

The Price of Polarization: Estimating Task Prices under Routine-Biased Technical Change

Michael J. Böhm *

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Abstract: The debate about the impact of routine-biased technical change on the labor market revolves around the question whether employment and wages polarized. This paper instead shows that RBTC's main prediction is that the prices paid for routine tasks should decline compared to abstract and manual tasks. I exploit the sorting of workers into tasks to estimate these price changes under relatively weak assumptions. Empirical results for male workers in two U.S. datasets reveal that task prices polarized during the 1990s and 2000s. The estimates go a long way in matching the change of the actual wage distribution over this period.

Keywords: Task Prices; Roy Model; Routine-Biased Technical Change; Polarization; Wage Distribution

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1 Introduction

A large literature has examined the effect of routine-biased technical change (“RBTC”) on the labor market (e.g., [Autor, Levy, and Murnane, 2003](#); [Autor, Katz, and Kearney, 2006](#); [Acemoglu and Autor, 2011](#)). In particular, several papers have shown that during the 1990s and 2000s employment in the United States and other developed countries polarized away from middle-wage occupations that are intensive in routine tasks and into high-wage and low-wage occupations that are intensive in abstract and manual tasks (“job polarization”). Moreover, in the United States, wages at the top and the bottom quantiles of the (occupational) wage distribution increased while wages at the middle of the (occupational) wage distribution stagnated (“(occupational) wage polarization”). These facts have been taken as evidence that RBTC was an important driver of employment and wages over the last decades (e.g., [Acemoglu and Autor, 2011](#)).

However, recently this interpretation has been challenged on several grounds. First, a couple of studies detect job polarization already before the 1980s, that is, during a time when RBTC should not have been very important (e.g., [Bárány and Siegel, 2014](#); [Mishel, Shierholz, and Schmitt, 2013](#)). Second, wage polarization only clearly occurred during the 1990s. In the 1980s wage inequality rose across the board and in the 2000s only wages at the top of the distribution increased while employment only expanded at the bottom ([Acemoglu and Autor, 2011](#); [Mishel, Shierholz, and Schmitt, 2013](#)). Moreover, average wages in some of the contracting routine occupations increased and they declined in some of the expanding manual occupations.¹ Finally, despite pervasive and substantial job polarization among European countries, there exists little evidence that the wage distribution is polarizing in Europe.

This paper shows how these seemingly contradicting facts may be reconciled. Like the preceding literature, I use a [Roy \(1951\)](#) model to specify labor supply in the context of RBTC. I demonstrate that different restrictions on the dependence structure of workers’ skills in the model lead to distributions of wages and employment which are consistent with any of the previous findings. The main prediction of the RBTC-Roy model is instead about the prices that are paid for skills in tasks:² the routine task price will decline

¹For example, average wages in routine clerical occupations increased while employment in these occupations declined in [Autor and Dorn \(2013\)](#). Also in [Autor and Dorn](#), and in [Goos and Manning \(2007\)](#), relative wages in the lowest-paying occupations declined when at the same time employment expanded.

²In the RBTC-Roy model a worker’s wage in a given task is the product of his task-specific productivity

compared to the abstract and the manual task price (“price polarization”).

I then propose a new method to estimate the changes in task prices in the Roy model, which derives identification from the interplay between workers’ sorting into tasks and their wage growth. Intuitively, the approach relies on first-differencing the earnings equation so that the skill levels in tasks are removed, and only workers’ relative skills and the associated sorting matter for wage changes. This new method has the advantages that it makes minimal assumptions about the distribution of workers’ skills and that it can be implemented in a simple linear wage regression for three (or more) tasks.³ I use the resulting task price changes across different time periods to check for the presence and importance of RBTC during these periods and to assess their effect on the overall wage distribution.

The estimation requires data on the sorting of detailed worker types into tasks and how this changes between respective points in time. I employ two such datasets, each with their specific advantages and disadvantages.⁴ First, I construct two cross-sections of 27 year old male workers between 1984–1992 and 2007–2009 from the cohorts of the National Longitudinal Survey of Youth (NLSY79 and NLSY97). The NLSY has one substantial advantage over more commonly used data sets in this literature: it provides early-determined, multidimensional, and comparable over time measures of worker talents—such as mathematical, verbal, and mechanical test scores and risky behaviors—which predict task choices and wages. This allows me to study the evolution of wages of the kind of individuals who are more and less likely to work in the routine compared to the abstract and the manual task over the two decades between the NLSYs at 27, which featured rapid job polarization.

Since the NLSY sample is a specific age group and in a particular time period, data from [Acemoglu and Autor \(2011\)](#)’s Handbook of Labor Economics chapter is used as a second sample. Acemoglu and Autor construct demographic cells by education, age, and region of residence together with their task specialization in the decennial censuses and

(“skill” in that task) times the prevailing equilibrium market price per unit of that task input (the “task price”).

³What is needed for identification is an approximation of the adjustment path of workers’ sorting between the initial sorting under the old task prices and the final sorting under the new task prices. In Monte Carlo simulations the method performs well against the fully structural estimation of the Roy model under different distributional assumptions (see Appendix A.3).

⁴As in most of the literature, the tasks are empirically approximated by three occupation groups, which are intensive in abstract, routine, and manual tasks, taken from [Acemoglu and Autor \(2011\)](#).

the American Community Survey (henceforth Census/ACS sample). Using my method, I employ this data for male workers of all ages to estimate the task price changes in the periods 1979–1989, 1989–1999, 1999–2007, and the joint period of 1989–2007.⁵

Both sets of results indicate that RBTC had an important impact on task prices during the joint period of the 1990s and 2000s. The relative price that is paid per unit of skill in the abstract (manual) task rose by 25 (33) log points between 1984–1992 and 2007–2009 in the NLSY and by 34 (41) log points between 1989 and 2007 in the Census/ACS. The absolute price paid for routine tasks declined in both datasets. The Census/ACS estimations by decade robustly show that the relative price of the abstract task increased and the relative price of the routine task decreased during 1989–1999 and 1999–2007. The price of the manual task robustly increased during 1989–1999, while its evolution over 1999–2007 is somewhat ambiguous. The task price estimates for 1980s are generally inconclusive, likely reflecting confounding forces such as skill-biased technical change (SBTC), a strong decline in the real value of the minimum wage, and a substantially changing supply of skill during that period.

Overall, the estimated task price polarization strongly supports RBTC over the joint 1990s and 2000s. This conclusion is unaltered when accounting for the effect of the changing real value of the minimum wage as in [Lee \(1999\)](#), when using an instrumental variables and a control variables strategy to account for the effects of changing unobservable talent selection into demographic cells in the Census/ACS, and when introducing different sets of regressors in the estimation to control for such forces as an increasing absolute demand for skills. It is also consistent with part of the task price polarization stemming from other factors, such as offshoring and trade (e.g., [Acemoglu and Autor, 2011](#)) or consumption spillovers to service tasks (e.g., [Mazzolari and Ragusa, 2013](#)).

The estimated task prices by themselves go a long way toward explaining the change of the overall U.S. wage distribution. In the data taken from [Acemoglu and Autor \(2011\)](#), assigning every worker the price change of their tasks done in the initial period yields a predicted change in the wage distribution which closely resembles the actual polarization of the wage distribution during the 1990s and 2000s—together as well as by decade. For the NLSY data, the task prices alone cannot match all of the polarization at the bottom of the actual wage distribution. However, adjusting for the increase in the real value of

⁵Results for females in the NLSY and the Census/ACS sample are summarized in Appendix B.2.

the minimum wage provides a good fit for these younger workers too. This demonstrates that task prices may have been an important driver of aggregate wage inequality over the last two decades, leaving relatively little room for factors such as skill endowments or an increasing absolute demand for skills aside from tasks.

Finally, [Acemoglu and Autor \(2011\)](#) regress workers' wage growth in the Census/ACS sample on their initial task specializations. I show that a variant of Acemoglu and Autor's estimation equation can be directly derived from the RBTC-Roy model. Empirically, regressions in the NLSY data confirm Acemoglu and Autor's finding that routine workers' wage growth is lagging behind abstract and manual task workers' wage growth. Relative wages of initial abstract and manual task workers rose by more than a third between 1984–1992 and 2007–2009, while routine task workers even suffered a decline in their real wages. That these findings are robust to controlling for absolute skill measures, such as educational attainment, suggests that it is relative skills in tasks rather than absolute skills whose returns have changed over time. Therefore, it further supports RBTC and the tasks approach over SBTC in explaining the evolution of workers' wages over the 1990s and 2000s.

A couple of recent papers also estimate the task prices under different restrictions on the selection of skills into tasks. [Firpo, Fortin, and Lemieux \(2013\)](#) and [Fortin and Lemieux \(2015\)](#) use a reweighting approach to account for a changing selection of observables into occupations. They find that technological change and de-unionization strongly affected the wage distribution during the 1980s and that offshoring became important from the 1990s onward. Setting up a one-dimensional skill model and assuming that task switches do not occur because of individual-specific skills shocks, [Cortes \(2014\)](#) identifies task prices from fixed effects in longitudinal data. He finds that abstract task prices rose by about 30 percent and manual task prices rose by 15 percent compared to routine task prices, which is qualitatively consistent with the findings in this paper. [Gottschalk, Green, and Sand \(2015\)](#) make statistical arguments and arguments based on different skill distributions in the Roy model to establish bounds on the changes in task prices. They find that all three task prices increased strongly throughout the 1990s, but then declined strongly and to a similar extent during the 2000s. Finally, other recent papers have implemented Roy-type models under the assumption of normally or extreme-value

distributed skills to analyze different aggregate labor market outcomes.⁶

In contrast, this paper derives and estimates a regression equation in the Roy model which identifies the task prices under an unrestricted multidimensional distribution of skills. I further discuss in detail the identification assumptions and provide Monte Carlo evidence supporting the estimation method.

The paper continues as follows. Sections 2.1 and 2.2 present the RBTC-Roy model and argue that its main prediction is that task prices polarize. Section 2.3 derives the new estimation method for task prices. Section 3 describes the empirical strategy and the two samples that are used. Section 4 presents the estimation results and assesses the task prices' effect on the overall wage distribution. The final section concludes.

2 The RBTC-Roy Model

2.1 Task Prices Polarize under Routine-Biased Technical Change

This section shows that task prices polarize under RBTC when routine labor and computer capital are perfect substitutes in a Cobb-Douglas production function. More generally, all models of RBTC proposed to date imply task price polarization.

The RBTC-Roy model is the combination of a production function (and consumer preferences) and a model of labor supply. In the production function, routine-biased technological change (RBTC) is represented by the increased availability of computer capital that is a relative substitute to labor performing routine tasks versus labor performing analytical or manual tasks. The Roy model of labor supply specifies workers' skills and choices in carrying out abstract, routine, and manual work given the task prices that they face.

To illustrate this combination, take the Cobb-Douglas production function for final output from Autor, Katz, and Kearney (2006):

$$Y = A^\alpha R^\beta M^\gamma \text{ with } \alpha + \beta + \gamma = 1.$$

⁶Hsieh, Hurst, Jones, and Klenow (2013) quantify the effect that an improving allocation of females and minorities into (high-skill) occupations may have had on U.S. economic growth since the 1960s. Burstein, Morales, and Vogel (2015) develop a model that exploits demographic groups' choices of occupations and capital equipment to decompose changes in between-group inequality from 1984 to 2003. Lindenlaub (2014) analyzes the effect of skill- and task-biased technical change on sorting and inequality in a two-dimensional assignment model.

In this production function, abstract and manual tasks can only be carried out by workers, that is, in equilibrium $A = L_A$, $M = L_M$, where L_K is labor supply to task $K \in \{A, R, M\}$. Routine tasks can be carried out by workers or computer capital so that $R = L_R + C$. Computer capital C is supplied inelastically at price ρ in terms of the final output good. Assume we are at an interior point where both nonzero L_R and C are employed in equilibrium. Profit maximization with respect to the three task inputs therefore yields the first order conditions

$$\begin{aligned}\Pi_A &= \alpha A^{\alpha-1} R^\beta M^\gamma \\ \Pi_R &= \beta A^\alpha R^{\beta-1} M^\gamma = \rho \\ \Pi_M &= \gamma A^\alpha R^\beta M^{\gamma-1},\end{aligned}$$

where Π_K is the prevailing market price per efficiency unit of task K . RBTC is represented by an exogenous drop in the price of computer capital ρ . This describes labor demand.

