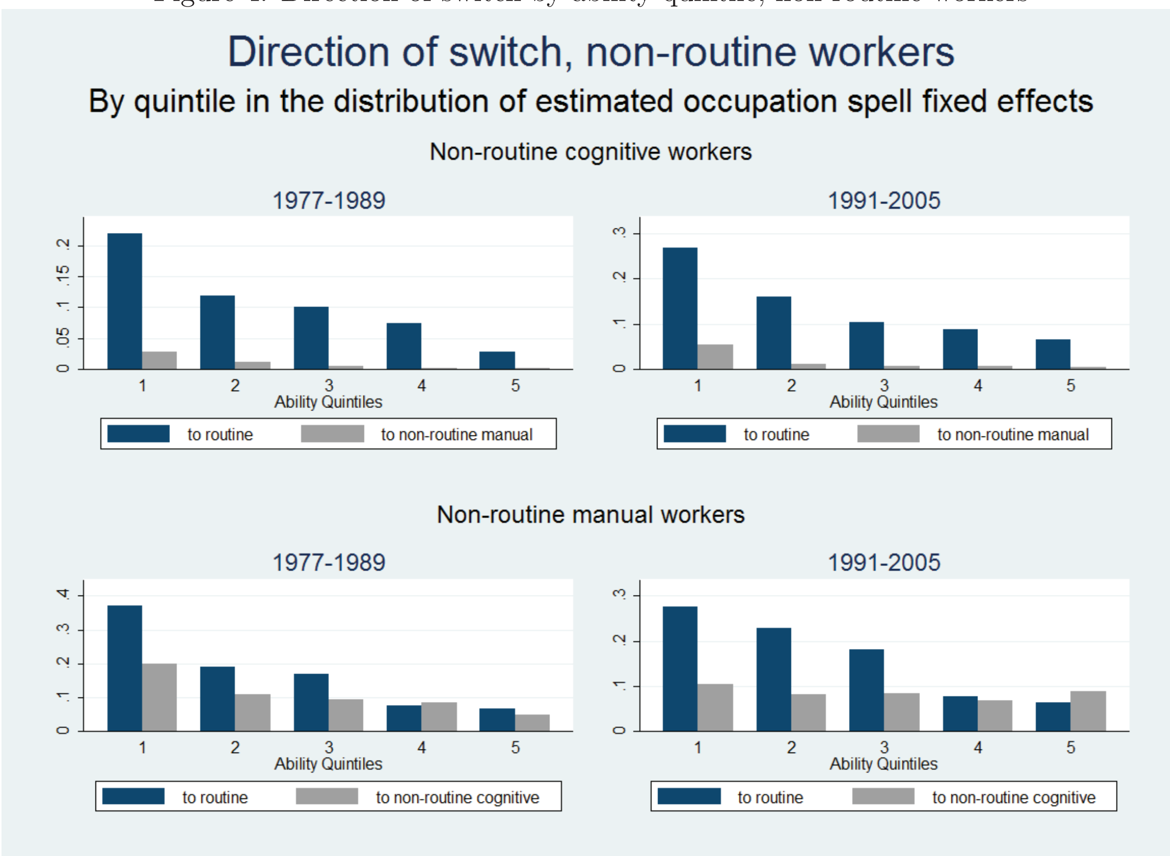
Note: Sample includes male household heads aged 16 to 64 employed in non-agricultural, non-military jobs, who are part of the PSID's core sample and have non-missing wage data. See Data Section for details on the occupation classification.

Figure 3: Exit probabilities by ability quintile



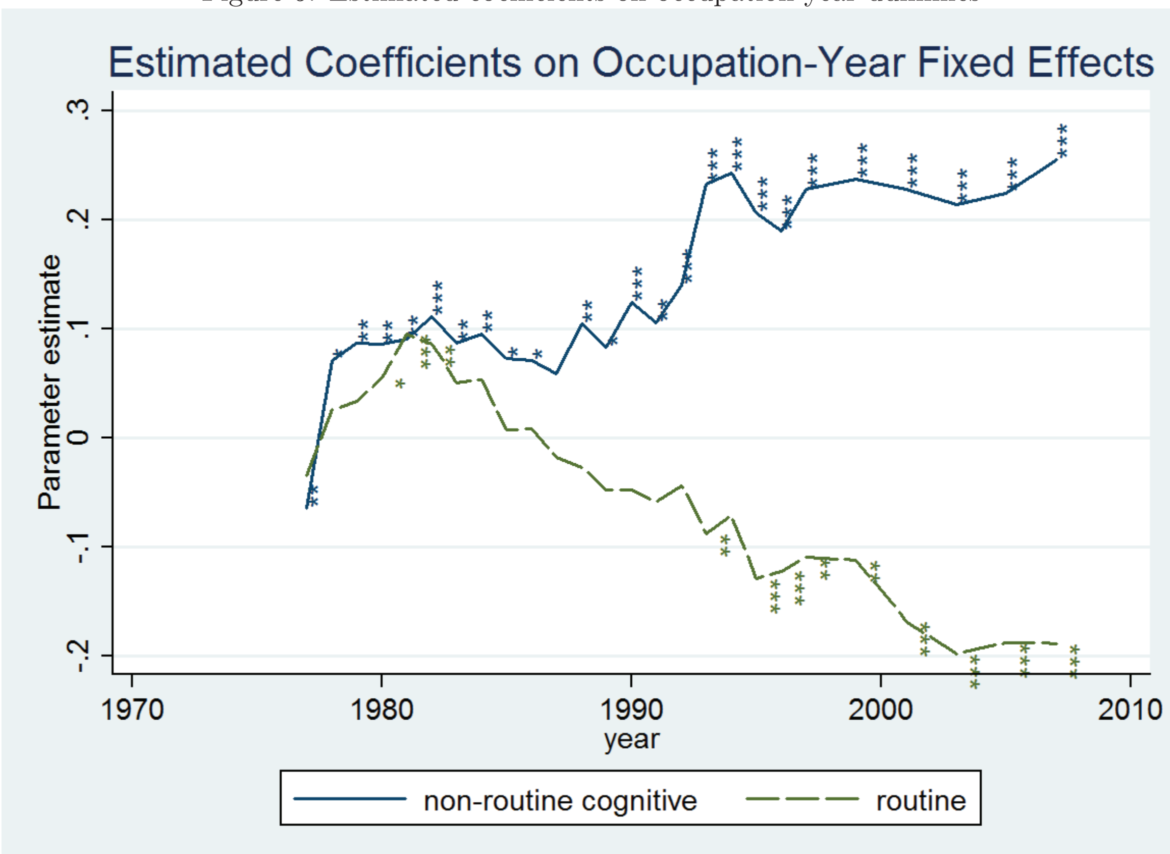
Note: Sample includes workers in routine occupations, and plots their probability of switching out of this type of occupation between years t and $t+2$, according to their ability quintile.