Labor supply is characterized by the Roy model. Workers possess skills in each task $S = \{S_A, S_R, S_M\}$ and they choose to perform the task that maximizes their wage:⁷

$$W = \max\{\Pi_A S_A, \Pi_R S_R, \Pi_M S_M\}.$$

Denoting the population distribution of skills by $F(S_A, S_R, S_M)$, overall labor supply to task K becomes

$$L_K = \int_0^\infty \int_0^\infty \int_0^\infty S_K I_K dF(S_A, S_R, S_M), \quad (1)$$

with the task choice indicators

$$\begin{aligned}I_A &= 1[\Pi_A S_A > \Pi_R S_R, \Pi_A S_A > \Pi_M S_M] \\ I_R &= 1[\Pi_A S_A \leq \Pi_R S_R, \Pi_R S_R \geq \Pi_M S_M] \\ I_M &= 1[\Pi_M S_M > \Pi_R S_R, \Pi_A S_A \leq \Pi_M S_M].\end{aligned}$$

This setup yields the first proposition, which is proved in Appendix A.1:

Proposition 1. *RBTC leads to task price polarization, that is, $\frac{\Pi_A}{\Pi_R}$ and $\frac{\Pi_M}{\Pi_R}$ rise when ρ drops.*

The specific example used here features perfect substitutability between routine la-

⁷The assumption that wages in tasks consist of the product (sum in logs) of task prices and skills, whereby only the prices change over time, was already made in the early general equilibrium Roy model of Heckman and Sedlacek (1985). Heckman and Sedlacek (1985) term it the “proportionality” or the “additivity hypothesis”. Assuming a normal distribution of workers’ skills, they estimate the task prices in levels, up to a constant, in repeated cross-sections.

bor and computer capital, which is an extreme version of the core notion of RBTC that computer capital is a *relative* substitute for routine labor compared to both types of non-routine labor. In other cases with a (nested) CES production function or where the routine labor-computer capital substitutability is not perfect, sufficiently strong restrictions on the relative substitutability between these two inputs versus the non-routine labor inputs and computer capital ensure task price polarization. For example, in a recent paper, [Autor and Dorn \(2013\)](#) assume that the substitutability of goods and services in final consumption and the substitutability of routine labor and capital are sufficiently large compared to the importance of the routine component in goods production.⁸

There also exist alternatives to the computer capital and three labor inputs production and consumption setup. First, another recent paper by [Cortes \(2014\)](#) proposes a model where improving computer capital increases the productivity of routine labor. Again, under a sufficiently low substitutability between routine tasks and abstract tasks, Cortes predicts task price polarization to occur. Second, the model by [Acemoglu and Autor \(2011\)](#) features a continuum of tasks that workers can perform but three fixed types of workers: high-, middle-, and low-skill. In this model, RBTC constitutes of the introduction of technologies which replace more and more of the medium tasks so that middle-skill workers are displaced into lower and higher ranked tasks that cannot yet be automated while high- and low-skill workers concentrate even further in the extremes of the task distribution. Although there are not just three task prices but a continuum of them, the Acemoglu and Autor model also features price polarization in the sense that the price paid for the more extreme tasks increases compared to the more central tasks that the displaced middle-skill workers move into.

I conclude from this discussion that task price polarization is a central implication of the models of RBTC proposed so far. However, task price polarization is not only central in this literature because it is a consistent implication of the different models of RBTC, but also because task prices summarize the impact that RBTC has on the labor market. That is, from a labor supply side view, task prices are a sufficient statistic of the effect of RBTC on employment and wages. The following section shows that task price polarization is

⁸Autor and Dorn call this the “empirically relevant” case. Note that their condition is only sufficient for price polarization to occur under Autor and Dorn’s specific restrictions on worker skills. Under a more general distribution of workers’ skills, a tighter sufficient condition on the substitutabilities is required for task prices to polarize.

also the only robust implication from RBTC. Other implications on employment and wages depend on strong and largely arbitrary restrictions on the distribution of workers' skills.

2.2 No Unambiguous Predictions for the Distributions of Employment and Wages

This section demonstrates that RBTC provides no further predictions concerning the distributions of employment and wages beyond task price polarization. Therefore, several empirical findings in the literature that have been taken as contradicting RBTC are in fact potentially consistent with it.

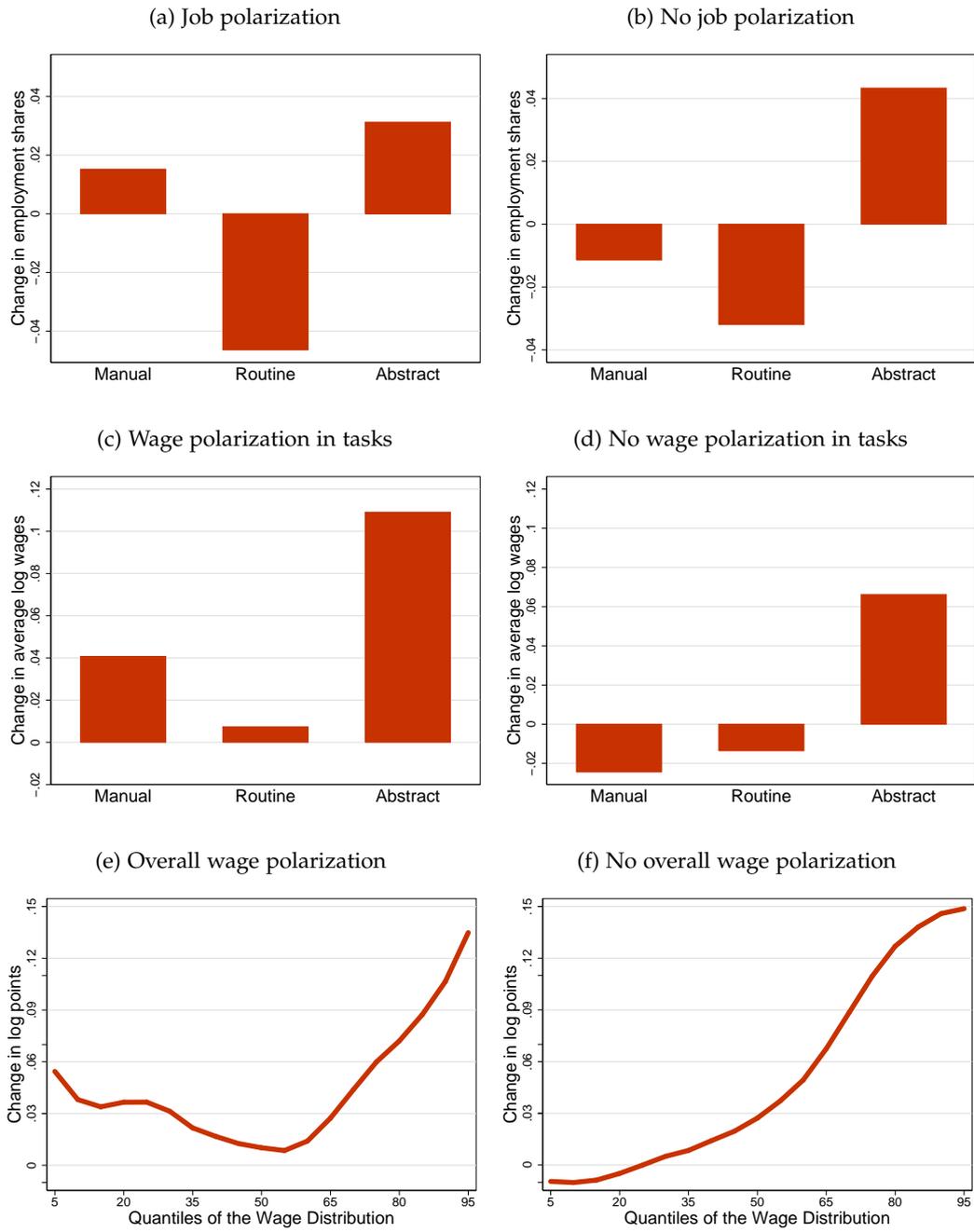
The theoretical propositions in the following are illustrated with simulated data using a multivariate normal distribution of skills in tasks. Normality implies that the variances and correlations of skill are the main parameters determining sectoral and aggregate outcomes. Under a different distribution, other parameters may matter (e.g., see [Heckman and Honoré, 1990](#)). Hence, this should be understood as just one specific illustration of the more general propositions. For brevity, sketches of the proofs, further intuition, and the parameter values of the simulations are relegated to [Appendix A.1](#).

Proposition 2. *Under task price polarization, employment in the routine task falls, but there need not be job polarization.*

The top row of [Figure 1](#) illustrates this proposition for a case where the price of the abstract task rises more than of the manual task and the price of the routine task falls. Employment polarizes in [Panel \(a\)](#) because the correlation between routine and manual tasks is relatively high, so that routine workers flow to the manual task when task prices polarize. In contrast, in [Panel \(b\)](#) the correlation of abstract tasks with routine and manual tasks is relatively high. Thus, workers from the latter two tasks move into the abstract task when the price of that task rises. One observes no job polarization, but a decline of employment in the manual task. In the extreme this may even decline more than in the routine task.

The result that RBTC, although it leads to task price polarization, does not necessarily lead to job polarization is consistent with the debate about whether there was job polarization in the 1980s in the United States and with the drop of routine *and* manual

Figure 1: Small differences in skill distributions can lead to qualitatively different outcomes, even under the same task price changes and a multivariate normal distribution of skills (simulation parameter values in Appendix A.1)



employment in some European countries. In addition, if only a limited number of workers can do abstract tasks at all (as assumed in Autor, Katz, and Kearney, 2006; Autor and Dorn, 2013), this may be consistent with a rise in bottom employment but of top wages as is observed in the U.S. during the 2000s (e.g., Acemoglu and Autor, 2011; Mishel, Shierholz, and Schmitt, 2013).

Proposition 3. *Task price polarization has no clear implication on wages in tasks. In particular, it need not lead to the polarization of average wages in tasks.*

The intuition behind proposition 3 is that a changing selection bias in tasks may invert the direct effect of the task prices themselves. For example, consider the middle row of Figure 1 (the task price changes are the same as in Panels (a) and (b)). In Panel (c) average wages in tasks polarize, however, in Panel (d) average wages in the manual task fall even compared to average wages in the routine task. This is because the correlation between manual and routine skills is low and the correlation between manual and abstract skills is high. Therefore, low-skill routine workers move into the manual task while high-skill manual workers move into the abstract task. The selection effect dominates the price effect.⁹

The result that RBTC need not lead to polarization of average wages in tasks is consistent with several empirical findings in the literature. In particular, during 1999–2007 employment in low-skill (service/manual-task-intensive) occupations rose strongly and at the same time wages dropped (Autor, 2014, Figures 2–4 and 6–7). Moreover, Autor and Dorn (2013) find that whereas employment contracted in routine-task-intensive clerical and sales occupations over 1980–2005, wages in these occupations increased.¹⁰ Mishel, Shierholz, and Schmitt (2013, p.5) also conclude from their analysis that there is “little or no connection between decadal changes in occupational employment shares and occupational wage growth” in the U.S. over the last decades.

Proposition 4. *Task price polarization does not imply (overall) wage polarization.*

⁹With the assumptions in the papers by Autor, Katz, and Kearney (2006) and Autor and Dorn (2013), wages in the routine task may either rise or fall, because the least able routine workers leave for the manual task. Since skills in the manual and abstract tasks are homogeneous, wages in both of these tasks always rise by assumption.

¹⁰The employment decline is strongest for occupations at the 20–30th percentile of the skill distribution while wage growth in these occupations exhibits a local peak (Autor and Dorn, 2013, Figure 1). In their early paper, Goos and Manning (2007) also mention that wages in the lowest skill occupations decline while employment rises.

The idea behind proposition 4 is that even if manual task workers are on average located at lower quantiles of the wage distribution than routine workers, it does not mean that these lower quantiles will rise more than the routine workers' quantiles. This is because (some of) the manual task workers will move up in the wage distribution and overtake (some of) the routine task workers. Thus, not only manual task workers' initial quantiles will rise, but also the quantiles where they end up in (and vice versa for the routine task workers).¹¹ Empirically, this "overtaking effect" is to a greater or lesser degree always part of a change in the overall wage distribution. However, it is often assumed away in theoretical models by making workers' skill ranking one-dimensional. Such a restriction implies that wage polarization immediately follows from task price polarization.¹²

Generally this is not the case. The last row of Figure 1 illustrates this with one distribution of skill where there is wage polarization and another where inequality increases across-the-board. In Panel (e) the variance of the routine skill is high, which leads to a relatively large difference in initial wages between routine and manual workers and thus little overtaking when task prices change. Therefore, we observe a relative increase in wages at the lowest quantiles of the wage distribution compared to the quantiles located toward the middle. In Panel (f), initial wage differences between routine and manual workers are not as large. This leads to substantial overtaking when task prices change and an increase in wage inequality across-the-board instead of wage polarization. Therefore, even when the task price changes are the same (which they will unlikely be in equilibrium), one may obtain wage polarization or not with just a small modification of the skill distribution.

The result that RBTC may or may not lead to wage polarization is consistent with

¹¹Rising abstract task prices have a compounding effect for inequality at the top of the wage distribution. They raise abstract workers' already high initial quantiles as well as the even higher quantiles that these workers end up in.

¹²For example, [Acemoglu and Autor \(2011\)](#) assume a fixed ranking of skill between individuals whereby high-skill workers have an absolute advantage in all task over middle-skill workers who in turn have an absolute advantage in all task over low-skill workers. [Cortes \(2014\)](#) makes a related assumption with a continuous distribution of skill. Focusing on the lower half of the wage distribution, [Autor, Katz, and Kearney \(2006\)](#) and [Autor and Dorn \(2013\)](#) assume that high-school (or low-skill) workers all have homogenous skills in the manual task and thus are ranked one-dimensionally by their heterogenous skills in the routine task. In none of these papers, by assumption, can a worker who initially earned less than another worker overtake that latter worker in the wage distribution when the relative price of the task that he has a comparative advantage in rises. In the context of assignment models, [Lindenlaub \(2014\)](#) also argues that a truly multidimensional skill setup is required to study the effects of task-biased technical change on the wage distribution.

several empirical findings in the literature. Both employment and the wage distribution polarized in the United States over the 1990s and early 2000s. However, only employment in manual tasks expanded in the subperiod of the early 2000s, while relative wages only increased at the top of the wage distribution compared to the middle during that period (e.g., [Acemoglu and Autor, 2011](#), Figures 7–10; [Mishel, Shierholz, and Schmitt 2013](#)). In addition, as mentioned above, several papers find that job polarization already started in the 1980s in the United States although we know that wage inequality rose firmly across-the-board during this period (as in Panel (f) of [Figure 1](#)). Finally, and probably most importantly, there exists strong evidence of job polarization across European countries during 1993–2010 (e.g., [Goos, Manning, and Salomons, 2009](#)), while wage inequality again increased across-the-board in most of these countries.¹³

At this point it is important to note that the argument made in [Propositions 1–4](#) and in the respective simulation illustrations does not imply that differences in the effect of RBTC on the labor market need to be explained by differences in workers’ skill endowments across countries and points in time. Task prices are an equilibrium outcome that depends on the interaction between production technologies, the extent and advancement of RBTC, and the skill distributions. All of these may differ across locations and will differ across time, and as one can verify in the simulated data, even small variations in these variables may lead to large differences in employment, wages, and the task prices themselves. What is to be learned from [Propositions 1–4](#) is therefore that RBTC and task price polarization are in principle consistent with a host of outcomes in labor markets over the last decades, while task price polarization itself is an implication that appears in all models of RBTC that have been proposed to date.

2.3 Workers’ Wage Growth and the Estimation Equation for Task Prices

This section shows that, apart from task price polarization, there is another robust implication of RBTC: routine workers’ wage growth over time lags behind abstract or manual workers’ wage growth. This implication leads to an approach for estimating the task prices, which works for a general distribution of skills and which is easy to implement.

I start by rewriting the labor supply side of [Section 2.1](#) with individual index i and

¹³For example, [Dustmann, Ludsteck, and Schönberg \(2009\)](#) and [Card, Heining, and Kline \(2013\)](#) find a strong increase of wage inequality across-the-board in Germany during that period. [Naticchioni, Ragusa, and Massari \(2014\)](#) report that they obtain little evidence of wage polarization in Europe.

time index t and in logs, which is denoted in lower-case letters. Individual potential wages in task K become

$$w_{Kit} = \pi_{Kt} + s_{Kit} \text{ with } K \in \{A, R, M\}.$$

Consider a marginal wage change of a worker i who starts out in the A , R , or M task in $t = 0$:

$$dw_{i0} = \begin{cases} d\pi_{A0} & \text{if } I_{Ai0} = 1 \\ d\pi_{R0} & \text{if } I_{Ri0} = 1 \\ d\pi_{M0} & \text{if } I_{Mi0} = 1. \end{cases}$$

Here d denotes a marginal change of the respective variable over time. Thus, due to the optimality of workers' task choice and the envelope theorem, the effect on wages of a marginal change in π_{Kt} s is only the direct price effect. In fact, in every point in time

$$dw_{it} = d\pi_{Rt} + I_{Ait}d(\pi_{At} - \pi_{Rt}) + I_{Mit}d(\pi_{Mt} - \pi_{Rt}). \quad (2)$$

Integrating this equation from $t = 0$ to $t = 1$ obtains the following result.¹⁴

$$\Delta w_i = \Delta \pi_R + \int_{\pi_{A0} - \pi_{R0}}^{\pi_{A1} - \pi_{R1}} I_{Ait}d(\pi_{At} - \pi_{Rt}) + \int_{\pi_{M0} - \pi_{R0}}^{\pi_{M1} - \pi_{R1}} I_{Mit}d(\pi_{Mt} - \pi_{Rt}) \quad (3)$$

In Equation (3) the overall wage change for worker i solely depends on his initial task choice and the change in his task choice on the adjustment path from price vector π_0 to price vector π_1 . That is, for changes in workers' wages over time, only relative but not absolute skills in tasks matter.

Proposition 5. *Task price polarization decreases the wages of workers who start in the routine task compared to abstract or manual workers or both.*

Sketch of proof in Appendix A.1. This result about workers' relative wage changes is helpful because it can be tested and because it has not received much attention in the empirical literature so far. The exception is Acemoglu and Autor (2011) who examine the wage profiles of worker groups depending on their initial task specialization over

¹⁴The steps of the integration as well as an instructive way of deriving Equation (3) for the simpler case of two tasks can be found in Appendix A.2.

the decades in the United States census.¹⁵ Equation (3) and Proposition 5 formalize Acemoglu and Autor’s intuition and at the same time show that under a general distribution of skill we can strictly speaking only expect that routine starters’ wages decline compared to one of the other two worker groups.

Result (3) is also helpful because it provides an approach of estimating the task price changes from data on workers’ task choices and wages. The practical challenge here is that one does not observe workers who in $t = 0$ specialized in the three different tasks again in $t = 1$ (at least not with the same age, experience, etc.). One does not directly observe workers’ task-specific skills either, but in some datasets one may observe characteristics that make workers more or less likely to choose different tasks. In the sense of the model, the s_{Kit} s depend on these characteristics in different ways.¹⁶

I use the idea that s_{Kit} partly depends on the observed characteristics x_{it} to rewrite result (3) in a way that is amenable to empirical analysis. Take expectations on both sides of (3) conditional on x_{it} to get

$$E(w_{i1} - w_{i0}|x_{it}) = \Delta\pi_R + \int_{\pi_{A0}-\pi_{R0}}^{\pi_{A1}-\pi_{R1}} p_A(x_{it}, \pi_t) d(\pi_{At} - \pi_{Rt}) + \int_{\pi_{M0}-\pi_{R0}}^{\pi_{M1}-\pi_{R1}} p_M(x_{it}, \pi_t) d(\pi_{Mt} - \pi_{Rt}), \quad (4)$$

where $p_A(x_{it}, \pi_t) = E[I_{Ait}|x_{it}]$ is the propensity of an individual with observables x_{it} to work in the abstract task given the prevailing task price vector π_t (equivalently for $p_M(x_{it}, \pi_t)$).

From Equation (4) I want to estimate the distances $\Delta(\pi_A - \pi_R)$, $\Delta(\pi_M - \pi_R)$, and $\Delta\pi_M$. $E(w_{it}|x_{it})$, $p_A(x_{it}, \pi_t)$, and $p_M(x_{it}, \pi_t)$ are known in points in time $t = 0$ and $t = 1$ in the sense that one can consistently estimate them from data with sufficiently detailed information about characteristics x_{it} . However, $p_A(x_{it}, \pi_t)$ and $p_M(x_{it}, \pi_t)$ within

¹⁵Cortes (2014) is also related: he examines the wage profiles of stayers in routine tasks compared to switchers out of those tasks and to stayers in abstract and manual tasks. The result here prescribes to look at all starters in the routine tasks, including the switchers, versus all the starters in the abstract and manual tasks. Burstein, Morales, and Vogel (2015) derive a similar prediction in their paper.

¹⁶An intuitive example to think about this is Heckman and Sedlacek (1985)’s linear factor formulation of log wages:

$$w_{Kit} = \pi_{Kt} + s_{Kit} = \pi_{Kt} + \beta_{K0} + \beta_{K1}x_{1it} + \dots + \beta_{KJ}x_{Jit} + u_{Kit},$$

where $x_{it} = [x_{1it}, \dots, x_{jit}, \dots, x_{Jit}]'$ are the observed characteristics, the β_{Kj} s are the corresponding linear projection coefficients, and u_{Kit} is an orthogonal regression error which represents the unobserved component of skill in task K . This specification is also similar to Firpo, Fortin, and Lemieux (2013) who postulate that skills in (occupation-specific) tasks are a linear combination of characteristics, some observed, others not.

the interval $t \in (0, 1)$ are unknown and one needs to make an assumption on them.

I linearly interpolate $p_A(x_{it}, \pi_t)$ and $p_M(x_{it}, \pi_t)$ (see Appendix A.2 for details) so that result (4) becomes

$$E(w_{i1} - w_{i0} | x_{it}) = \Delta\pi_R + \frac{p_A(x_{it}, \pi_1) + p_A(x_{it}, \pi_0)}{2} \Delta(\pi_A - \pi_R) + \quad (5)$$

$$+ \frac{p_M(x_{it}, \pi_1) + p_M(x_{it}, \pi_0)}{2} \Delta(\pi_M - \pi_R).$$

This constitutes an estimable equation. In particular, consider the following linear wage regression:

$$w_{it} = \alpha_0 + \alpha_1 \bar{p}_A(x_{it}) + \alpha_2 \bar{p}_M(x_{it}) + \alpha_3 \times 1[t = 1] + \quad (6)$$

$$+ \alpha_4 \bar{p}_A(x_{it}) \times 1[t = 1] + \alpha_5 \bar{p}_M(x_{it}) \times 1[t = 1] + \varepsilon_{it}$$

with $\bar{p}_K(x_{it}) \equiv \frac{p_K(x_{it}, \pi_1) + p_K(x_{it}, \pi_0)}{2}$. By property of OLS, $\alpha_3 + \alpha_4 \bar{p}_A(x_{it}) + \alpha_5 \bar{p}_M(x_{it})$ provides the best linear predictor of $E(w_{i1} - w_{i0} | \bar{p}_A(x_{it}), \bar{p}_M(x_{it}))$. But according to result (4), this is the same as $E(w_{i1} - w_{i0} | x_{it})$. Therefore, α_3 , α_4 , and α_5 identify the task price changes $\Delta\pi_R$, $\Delta(\pi_A - \pi_R)$, and $\Delta(\pi_M - \pi_R)$, respectively.

Most existing approaches to estimating the Roy model rely on an exclusion restriction or a strong assumption about the distribution of individuals' unobserved characteristics to achieve identification.¹⁷ The method of estimating task price changes (i.e., the changing intercepts in the Roy model) that was derived in Equations (2)–(6) gets by without either of these assumptions (it does need a comparability assumption on the x_{it} —see below). The intuition why this works is that by being interested in wage changes and by essentially first-differencing the earnings equation in (2) and (3), skill levels in tasks cancel out and only workers' relative skills in tasks matter. These relative skills are closely related to the choice probabilities that one can measure in the data.¹⁸

The proposed “regression-on-propensities” approach does however require the ap-

¹⁷See Dahl (2002) and the references therein for examples of parametric and semi-parametric approaches to estimating the Roy model. In Dahl's example of estimating the skill premium across U.S. states, the exclusion restriction is that an individual's state of origin affects his migration probabilities to different states through non-pecuniary motives while it does not affect the potential earnings across states.

¹⁸In the application below I use a parametric and a non-parametric approach to estimating $p_K(x_{it})$ in the first-stage. In the NLSY data, with several continuous worker traits, a multinomial logit model of occupational choice is fitted, while in the Census/ACS data, taken from Acemoglu and Autor (2011), the actual choice frequencies for discrete demographic cells are used.

proximation of the adjustment path in Equation (4). With successively more observations of $p_K(x_{it}, \pi_t)$ within the interval $t = (0, 1)$ one could improve this approximation until it becomes exact. This is the sense in which the specific approach in Equations (2)–(6) is reminiscent of the general result from Heckman and Honoré (1990) that the Roy model is identified with data from multiple markets, that is, with sufficient variation in π_t . Appendix A.3 provides Monte Carlo simulations which indicate that the regression-on-propensities performs well in identifying the correct task prices under different distributional assumptions for the unobservable components of skill.¹⁹

3 Empirical Strategy and Data

3.1 Identification Assumptions

This section discusses the assumptions that need to hold in order to estimate the correct task price changes. It further explains how tasks are empirically approximated by occupation groups and why I focus on males in both datasets.

Empirically, the estimation approach for task prices proposed in Equation (6) requires data on worker characteristics x_{it} that fulfill the following two assumptions:

Assumption 1 (First-stage). *The vector x_{it} predicts workers' task choices $p_K(x_{it}, \pi_t)$ in both periods of time.*

Assumption 2.a (Comparability). *Individuals with the same x_{it} vector are comparable over time. That is, for all $x_{i0}=x_{i1}$ and $\pi_t \in \{\pi_0, \pi_1\}$,*

$$\begin{aligned} p_A(x_{i1}, \pi_t) &= p_A(x_{i0}, \pi_t) \\ p_M(x_{i1}, \pi_t) &= p_M(x_{i0}, \pi_t). \end{aligned}$$

Assumption 1 on the first-stage is an obvious requirement. If the traits x_{it} do not discriminate between workers' task choices sufficiently well, Equation (6) cannot be estimated.

The comparability Assumption 2.a implies that $p_K(x_{it}, \pi_t)$ functions are time-invariant with respect to their x_{it} argument holding constant π_t (this is in fact an abuse of nota-

¹⁹ Another attractive feature of the regression-on-propensities approach is that it is easily derived and carried out for three tasks, as in the current application, and beyond. One just needs the choice probabilities in $t = 0$ and $t = 1$ for the tasks of consideration and plug them as additional regressors into (6).

tion²⁰). If one observes an individual with x_{it} in $t = 1$, his counterfactual employment in tasks in $t = 0$ would have been the employment of an individual with the same x_{it} in $t = 0$. That is, individuals with the same observable characteristics in $t = 0$ and $t = 1$ have the same (counterfactual) employment probabilities in tasks within each period t .²¹

In one of the two datasets that is used, the NLSY, comparability is quite clearly fulfilled. The NLSY features an x_{it} vector with achievement test scores in high-school whose distribution has been virtually stable (in levels and correlations) over time. If there are no worker groups who behave sub-optimally and acquire less of a characteristic that becomes more desirable over time (i.e., decrease their math or verbal test scores), comparability holds in that data.