Figure 4: Direction of switch by ability quintile, non-routine workers



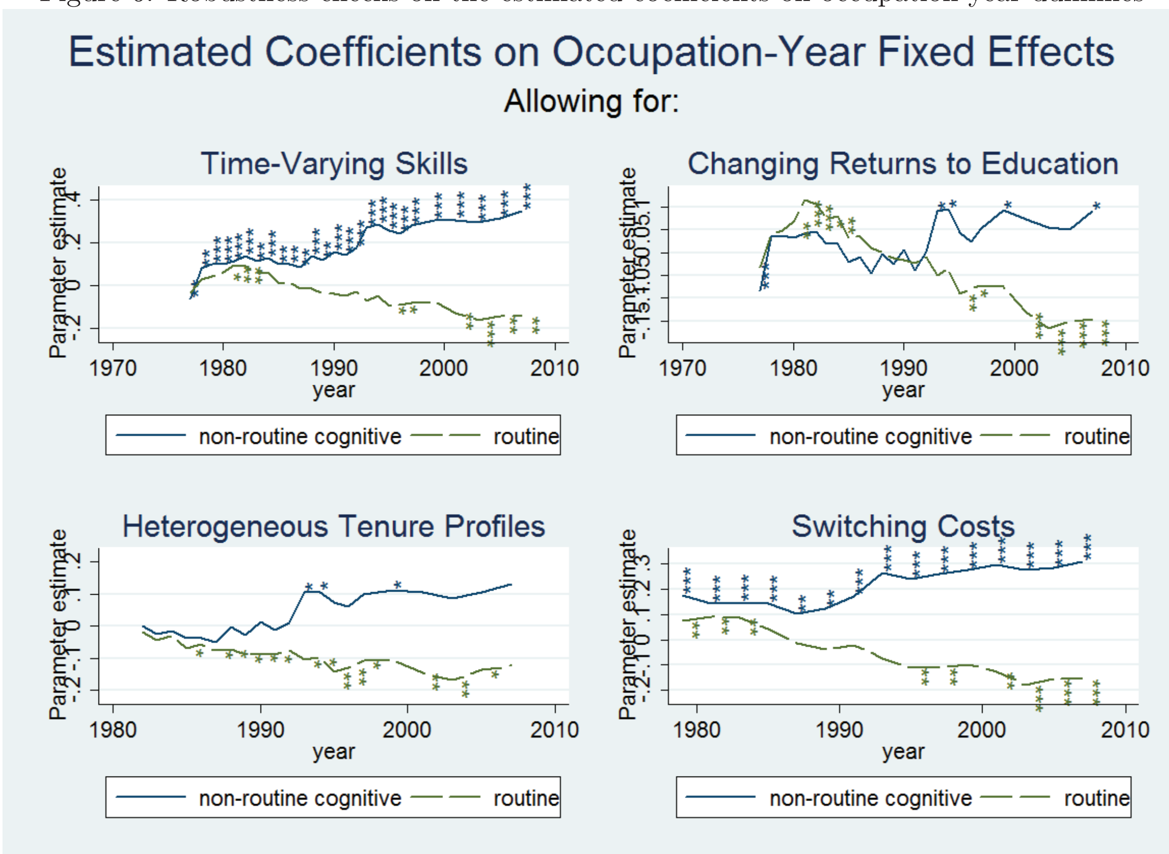
Note: Sample includes workers in non-routine occupations, and plots their probability of switching out of this type of occupation between years t and $t + 2$, according to their ability quintile.

Figure 5: Estimated coefficients on occupation-year dummies



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

Figure 6: Robustness checks on the estimated coefficients on occupation-year dummies



Note: The figures show the estimates of the time-varying occupation fixed effects $\widehat{\theta}_{rt}$ and $\widehat{\theta}_{cog}$ obtained from the estimation of Equations (8), (11), (12), and (13), respectively. Stars denote the level at which the estimated coefficients are significantly different from zero.