In the other dataset, the Census/ACS, education-age-region demographic cells are used as components of the x_{it} vector. I will argue that also in this case the correct task prices are likely to be identified. First, previous literature (e.g., Autor, 2014) has shown that males' educational attainment was remarkably slow to respond to differential wage premia, which is reflected in descriptive statistics below. Employment trends across regions were also modest, and aging in the population was mostly driven by birth rates decades earlier and thus unlikely to be affected by RBTC.

Second, inspection of Equation (6) reveals that adding a constant to the regressors does not change the regression coefficients α_4 and α_5 (α_3 is affected, though). This allows for a generalization of the comparability assumption under which the correct relative task prices $\Delta(\pi_A - \pi_R)$ and $\Delta(\pi_M - \pi_R)$, but not the level $\Delta\pi_R$, can still be identified:

Assumption 2.b (Comparability-in-differences). *Differences between individuals i and j with the vectors x_{it} and x_{jt} are comparable over time. That is, for all $x_{i0}=x_{i1}$, $x_{j0}=x_{j1}$, and $\pi_t \in \{\pi_0, \pi_1\}$,*

$$\begin{aligned} p_A(x_{i1}, \pi_t) - p_A(x_{j1}, \pi_t) &= p_A(x_{i0}, \pi_t) - p_A(x_{j0}, \pi_t) \\ p_M(x_{i1}, \pi_t) - p_M(x_{j1}, \pi_t) &= p_M(x_{i0}, \pi_t) - p_M(x_{j0}, \pi_t). \end{aligned}$$

What Assumption 2.b implies economically can be best explained using an example. Suppose workers with different unobservable talent enter a given education group x_{it}

²⁰To be formally correct, for $p_K(x_{it}, \pi_t)$ to differ when the x_{it} are the same but taken from different points in time, one would have to explicitly introduce unobservable skill components or another time index into the propensities. I leave this out in assumptions 2.a and 2.b to keep the notation concise.

²¹Note that Assumption 2.a does not mean that $p_K(x_{it}, \pi_t)$ is time-invariant with respect to π_t holding constant x_{it} . In fact, the probability for a given x_{it} to choose the abstract or the manual task should increase when task prices polarize according to Proposition 2.

over time. The relative task price estimates from such data may still be correct as long as the shifts in counterfactual task propensities that the changes in unobservable talent induce are similar across x_{it} groups. That is, if all x_{it} groups become equally less unobservably inclined toward abstract tasks over time (e.g., because the most talented of a given education group become the least talented of the next higher education group), $p_A(x_{i1}, \pi_t) = p_A(x_{i0}, \pi_t) + c_{A01}$ for all $x_{i0} = x_{i1}$ and $c_{A01} < 0$, and comparability-in-differences for the abstract task is not violated (similarly for the manual task).

Consistent with this, an instrumental variables strategy carried out below, which removes potential unobservable talent selection effects from task propensities, yields very similar task price estimates as the baseline OLS specification. In another robustness check, I directly control for education, age, and region main effects to exploit only the differential variation across demographic cells with the same levels of these variables. Again, the estimated task prices for the joint 1990s and 2000s, which are comparable to the NSLY and long enough for RBTC—if important—to dominate alternative forces, hardly change.

Finally, the aim of the empirical analysis is to assess whether the basic RBTC-Roy model is a good description of the qualitative (returns to appropriately combined x_{it} measures) and quantitative (change in the overall wage distribution) wage trends in the data. Alternative forces that may have driven employment and wages include the skill-biased technical change hypothesis (SBTC), the precursor to RBTC, which states that the demand for skills increased directly over time and affected such quantities as the college wage premium (e.g., [Katz and Murphy, 1992](#)). Another force may be changes in the supply of skills, such as increasing educational attainment, that is not solely transmitted via task prices. In different robustness checks, college dummies and more detailed absolute skill measures are directly included into the regression-on-propensities (6) in order to (partly) remove these alternatives. When this is done in [Section 4.1](#), the results indicate that relative skills in tasks are much more important than absolute skills in accounting for workers' wage growth over the joint 1990s and 2000s.

What cannot be done is to remove other factors than RBTC that may have influenced the task prices. The task prices are general equilibrium outcomes which also depend on the supply of skills (of males or females). They may further be influenced by trade and offshoring of tasks or by consumption spillovers into services (e.g., [Acemoglu and Autor, 2011](#); [Mazzolari and Ragusa, 2013](#)). The identification assumptions spell out the require-

ments for the estimation of the correct task price changes, regardless of the contribution of these respective factors.

In the following I use two samples for which Assumptions 1 and 2.a (or 2.b, respectively) are as close to being fulfilled as possible. The first sample is constructed from the two cohorts of the NLSY, which provide pre-labor market characteristics (“talents”) that are difficult to influence for an individual and which have hardly changed over time (Altonji, Bharadwaj, and Lange, 2012; Speer, 2014). Compared to this, the Census/ACS sample, taken from Acemoglu and Autor (2011), has the advantage that it represents all the age groups from 16 to 64 and that the task price estimation can be done for different (sub-)periods.

The identification assumptions are more plausibly fulfilled for male workers than for females. First, female educational attainment as well as their participation in the labor market have much increased over the last decades. In fact, even for the different test scores, female performance improved noticeably between the two cohorts of the NLSY while male performance remained constant. Therefore, the comparability assumption is more likely to be violated with the available characteristics x_{it} for females than for males. Moreover, female wages rose substantially across-the-board compared to males and some argue that discrimination against them in different high-skill occupations has declined quite drastically (e.g., Hsieh, Hurst, Jones, and Klenow, 2013). Therefore, it is likely that a large part of the returns to characteristics x_{it} is driven by other factors than RBTC and task prices. Finally, the “mechanical” talent does not have a strong and consistent effect on task choice for females in the NLSY cohorts. This data limitation is a problem for the sorting regressions in the first-stage (Assumption 1). For these reasons, the analysis in the main text is restricted to males. Estimates for females are summarized in Appendix B.2.

Throughout the empirical analysis, task choices are measured by the delineation of three broad occupation groups introduced in Acemoglu and Autor (2011). Specifically, Acemoglu and Autor show that high-wage professional, managerial, and technical occupations are intensive in abstract tasks; middle-wage clerical, sales, production, and operator occupations are intensive in routine tasks; and low-wage protective, food, cleaning, and personal service occupations are intensive in non-routine manual tasks.²²

²²As in Acemoglu and Autor (2011), occupations are first converted from their respective scheme into

The [Acemoglu and Autor \(2011\)](#) delineation is used in most subsequent papers on job polarization and RBTC (e.g., [Mishel, Shierholz, and Schmitt, 2013](#); [Beaudry, Green, and Sand, 2013](#); [Cortes, 2014](#); [Autor, 2014](#); [Bárány and Siegel, 2014](#); [Gottschalk, Green, and Sand, 2015](#)).²³ It also has the advantage that it provides a balanced panel of abstract, routine, and manual occupations over time. A limitation of the [Acemoglu and Autor \(2011\)](#) delineation—which it shares with other delineations—is that the occupations are not homogeneous in the tasks that they represent. This implies that in fact the prices for skills in the abstract, routine, and manual occupation groups are estimated and not the “pure” task prices themselves. Another potential limitation, which again faces most of the work in this literature, is that the task content of the occupations as well as the skill content of tasks may have changed over time.²⁴ Keeping these limitations in mind, I refer to the three occupation groups by *abstract*, *routine*, and *manual tasks* in the following.

3.2 The NLSY Sample of 27 Year Old Males

This section introduces the NLSY sample and computes the main facts concerning the distributions of employment and wages therein. Then the talent measures are presented and it is shown that they predict the sorting into abstract, routine, and manual tasks.

The first sample uses data from the two cohorts of the National Longitudinal Survey of Youth (NLSY) and, for comparison, from the Current Population Survey Outgoing Rotation Groups (CPS) over the same period. I focus on 27 year old males in 1984–1992 and 2007–2009 in the NLSY 1979 and 1997, respectively.²⁵

a time-consistent classification. They are then assembled into ten occupation groups, which are further aggregated into an abstract category (professional, managerial, and technician occupations); a routine category (sales, office/admin, production, and operator/labor occupations); and a manual category (protective, food/cleaning, and personal care occupations).

²³[Autor and Dorn \(2013\)](#) use a somewhat different delineation of occupations whereas [Firpo, Fortin, and Lemieux \(2013\)](#) construct their own five-dimensional and continuous task measures including offshorability from data provided by the Occupational Information Network (O*NET).

²⁴[Autor, Levy, and Murnane \(2003\)](#) and [Spitz-Oener \(2006\)](#) provide evidence that the task as well as the skill content of occupations changed over time in the U.S. and in Germany, respectively. Nonetheless, most existing models and empirical work (need to) abstract from this (e.g., [Acemoglu and Autor, 2011](#); [Firpo, Fortin, and Lemieux, 2013](#)).

²⁵The sample selection and attrition weighting for the NLSY data is done closely in line with a recent paper by [Altonji, Bharadwaj, and Lange \(2012\)](#). Since attrition in the NLSY97 is higher and test taking is lower than in the NLSY79, [Altonji, Bharadwaj, and Lange \(2012\)](#) examine it in detail. They conclude that after appropriate sample weighting any potential biases are not forbidding. I do not use the 2010 and 2011 samples of the NLSY97 because wages are substantially lower and less abstract (more manual) tasks are chosen compared to the CPS. Also, the AFQT scores of those members of the 1983–84 birth cohorts who work as 27 year olds in 2010–11 are substantially lower than the AFQT scores of the working 1980–82 birth cohorts. I construct labor supply by hours worked and real hourly wages as in [Lemieux \(2006\)](#). The details

Figure 6 in the Appendix presents the labor market facts of 27 year olds between 1984–1992 and 2007–2009 for the NLSY and the CPS corresponding to Figure 1 in the simulations. Employment polarized substantially during this period (Panel (a)). However, Panel (b) shows that average wages in the manual task hardly increased in the CPS and fell in the NLSY such that wages in tasks did not polarize. As argued above, this could be due to changing selection bias into the manual task even under RBTC and task price polarization. Finally, the overall wage distribution polarized substantially, both in the NLSY and in the CPS (Panel (c)).

The attractiveness of the NLSY data for the purpose of this study is that it provides measures of workers’ early skill determinants (“talents”). These talents are determined pre-entry into the labor market and relatively hard to change for an individual since they are constructed from different components of an aptitude test. As elements of the x_{it} vector, the NLSY talents therefore come as close as possible to fulfilling the comparability Assumption 2.a.²⁶

I construct measures of mathematical, verbal, and mechanical talent by using test scores on mathematics knowledge, the average of paragraph comprehension and word knowledge, and the average of mechanical comprehension and auto- and shop information, respectively, from the components of the Armed Services Vocational Aptitude Battery of tests (ASVAB). A similar definition of talents has been adopted by a couple of subsequent papers on the education and labor market effects of different worker abilities in the NLSY (e.g., Prada and Urzúa, 2014; Speer, 2014).²⁷

of the sample construction can be found in section B.1 of the Appendix. Table 8 in the Appendix accounts for how I end up with a sample of 3,054 and 1,207 individuals in the NLSY79 and the NLSY97, respectively.

²⁶In the NLSY97, for which there might be a concern about the endogenous investment in talents as a response to RBTC, the tests are taken at age 12–16 in 1997. What would be required for a violation of the comparability assumption here is not that more able students generally achieve higher test scores, but that students increase their math and verbal scores, which predict abstract and manual tasks, in response to RBTC already before age 12–16. And, if that’s the case, some students need to do this more systematically than others (comparability has to only hold in differences). While one may debate this possibility, it is also not clear whether high school students and their parents were even aware of the shifts in task demands that were going on by 1997 as, for example, the first academic papers about this phenomenon by Autor, Levy, and Murnane and Goos and Manning were only published in 2003 and 2007, respectively.

²⁷All the measures used here are taken from the ASVAB, which consists of ten components: arithmetic reasoning, word knowledge, paragraph comprehension, mathematics knowledge, general science, numerical operations, coding speed, auto and shop information, mechanical comprehension, and electronics information. The breakup into mathematical, verbal, and mechanical talent is similar to what a factor analysis of the test scores suggests. AFQT is essentially the average of arithmetic reasoning, word knowledge, paragraph comprehension, and mathematics knowledge. The popular non-cognitive skill measures of locus of control and self-esteem, which are used in other papers, have to be left out of my analysis because they are not available in the NLSY97.

Table 1: Pairwise Correlations between Talents, NLSY 1979 and 1997

	NLSY79			NLSY97		
	AFQT	Math	Verbal	AFQT	Math	Verbal
AFQT (NCE)	1			1		
Math Score (NCE)	0.82	1		0.83	1	
Verbal Score (NCE)	0.93	0.71	1	0.92	0.75	1
Mechanical Score (NCE)	0.63	0.53	0.61	0.63	0.54	0.63
Nbr Observations	2,936			1,207		

Notes: The table shows the pairwise correlations between composite test scores after standardizing to normal curve equivalents with mean 50 and standard deviation 21.06.

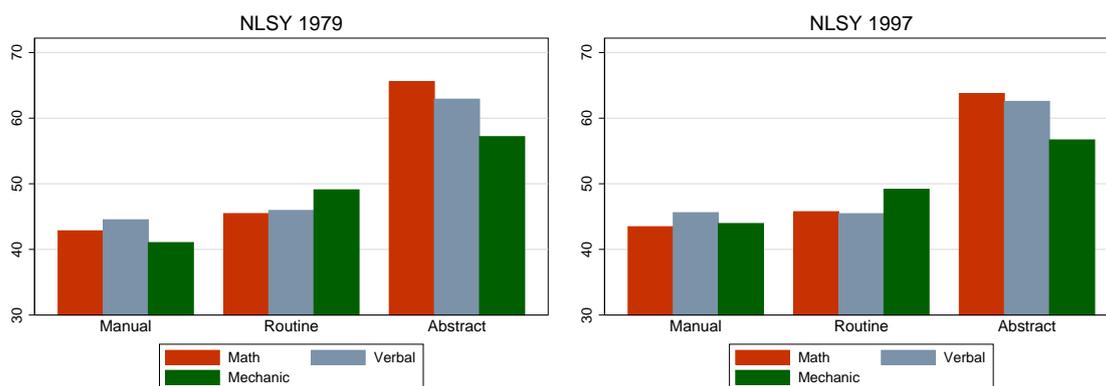
Table 10 in the Appendix presents labor force averages of talents as well as some demographic variables and contemporary skill measures that are available in more standard datasets. One can see that the absolute value of AFQT, which is frequently taken as a proxy for general intelligence, does not change in the male labor force over the two cohorts. In addition, Table 1 reports that the cross-correlation of the composite test scores and AFQT remained virtually the same. Taken together, the two tables show that the joint distribution of talents remained stable over time, which lends support to the comparability assumption 2.a for them as components of the x_{it} vector.²⁸

Figure 2 depicts average mathematical, verbal, and mechanical talent in the three tasks in both cohorts. The levels of the three talents are substantially higher in the abstract task than in the routine task which, in turn, is higher than the manual task. Thus, there is a clear ordering of absolute advantage in tasks independent of the talent considered. However, in the absence of restrictions to enter tasks, workers' choice should be governed by their comparative advantage and thus depend on their relative skills. This principle seems to be borne out in Figure 2. Average mathematical talent in the abstract task is higher than average verbal or mechanical talent, while average mechanical talent is considerably higher in the routine task than mathematical or verbal talent. Verbal talent is higher than mathematical and mechanical talent in the manual task.

To quantify the sorting with respect to the talent measures, Table 11 in the Appendix

²⁸One early determined characteristic that is not constant is the share of Hispanics, which rose by 8 percentage points. I therefore control for race in all analyses. Also, when excluding Hispanics from the dataset, the cross-correlation between talents remains virtually the same in both cohorts while the level of AFQT rises from 168.5 to 169.7 over time. At a standard deviation of 31.4 and 31.7, respectively, this is still small.

Figure 2: Average talents in tasks, NLSY 1979 and 1997



reports the coefficients from a multinomial logit task choice regression. These coefficients extract the marginal effect of an additional unit of each talent on choosing the abstract and manual task relative to the omitted routine task. In the first column, conditional on the other talents, a one unit higher math score is associated with an about 4.7 percent higher probability to enter the abstract versus the routine or the manual task. A one unit higher mechanical score is associated with a 1.4 and 2.3 percent lower probability to enter the abstract and the manual task as opposed to the routine task, respectively. In contrast, a one unit higher verbal score decreases the probability to enter the routine as opposed to the abstract or the manual task by about two percent. The results are similar in the NLSY97 in column three of the table.²⁹

3.3 The Census/ACS Sample from Acemoglu and Autor (2011)

This section introduces the Census/ACS sample, reports descriptive statistics, and compares it to the NLSY sample.

The second sample used for the empirical analysis is from Acemoglu and Autor (2011)'s chapter in the Handbook of Labor Economics. In particular, in section 5 of their paper, Acemoglu and Autor construct a dataset of 16 to 64 year old workers from the Census / American Community Survey (ACS), which they split into demographic cells

²⁹The regressions in columns two and four of Table 11 are run for creating the propensities to enter tasks based on observables which are used in wage regressions that follow. The test scores are split into terciles in order to also allow for polarization in the demand for skill levels as suggested by one-dimensional skill models. Moreover, normalized measures of illicit activities and engagement in precocious sex are added.

indexed by education, age, and region.³⁰ They then examine the wage changes of the demographic cells in relation to their initial specializations in abstract, routine, and manual tasks in 1959 separately by gender and by decade. I focus on [Acemoglu and Autor](#)'s data for males in the main text, while the results for females are summarized in Appendix B.2. The labor market facts in these Census/ACS data are qualitatively similar to the ones plotted in Appendix Figure 6 for the NLSY.³¹

The data from [Acemoglu and Autor \(2011\)](#) is an attractive complement to the NLSY sample for the task price estimation because it alleviates a couple of concerns that one might have with the NLSY. In the NLSY sample the analysis is conducted for the periods 1984–1992 versus 2007–2009. This may confound the effect of RBTC with the business cycle, as the years 2008 and 2009 are part of the great recession. In contrast, in the [Acemoglu and Autor \(2011\)](#) Census/ACS data, the task price changes can be estimated for the comparable period 1989–2007 as well as the separate sub-periods 1979–1989, 1989–1999, 1999–2007. Another relative concern in the NLSY data is that its analysis is based on the specific age group of 27 year olds who are observed in differing time spans (1984–1992 for the NLSY79 and 2007–2009 for the NLSY97). Using the Census/ACS data, I can examine a large and representative sample of all workers age 16–64 for every respective point in time and compare the results.

The identifying variation in the Census/ACS data are average abstract and manual task propensities for 80 demographic cells, which, due to the large sample size, can be computed non-parametrically as simple cell averages. Appendix Table 12 reports for each sample year the shares among male employment of the underlying interacted five education, four region, and four age groups. The table shows that male workers' educational attainment rises, that they are aging, and that they are moving to the South and West over time. However, the regional and especially the educational trends appear quite

³⁰Data are downloaded from David Autor's website <http://economics.mit.edu/faculty/dautor/data/acemoglu>, accessed 2014-12-15. Individuals need to report having worked last year but military and agricultural workers are excluded. Occupations are aggregated to be consistent over time and grouped into three broad categories (abstract, routine, and manual) exactly as explained above.

³¹Figure 13c in [Acemoglu and Autor \(2011\)](#)'s paper shows that there was job polarization among males in the Census/ACS data during 1989–2007. I reproduce this finding in my own computations (unreported). I further find that wages in the manual and the routine task stagnate during 1989–2007, while wages in the abstract task rise strongly. Therefore, there is again no clear evidence of wage polarization in tasks. Figure 9 in [Acemoglu and Autor \(2011\)](#) shows that hourly wages polarized in an additional sample that they construct from the CPS ORG during 1988–2008. [Acemoglu and Autor \(2011\)](#)'s Figure 9b is reproduced in Panel (b) of Figure 3 below, and it is qualitatively comparable to the bottom panel of Figure 6 for 27 year olds in the NLSY data.

modest after 1989, which is consistent with the findings in Autor (2014), among others, that young males' educational attainment has increased remarkably little since the 1980s. The changing overall age structure is predetermined by birth rates decades earlier and hardly a reaction to RBTC. Therefore, these moderate trends may not indicate a critical violation of the comparability-in-differences assumption, especially for the estimation periods after 1989. In robustness checks, I use an instrumental variables strategy to extract some arguably unconfounded variation in task propensities and I directly control for main effects, exploiting only the differential variation in task propensities and wage growth across demographic cells with the same levels of education, age, and region.

To conclude, while the Census/ACS sample has a couple of advantages over the NLSY, it comes at the cost that the argument for comparability is more involved. If the NLSY and the Census/ACS samples with their different strengths and weaknesses lead to similar task price estimates, this should increase confidence in the empirical results below.

4 Results

4.1 Workers' Wage Growth in the NLSY over the 1990s and 2000s

Before estimating the task price changes, this section examines workers' wage growth by initial task specialization in the NLSY sample. Supportive of RBTC, routine workers' wage growth is lagging behind abstract and manual task workers' wage growth. Acemoglu and Autor (2011) do a related analysis in the Census/ACS sample and they obtain largely similar results (for details see footnote 33).

Proposition 5 states that workers who start out in routine tasks will see their relative wages decline under task price polarization, which directly motivates a reduced form regression of the form:

$$w_{it} = \alpha_0 + \alpha_1 p_A(x_{it}, 0) + \alpha_2 p_M(x_{it}, 0) + \lambda_{it} + \alpha_3 \times 1[t = 1] + \alpha_4 p_A(x_{it}, 0) \times 1[t = 1] + \alpha_5 p_M(x_{it}, 0) \times 1[t = 1] + \lambda_{it} \times 1[t = 1] + \varepsilon_{it} \quad (7)$$

This regression differs from the regression-on-propensities approach (6) for estimating task prices in that it uses only the period $t = 0$ task choice probabilities. In addition, λ_{it}

can be added to the “baseline specification” to control for alternative factors than RBTC that may have shifted wages for different workers. The two identification assumptions, first-stage and comparability, need to hold in order for the parameters α_4 and α_5 to identify the changing returns to initial propensities of working in the abstract and manual tasks as opposed to the routine task. According to theoretical Proposition 5, at least one of these parameters should be positive.

The task choice propensities in Equation (7) have to be estimated in a first-stage. This is done here running a multinomial logit regression as discussed in Section 3.2 and presented in column two of Table 11 in the Appendix. Multinomial probit or linear probability models give similar results. The predicted values, that is, the second-stage regressors, are remarkably stable over the two cohorts of the NLSY (explicitly reported only in previous versions of this paper). This supports the comparability Assumption 2.a, as labor supply into tasks according to observables remained largely unchanged.

Table 2 displays the results from the second stage regression on task propensities (7). The first-stage multinomial choice regression and the second stage wage regression are bootstrapped in order to obtain the correct standard errors given that $p_A(x_{it}, 0)$ and $p_M(x_{it}, 0)$ are estimates with sampling variation. Unsurprisingly, in column one a higher propensity to enter the abstract task compared to the omitted routine task is associated with a significantly higher wage. The reverse is true for the propensity to enter the manual task. RBTC should however change the returns to propensities over time, which are indicated in the table by “x NLSY97”. Indeed the coefficients change strongly and significantly in the direction predicted by theoretical Proposition 5. For the propensity to enter the abstract task, the coefficient almost doubles (from .31 to .60) while the coefficient for entering the manual task rises by more than a third (from -1.65 to $-.95$).³²

Column two of Table 2 adds to the first-stage task choice regression a dummy for whether the individual completed a four year college or more. On top of the talents, this contemporary skill determinant does not alter the conclusions about the changing returns to task propensities between the two NLSYs. The results are similar if more detailed education dummies are added in the first-stage.

One concern for the returns to task propensities estimates in Table 2 is that other

³²Previous versions of this paper (e.g., Boehm, 2013) included a figure showing that for individuals with a high propensity to enter the routine task, which is quite frequent in the data, predicted real wages even decline during the two decades between the NLSY79 and the NLSY97.

Table 2: Returns to NLSY79 Task Propensities over Time

	(1)	(2)	(3)	(4)
	Log Wage	Log Wage	Log Wage	Log Wage
Propensity Abstract Task	0.31 (0.07)	0.35 (0.05)	0.03 (0.08)	-0.06 (0.08)
Propensity Abstract Task x NLSY97	0.29 (0.11)	0.27 (0.10)	0.25 (0.13)	0.30 (0.13)
Propensity Manual Task	-1.65 (0.17)	-1.64 (0.16)	-1.80 (0.17)	-1.75 (0.17)
Propensity Manual Task x NLSY97	0.70 (0.39)	0.83 (0.38)	0.86 (0.38)	0.91 (0.38)
College			19.23 (2.92)	
College x NLSY97			4.04 (5.20)	
Observations	4154	4149	4149	4149
R^2	0.09	0.11	0.11	0.12
College 1st-stage	No	Yes	No	No
Degree dummies	No	No	No	Yes

Notes: The table reports OLS wage regressions of 100 times the deflated log wage on predicted propensities to enter tasks. The propensities are estimated from the NLSY79 only according to column two in Table 11. "x NLSY97" stands for the change in the coefficient between the NLSY79 and the NLSY97. Bootstrapped standard errors (500 iterations) below the coefficients.

forces than RBTC may have driven the returns to task propensities. First, the returns to skills in general and the returns to college in particular may have increased due to skill-biased technical change (SBTC). Moreover, workers with a specific talent vector x_{it} might have adjusted their formal skills in response to RBTC—possibly as part of a switch in tasks. Such a change in educational attainment, whether endogenous or not, could command direct returns in the labor market.

The remaining columns of Table 2 control for these potential forces by directly adding education measures as λ_{it} into the baseline specification (7). Column three includes in the wage regression a dummy for whether the individual completed a four-year college or more. On the one hand, the level of the coefficient on the propensity to enter the abstract task drops all the way to zero, but the changes in both coefficients are remarkably stable. On the other hand, the level of the return to college is large and highly significant, while its change does not significantly increase once the propensities are accounted for. The result is similar when I control for four different degree dummies (high school dropout and graduate, some college, and at least four year college) in column four.

This suggests that Mincerian returns to education are important to explain wages in the cross-section, but that they seem to have less power than relative skills in tasks to explain the change in wages that took place over the twenty years from the NLSY79 to the NLSY97. The task model, and RBTC in particular, are therefore supported by the results in Table 2.³³

4.2 Task Price Estimates

This section estimates the task price changes in the NLSY and the Census/ACS sample. Consistent with RBTC, task prices polarize over the joint 1990s and 2000s.

³³Acemoglu and Autor (2011) conduct a similar analysis to the one reported in Table 2 in the Census/ACS sample. The difference is that they estimate a first-differenced version of (7) using the demographic cells' initial task specialization in 1959 for all subsequent decadal changes instead of the predicted propensities at the beginning of the period that is analyzed. Results for males reported in the first column of their Table 10 show that the relative returns specializing in the abstract and manual (service) tasks have been increasing in the Census/ACS since the 1980s while the intercept (i.e., the routine task) declined. In the second column of their table, Acemoglu and Autor control for main effects of education, age, and region. As in the NLSY, the results on the returns to task specialization in the sample remain largely unchanged by this addition.

4.2.1 The NLSY Sample

The task prices changes are estimated from the regression-on-propensities (6), a version of which is reproduced here:

$$w_{it} = \alpha_0 + \alpha_1 \bar{p}_A(x_{it}) + \alpha_2 \bar{p}_M(x_{it}) + \lambda_{it} + \alpha_3 \times 1[t = 1] + \alpha_4 \bar{p}_A(x_{it}) \times 1[t = 1] + \alpha_5 \bar{p}_M(x_{it}) \times 1[t = 1] + \lambda_{it} \times 1[t = 1] + \varepsilon_{it} \quad (8)$$

As in regression (7), the first-stage propensities are estimated in a multinomial logit model and λ_{it} can be included in the equation to account for factors whose returns might have changed other than via the task prices. The whole procedure is again bootstrapped to obtain the correct standard errors for the second-stage estimates.

Table 3 reports the resulting task price estimates in the NLSY data. The equilibrium prices being paid for tasks have changed substantially between the two NLSYs. According to the baseline specification in the first row of Table 3, the relative prices for the abstract and manual task increased by 25 and 33 log points, respectively, while the absolute price of the routine task decreased by 4 log points. Task prices therefore polarized between the two cohorts of the NLSY with the qualification that the estimate for the manual task price is insignificant.

The remaining rows of Table 3 examine the robustness of this result. In rows two and three, college dummies are added to the first and the second stage of the baseline specification similar to columns two and three of Table 2. The task price estimates are qualitatively the same with the relative price of the abstract task somewhat decreasing and the relative price of the manual task somewhat increasing compared to row one. The task price polarization result therefore persists when controlling for a potential violation of the comparability assumption and for alternative forces than RBTC, respectively.³⁴

In row four of Table 3 the task price changes from an optimal minimum distance (OMD) estimation are reported. Intuitively, the OMD is derived from the fact that the theoretical result (5) holds for every component of the x_{it} vector separately and thus constitutes a moment condition of the RBTC-Roy model (for details refer to Boehm, 2013). An advantage of the OMD estimate is that it does not suffer from potentially incorrect

³⁴See discussion in Sections 3.1 and 4.1. Adding education dummies as in column four of Table 2 gives similar task price estimates.

Table 3: Estimated Task Price Changes in the NLSY (1984/92 to 2007/09)

	$\Delta(\pi_A - \pi_R)$ in log points (s.e.)	$\Delta(\pi_M - \pi_R)$ in log points (s.e.)	$\Delta\pi_R$ in log points (s.e.)	Model Test (p-value in %)
OLS on Propensities	25.1 (12.3)	32.9 (38.4)	-4.2 (7.7)	
OLS on Propensities (1st-stage college)	22.9 (10.9)	41.3 (38.6)	-5.3 (7.8)	
OLS on Propensities (2nd-stage college)	19.5 (13.7)	46.6 (37.9)	-6.4 (7.8)	
Opt. Min. Distance	20.2 (6.6)	38.9 (26.4)	-3.2 (3.3)	12.3 (13.8)
OLS on Propensities (Adj. for min. wage)	27.3 (12.7)	32.0 (40.0)	-5.7 (8.0)	

Notes: The first row of the table presents estimated task price changes for the baseline regression-on-propensities (8). The second and third row add college dummies in the first- and second-stage of the estimation, respectively. The next row reports the task price changes from a minimum distance estimation explained in detail in previous versions of this paper (i.e., [Boehm, 2013](#)). This estimation approach also provides a test of the restrictions on talent returns implied by comparability and the RBTC-Roy model. The last row reports baseline estimates when wages are first adjusted for the change in the real value of the minimum wage as in [Lee \(1999\)](#). Bootstrapped standard errors (500 iterations) below the coefficients.

standard errors or attenuation bias due to sampling variation in the first-stage estimates $\hat{p}_K(x_{it}, \pi_t)$. The (asymptotic) standard errors are lower due to its optimality. Reassuringly, the point estimates in row four of Table 3 are similar to those in the previous rows.³⁵ The estimate for the change in the manual task price is now close to significant at the ten percent level.³⁶

Finally, one could be concerned about another another force that might have worked aside from RBTC and confounded the task price estimates: the increase in the real value of the minimum wage in the U.S. between the end of the 1980s and the end of the 2000s. This may have raised the wages in the lower end of the distribution as depicted in the bottom panel of Appendix Figure 6 and, since the manual task workers are more frequently found in this lower end, it may distort the task price estimates. I account for this effect by constructing adjusted wages that would prevail in the absence of a change

³⁵The estimates are different from the ones reported in [Boehm \(2013\)](#), as an intercept was included to be consistent with the other specifications of Tables 3 and 4. Attenuation bias due to sampling variation in the regressors is also not detectable in the Monte Carlo simulations in Appendix A.3.

³⁶The OMD also provides an overidentifying restrictions test (“J-test”) of the moment conditions implied by the empirical model. This includes the identification assumption of comparability. The test statistic and the p-value are reported in the last column of row four. The model is not rejected at conventional significance levels.

in the real minimum wage following Lee (1999).³⁷

The wage distribution for 27 year olds in the NLSY and the CPS is now substantially flatter in the bottom than without the adjustment (compare the solid lines in Figures 3 and 4 below). Row five of Table 3 presents the results from the task price estimation with the minimum wage adjustment. The price estimates remain similar to the preceding rows, which further strengthens the evidence that task prices polarized between the times when the members of the NLSY79 and the NLSY97 were 27 years old.

4.2.2 The Census/ACS Sample

This section estimates the task price changes for all males in the Census/ACS over the joint 1990s and 2000s, and additionally by decade.

Panel A in Table 4 reports task price estimates under the same baseline specification as in row one of Table 3. During the 1980s (1979–1989), the prices for the routine as well as the manual tasks declined substantially while the price for the abstract task increased. In contrast, during the 1990s, manual task prices increased strongly and overall task prices polarized. The trend then reversed in the 2000s before the great recession (1999–2007), when only the price for the abstract task rose. This is in line with the findings in the literature that, despite strong employment gains in the manual task, the bottom of the wage distribution did not rise during this period (Acemoglu and Autor, 2011; Mishel, Shierholz, and Schmitt, 2013).

The last row of Panel A reports the results for the joint 1990s and early 2000s (1989–2007), which is broadly comparable to the period examined in the NLSY sample without the great recession part. During that period, task prices overall polarized substantially and by about one third more strongly than in the NLSY sample. That the effect is stronger

³⁷In order to generate wages in the face of a minimum wage at its 1989 level, I apply the method to compute the counterfactual from Lee (1999) together with the estimates of the effect of the minimum wage therein. Define the deflated minimum wage $\widetilde{mw}_t = (\text{minwage}_t - \bar{w}_t^t)$ as the minimum wage in t adjusted by the trimmed mean wage in the population where the bottom and top 30 percent of wages are removed (everything in logs). Then, analogous to Equation (9) in Lee (1999), the amount

$$\Delta_{p,t} = \hat{\beta}_p(\widetilde{mw}_{1989} - \widetilde{mw}_t) + \hat{\gamma}_p(\widetilde{mw}_{1989}^2 - \widetilde{mw}_t^2)$$

is added to a worker's wage in time t , where p denotes the worker's wage percentile, and $\hat{\beta}_p, \hat{\gamma}_p$ the estimated coefficients for the effect on each quantile reported in Lee's Table 1, Panel A, column (5). Coefficients for the percentiles below the 10th and between the 10th and the 50th are linearly imputed. From the 50th percentile upward wages remain unadjusted as in Lee's paper. For example in the NLSY data, $\widetilde{mw}_{1989} = \log(3.35) - 2.103$ where 3.35 is the nominal minimum wage in 1989 and 2.103 the trimmed mean log wage among 27 year old males in that year.

Table 4: Estimated Task Price Changes in the Census/ACS (Different Periods)

		$\Delta(\pi_A - \pi_R)$ in log points (s.e.)	$\Delta(\pi_M - \pi_R)$ in log points (s.e.)	$\Delta\pi_R$ in log points (s.e.)
Panel A: OLS on Demogr. Cells (Baseline)	1979-1989	30.5 (4.6)	-1.2 (17.9)	-16.8 (3.2)
	1989-1999	17.6 (3.4)	54.2 (13.2)	-8.5 (3.3)
	1999-2007	14.1 (2.8)	-15.0 (10.0)	-8.7 (2.2)
	1989-2007	33.6 (3.2)	41.3 (11.2)	-19.0 (2.4)
Panel B: OLS on Demogr. Cells (IV using 1959&69 Propnsts)	1979-1989	36.1 (4.8)	21.9 (19.2)	-20.9 (3.4)
	1989-1999	16.5 (3.8)	51.6 (14.7)	-7.9 (2.7)
	1999-2007	15.2 (3.1)	-10.3 (11.4)	-9.7 (2.5)
	1989-2007	33.6 (3.4)	43.2 (12.8)	-19.2 (2.7)
Panel C: OLS on Demogr. Cells (Educ, Age, Region Cntrls)	1979-1989	3.5 (19.9)	25.2 (21.4)	-18.1 (5.7)
	1989-1999	23.8 (14.9)	23.8 (15.7)	-3.8 (4.7)
	1999-2007	12.9 (8.2)	32.0 (10.0)	-23.0 (3.3)
	1989-2007	42.3 (16.0)	49.8 (19.0)	-25.4 (6.2)
Panel D: OLS on Demogr. Cells (Adj. for min. wage)	1979-1989	40.1 (4.5)	82.6 (17.5)	-26.9 (3.1)
	1989-1999	16.4 (3.4)	42.0 (12.7)	-7.1 (2.5)
	1999-2007	14.7 (2.8)	-9.9 (10.0)	-9.5 (2.2)
	1989-2007	33.0 (3.2)	34.3 (11.0)	-18.1 (2.4)

Notes: Panel A of the table presents estimated task price changes for the baseline regression-on-propensities (8) in different time periods. Panel B instruments the task propensities with their values from before the sample period (1959 and 1969). Panel C adds main effects for education, age, and region categories. Panel D reports baseline estimates when wages are first adjusted for the change in the real value of the minimum wage as in Lee (1999). Standard errors in parentheses next to the coefficients.

for the Census/ACS seems plausible, since the on average more experienced workers in that sample are probably less able to adjust their tasks than the young workers in the NLSY. In addition, the effects on all task prices are now clearly statistically significant.

If the comparability-in-differences Assumption 2.b were violated in Panel A of Table 4, the changing unobservable talent selection into a given education-age-region cell would lead to counterfactual task propensities that deviate systematically from the actual task propensities that they are supposed to capture. The instrumental variables estimation in Panel B extracts good variation from the task propensities, removing some potential bad variation that is due to changing selection of unobservable talent into education-age-region cells. Practically, I instrument for all $p_K(x_{it}, \pi_t)$ using occupational propensities in the periods before the estimation sample (1959 and 1969), which leads to regressors entering estimation equation (8) that contain the time-invariant comparative advantage of x_{it} cells in the abstract and manual tasks.³⁸ With the exception of the manual task in the 1980s, the task prices in Table 4, Panel B are very close to those in Panel A. This suggests that differentially changing unobservables selection into education-age-region cells does not play a large role in the estimates of Panel A, and that comparability-in-differences is not critically violated in the Census/ACS data.

Panel C of Table 4 reports a different robustness check for the task price estimates, controlling for education, age, and region main effects. The identifying variation that is left with these controls are the differential task propensities across demographic cells for given levels of education, age, and region. Therefore, this specification removes violations of the comparability-in-differences assumption that occur due to overall shifts in the demographic composition of the population. It also removes the effects of alternative forces to RBTC that are based on directly changing supply or demand for specific education, age, or region groups.

³⁸For example, in the case of the abstract task under $t = 0$ prices, a violation of assumption 2.b implies that $p_A(x_{i1}, \pi_0) = p_A(x_{i0}, \pi_0) + c_{A01} + g(x_{i0}, x_{i1})$, where $g(\cdot)$ is a mean-zero non-constant function. Further, the RBTC-Roy model predicts that when the abstract task price increases from $t = 0$ to $t = 1$, workers with a given x_{it} should become more likely to enter that task (this is a simplification—see Proposition 2). Formally, $p_A(x_{it}, \pi_1) = f(p_A(x_{it}, \pi_0))$, with $f'(\cdot) \geq 0$. Assuming $f(\cdot)$ to be approximately linear obtains the actual $t = 1$ task propensity as a weighted sum of the actual $t = 0$ task propensity and a systematic error due to changing unobservable talent selection into x_{it} over time,

$$p_A(x_{i1}, \pi_1) \approx \phi_1 + \phi_2 p_A(x_{i0}, \pi_0) + \phi_3 g(x_{i0}, x_{i1}) \text{ with } \phi_2 \geq 0.$$

The instrumental variables estimation in Panel B of Table 4 extracts good variation $\hat{\phi}_1 + \hat{\phi}_2 p_A(x_{i0}, \pi_0)$ from the propensity $p_A(x_{i1}, \pi_1)$, removing some of the $\phi_3 g(x_{i0}, x_{i1})$ variation that is due to changing selection of unobservable talent into education-age-region cells.

A limitation of this specification is that, with the main effects included, there is not a lot of variation remaining for identification. This is reflected in the first three rows of Panel C, where the relative task prices are insignificant for all but one of the decadal changes (qualitatively, task prices still polarize during the 1990s). However, it is supportive of Panels A and B that the task price estimates for the long period of 1989–2007, where the impact of RBTC should dominate alternative forces in the data, are similar and remain statistically significant. Consistent with these arguments, a Hausman test does not reject the restricted estimation model (Panel A) against the unrestricted model (Panel C) in any of the four periods (details available upon request).

Finally, Panel D of Table 4 reports the task price estimates when wages are adjusted for the increase in the real value of the minimum wage analogous to row five in Table 3. As in that latter table, the adjustment for the real value of the minimum wage does not have a large effect on the task price estimates for the 1990s and 2000s. The only difference is the changing and high increase of the manual task price during the 1980s. This may be related to Lee (1999)'s finding that the wage distribution (for males and females) would have polarized during the 1980s without the decline in the real value of the minimum wage.

More generally, the task price estimates for the 1980s are quite sensitive to the different specifications in Panels A–D of Table 4. This could be due to a couple of forces that may have compromised comparability-in-differences or worked aside from RBTC during that period. First, the substantial decline in the real value of the minimum wage seems to be responsible for the difference between Panels A and D. In addition, previous literature has found a strong influence of SBTC on wages and a rapidly rising college premium during the 1980s (e.g., Katz and Murphy, 1992). This may have affected the labor market separate from RBTC, leading to the difference between Panels A and C. Educational attainment also rose rather substantially during the 1980s (see Appendix Table 12). This may have changed the unobservable talent composition within education-age-region cells and affected the comparison between Panels A and B.

Overall, there exists robust evidence for task price polarization over the joint 1990s and 2000s in two different U.S. datasets.³⁹ This result substantiates RBTC's importance

³⁹In a recent paper using the Panel Study of Income Dynamics (PSID), Cortes (2014) estimates a longitudinal model of wages with fixed effects by year for the abstract and routine tasks, which, under some assumptions, can be interpreted as task prices relative to the omitted manual task. Reading off his Figure 5,

during that period beyond the existing, and at first glance partly contradicting, evidence on employment and wages (discussion in Section 2.2). It also lends support to the estimation method for task prices, which derives its identification from the interplay between workers' sorting into tasks and their wage growth.

4.3 The Task Prices' Effect on the Overall Wage Distribution

One of the most debated questions in the literature on inequality is to what extent the demand for skills and tasks, the supply of skills, and policy factors have been responsible for the polarization of the U.S. wage distribution over the last couple of decades. This last section shows that task prices may have caused a large part of these developments, with the minimum wage playing an additional role for younger workers.

I assess the effect of task prices on the overall wage distribution by assigning every worker the respective task price estimates from the NLSY and the Census/ACS:

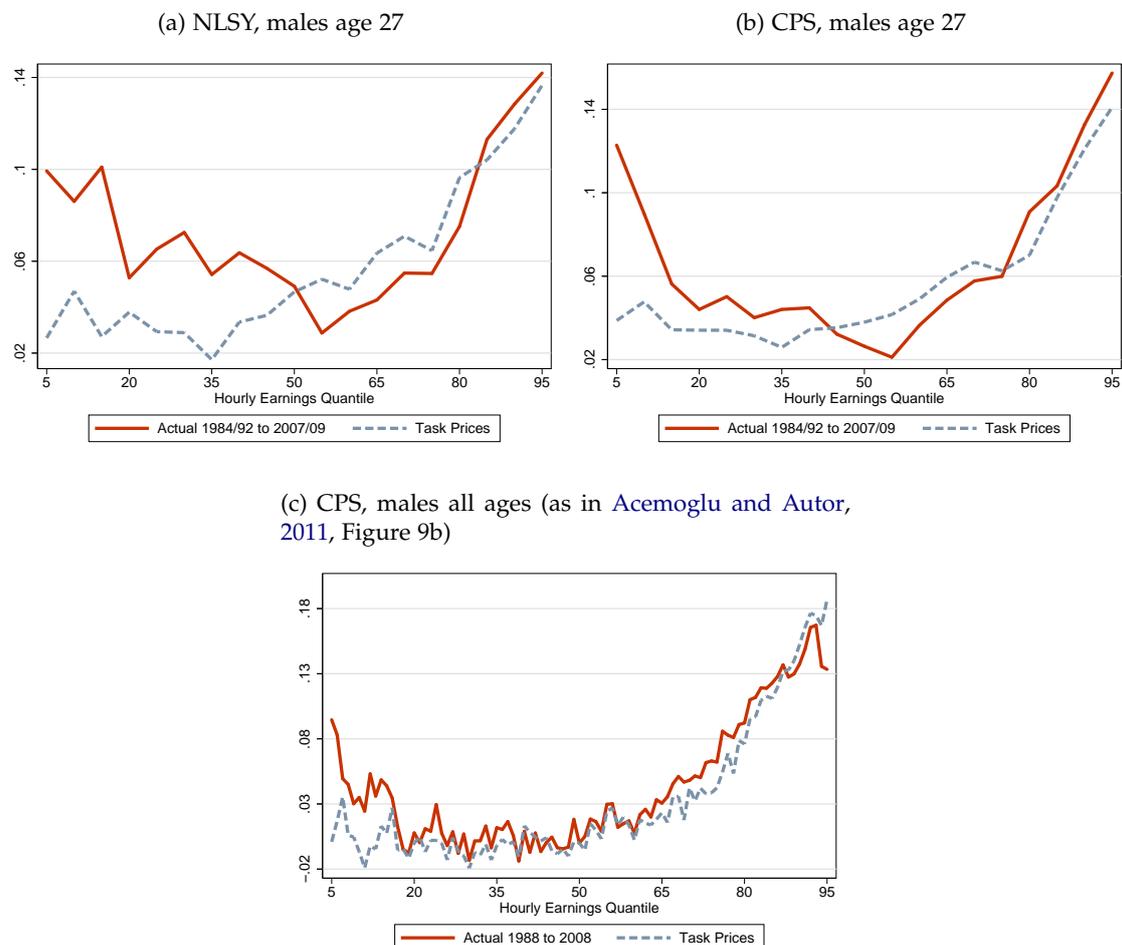
$$\widehat{w}_{i1}^{TP} = w_{i0} + \widehat{\Delta\pi_R} + I_{Ai0}\widehat{\Delta(\pi_A - \pi_R)} + I_{Mi0}\widehat{\Delta(\pi_M - \pi_R)}$$

The predicted wage \widehat{w}_{i1}^{TP} captures the effect of the task prices only. Within the RBTC-Roy model, the other factors that may affect wages are shifts in skill endowments and the wage effects of workers' task switching in response to the task price changes (to assess the latter effect, the entire distribution of skills would have to be known). Outside the RBTC-Roy model, factors that could have affected wages include SBTC and policy or institutional variables such as changes in the minimum wage. The results so far suggest that SBTC and changing skill supply are not too important in explaining workers' wage growth conditional on skills in tasks, and that adjustments for the minimum wage do not affect the task price estimates. Nonetheless, it is unclear ex ante whether the task prices by themselves can account for any substantial portion of the evolution of U.S. wage inequality.

The top row of Figure 3 plots the predicted change in the wage distribution (the quantiles of the distribution of \widehat{w}_{i1}^{TP} minus the respective quantiles of the distribution of w_{i0}) together with the actual change in the wage distribution (" w_{i1} minus w_{i0} ") for 27

the abstract fixed effect rises by about 15 log points and the routine fixed effect falls by about 15 log points from the end of the 1980s to 2007. Thus, the PSID data also suggests that task prices polarized during this period.

Figure 3: Change in log real wages by quantile of the wage distribution, actual and predicted due to changing task prices



year olds in the NLSY and the CPS. The task price changes used in the predicted wage distribution are from the baseline specification in Table 3 for the NLSY (the specifications in rows 2–4 yield similar predicted wage distributions). One sees that the predicted wage distribution matches well the rise of the actual wage distribution in its upper half. However, it cannot account for much of the polarization of the actual wage distribution in its lower half.

In contrast, for males of all ages, the fit between the predicted and the actual is remarkably good almost everywhere in the distribution. In the bottom panel of Figure 3, I use the task price estimates from the baseline specification in Table 4 to plot the predicted wage distribution into Figure 9b of Acemoglu and Autor’s Handbook chapter (Figure 9b uses CPS data for males of all ages and the period is 1988–2008 while the task

price estimates are from the Census/ACS for 1989–2007). The resulting predicted wage distribution closely follows the actual at the top, in the middle, and almost to the lower end of the distribution. Only at the very bottom is the predicted wage distribution again lower than the actual as for the 27 year olds.⁴⁰

The reason why the predicted wage distribution hardly rises at the bottom, despite a strong increase in the manual task price (33 percent for 27 year olds, 41 percent for all ages), is the “overtaking effect”. This was theoretically discussed in relation to Proposition 4: manual task workers, who are predominantly located at the bottom of the wage distribution, move up under the new task prices. This lifts not only the low quantiles where the manual task workers start out, but also the more middling quantiles of the wage distribution where they end up. The inverse happens for workers in routine tasks with the same effect on the wage distribution. This effect only exists in a truly multidimensional skill model. Figure 7 in the Appendix illustrates it, by plotting the predicted wage distribution when workers are fixed at their original quantiles so that overtaking is shut down. The increase is now weaker at the top and stronger at the bottom, since overtaking compounds the increase of wages in the upper half and weakens the increase of wages in the lower half of the distribution when task prices polarize.⁴¹

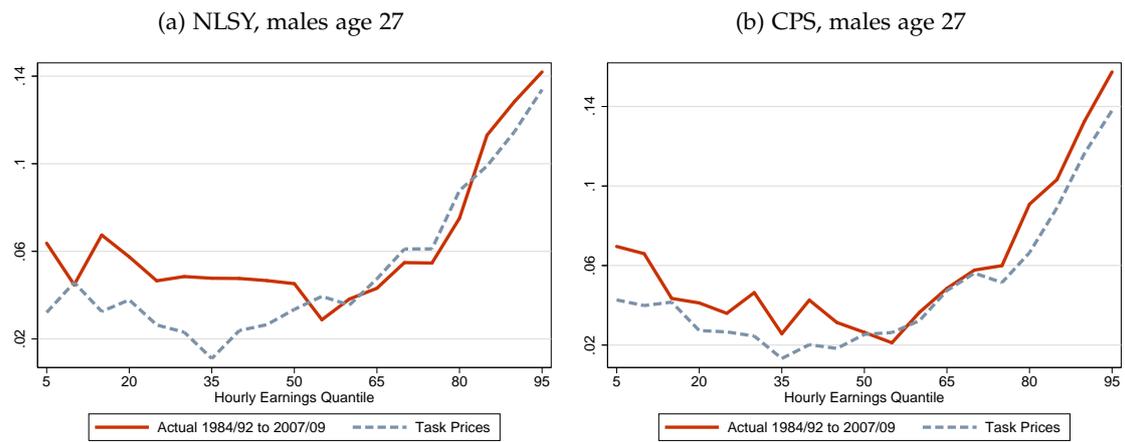
One factor that works apart from the task prices and that may have lifted the bottom of the wage distribution, particularly for the relatively young 27 year old workers, is the minimum wage. Figure 4 plots the actual and the predicted distribution when wages are adjusted for the change in the real value of the minimum wage as in Section 4.2 and the task price estimates are taken from row 5 of Table 3 and Panel C of Table 4, accordingly. The fit in the bottom of the wage distribution for 27 year olds is now substantially better. In the CPS, apart from a modest difference in levels, the polarization in the lower as well as the upper half of the predicted and the actual wage distribution are now comparable. In the NLSY, the difference is much reduced. The fit for males of all ages is also even slightly better (Figure 4, Panel (c)).

Finally, the task prices’ contribution to the evolution of the wage distribution can also be examined by decade. Using the estimates from the Census/ACS sample for the sub-

⁴⁰Using the estimates in Table 4, Panel C, the predicted wage distribution increases more strongly at the very top, but is otherwise similar.

⁴¹Note that overtaking not only exists when workers keep their original tasks (as in this section), but that it may also be substantial when one allows for the wage effects of switching tasks (as in Figure 1 Panel (f)).

Figure 4: Actual and predicted change in the wage distribution, adjusted for minimum wage



(c) CPS, males all ages (as in Acemoglu and Autor, 2011, Figure 9b)

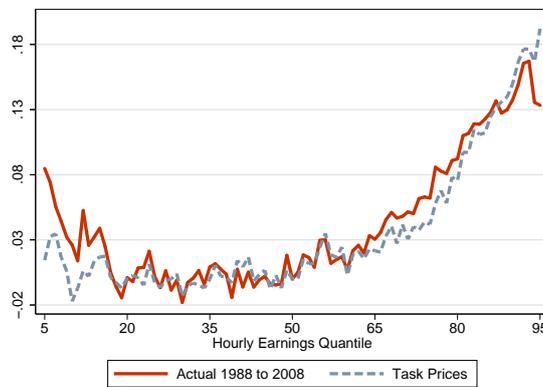
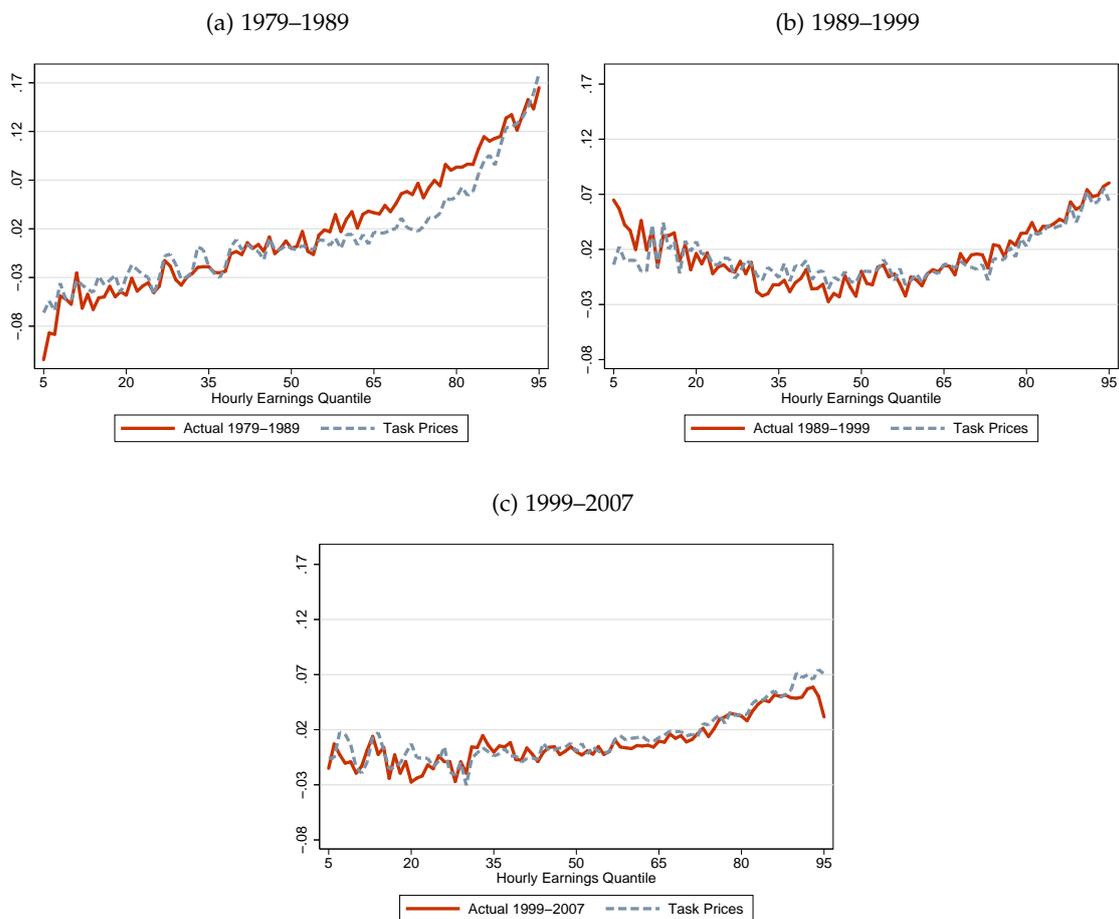


Figure 5: Actual and predicted change in the wage distribution by decade, CPS data for males of all ages from Acemoglu and Autor (2011)



periods in Panel A of Table 4, I plot the actual and the predicted distributions for all males in 1979–1989, 1989–1999, and 1999–2007. During the 1980s, the fit is decent (Figure 5, Panel (a)). Inequality rises across-the-board in the predicted as well as the actual wage distribution, with the predicted dropping less in the very bottom and rising somewhat less between the 50th to 90th percentile.

During the 1990s and the 2000s, the fit is very good. In both the actual and the predicted distribution, wages are polarizing in the 1990s and the two lines essentially overlap everywhere except the very bottom. In 1999–2007, both, the actual and the predicted wage distribution, are largely flat up to the 60th percentile, after which they grow continuously together. Therefore, the task prices by themselves do well in explaining the polarization of the wage distribution by decade and overall during the 1990s and 2000s

before the great recession. This seems even more remarkable given that the task prices are estimated in a different dataset (Census/ACS) than the one in which their predicted effect is computed (CPS).

To summarize, the empirical findings in Section 4 are strongly supportive of the task approach to explaining wage inequality and of RBTC during the joint 1990s and 2000s. First, the returns to characteristics that put workers into abstract tasks increased over time. While this may not be too surprising by itself, it persists equally strongly when controlling for education dummies as direct measures of skill (Tables 2–4). Moreover, appropriately scaling the return to these observable propensities goes a long way at matching the upper part of the wage distribution in both the NLSY and the Census/ACS (Figures 3–5). Second, the estimates in Table 2 (and the corresponding Table 10 in [Acemoglu and Autor, 2011](#)) show that the relative wages of initial manual task workers have increased. While the manual task prices in the NLSY are not statistically significant (Table 3; the OMD being borderline), the point estimates in the Census/ACS are similar, significant, and robust in an instrumental variables and a control variables strategy. Taking the results in Figures 3–5 at face value, the task prices (with a minimum wage adjustment for younger workers) match a large portion of the evolution of the U.S. wage distribution over the last two decades. This also affords limited explanatory power to additional factors such as SBTC, skill supply, or policy variables beyond the minimum wage.

5 Conclusion

Task prices are of particular interest in the debate about routine-biased technical change (RBTC), as the polarization of task prices is the main prediction from models of RBTC on the labor market. In this paper, a new method to estimate the evolution of prices for skills in abstract, routine, and manual tasks has been proposed. The method exploits the relationship between workers' sorting into tasks and their wage growth in the Roy model to derive a linear regression equation for the changes in task prices. Beyond its simplicity, advantages of this approach are that it is independent of a particular distribution function for workers' skills in tasks and that it does not require an often hard-to-come-by exclusion restriction.

The empirical results indicate that RBTC played a major role in the U.S. labor market

over the last two decades. As predicted by RBTC, over the joint period of the 1990s and 2000s, task prices strongly polarized for young males and for males of all ages. In the estimations by decade, task prices also polarized during 1989–1999, while during 1999–2007 the price of the abstract task increased, the price of the routine task decreased, and the price of the manual task remained somewhat ambiguous. Task price estimates in 1979–1989 turn out inclusive, which may be due to confounding factors such as SBTC, the minimum wage, and a substantial increase in the supply of skill.

The evolution of task prices further accounts for the majority of changes in the overall U.S. wage distribution over the last decades. In particular, the observed polarization of wages during the 1990s and the joint 1990s and 2000s is closely matched by the task prices (plus a minimum wage adjustment for young workers), leaving little room for other factors such as changes in skill endowments. The wage growth of young workers over time is also better explained by relative skills in tasks than by absolute skill measures such as college degrees. These findings underscore the importance of the tasks approach more generally in explaining the trends in wage inequality over the last decades.

The new estimation method proposed in this paper may be used to analyze other shifts in the demand for (or supply of) work in different tasks, occupations, or sectors. Examples for such phenomena include rising import competition across different occupations and industries (e.g., [Autor, Dorn, Hanson, and Song, 2014](#)), structural change ([Young, 2014](#)), or the evolution of employment demand for specific sectors ([Philippon and Reshef, 2012](#)). The benefits from this would be to obtain structural model parameters under fairly general conditions in otherwise reduced-form analyses. The parameters could be employed to compute labor supply elasticities, to disentangle price and composition effects, and to analyze effects on the overall wage distribution. In the context of these different applications, a further avenue of future research will be to extend the current estimation method for use in longitudinal data, so that individuals' past task affiliations may assume the role of observable talents in the estimation.

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Appendix

A Theory

A.1 Proofs of Propositions and Simulation Parameters for Figure 1

Proof of Proposition 1. By contradiction. Consider the relative FOCs

$$\frac{\Pi_A}{\Pi_R} = \frac{\alpha R}{\beta A} \text{ and } \frac{\Pi_M}{\Pi_R} = \frac{\gamma R}{\beta M} \quad (9)$$

1. Suppose $\frac{\Pi_A}{\Pi_R}$ and $\frac{\Pi_M}{\Pi_R}$ fall. This implies $\frac{A}{R}$ and $\frac{M}{R}$ rise and $\Pi_R = \beta \left(\frac{A}{R}\right)^\alpha \left(\frac{M}{R}\right)^\gamma = \rho$ rises. Contradiction of FOC.
2. Suppose $\frac{\Pi_A}{\Pi_R}$ rises and $\frac{\Pi_M}{\Pi_R}$ falls. From labor supply, this implies $L_A = A$ rises and $L_M = M$ falls. Thus R has to rise and fall. Contradiction of market clearing.
3. Suppose $\frac{\Pi_A}{\Pi_R}$ falls and $\frac{\Pi_M}{\Pi_R}$ rises. Analogous to 2.

□

From now consider the notation from Section 2.3 in logs with individual index i and time index t so that, e.g., potential wages in K become $w_{Kit} = \pi_{Kt} + s_{Kit}$.

Sketch of Proof of Proposition 2. It is easy to see from $I_{Rit} = 1[\pi_{At} + s_{Ait} \leq \pi_{Rt} + s_{Rit}, \pi_{Rt} + s_{Rit} \geq \pi_{Mt} + s_{Mit}]$ and Equation (1) that aggregate employment in the routine task (weakly) falls. The proof that there need not be job polarization is by giving a counterexample: suppose that $\Delta\pi_A > \Delta\pi_M$ and that, initially, very few of the routine workers are sufficiently close to indifference with the abstract or manual task for switching, while many of the manual workers are close to indifference with the abstract task. In this case, employment in the routine task hardly changes and at the same time many workers flow out of the manual task into the abstract task. □

Sketch of Proof of Proposition 3. The change in average wages in task K can be split into a price and a selection effect:

$$E(w_{Ki1} - w_{Ki0} | I_{Kit} = 1) = \pi_{K1} - \pi_{K0} + E(s_{Ki1} - s_{Ki0} | I_{Kit} = 1)$$

While the (relative) prices $\pi_{K1} - \pi_{K0}$ may rise, the (relative) skills $s_{Ki1} - s_{Ki0}$ selected into K may fall, depending on the overall distribution of worker skills in tasks. This is the classic idea of (changing) selection bias. In some cases $E(w_{Ki1} - w_{Ki0} | I_{Kit} = 1)$ will be the inverse of the task price change. Figure 1 Panel (d) provides such a case and a counterexample that there need not be wage polarization in tasks (parameters in Table 5). □

Sketch of Proof of Proposition 4. Focus on the lower half of the wage distribution. Consider manual task worker m and routine task worker r who are initially located at the 10th and 50th percentile of the wage distribution. For simplicity assume they do not switch tasks. If they stay at their original quantiles, the relative change in the quantiles becomes $\Delta w^{10} - \Delta w^{50} = \Delta\pi_M - \Delta\pi_R > 0$, that is, we observe wage polarization. However, suppose the

manual worker overtakes the routine worker (he benefits from the higher price change for the manual task) and that they exchange positions in the wage distribution. In this case the relative change in quantiles becomes $\Delta w^{10} - \Delta w^{50} = \underbrace{(w_{r1} - w_{m1})}_{-} + \underbrace{(w_{r0} - w_{m0})}_{+}$,

which is flatter and may even be negative. Figure 1 Panel (f) provides a counterexample where the overall wage distribution does not polarize (parameters in Table 5). \square

Sketch of Proof of Proposition 5. Suppose that $\Delta\pi_A \geq \Delta\pi_M > \Delta\pi_R$. Every worker who starts in the A task will stay there and gain $\Delta\pi_A$. The stayers in the routine task will gain the smaller $\Delta\pi_R$. Even if they switch to the abstract or the manual task, none of the routine workers will gain the full $\Delta\pi_A$. These switchers will rather gain a weighted average of $\Delta\pi_A$ (or $\Delta\pi_M$) and $\Delta\pi_R$ (with nonzero weights depending on how quickly they switch), which is strictly smaller than $\Delta\pi_A$. However, it is theoretically possible that R starters (even on average) have higher gains than *either* A or M starters. For example, assume that $\Delta\pi_A > \Delta\pi_M$ and that the initial manual workers can only do the manual task, while the initial routine workers are (almost) indifferent between the routine and the abstract task. Then the wage gain of the manual workers will be $\Delta\pi_M$ and of the routine workers (almost) $\Delta\pi_A$. \square

Table 5 provides the parameters for the simulations in Figure 1. As discussed in the main text, the differences between the respective left and right panels are always either with respect to the variances or the correlations of skills and highlighted in bold. In Panels (a)–(d) the same task price polarization with $\Delta(\pi_A - \pi_R) = .35$, $\Delta(\pi_M - \pi_R) = .10$, and $\Delta\pi_R = -.05$ is used. In Panels (e)–(f), $\Delta(\pi_M - \pi_R) = .30$ and $\Delta\pi_R = -.20$, as, because of the overtaking effect, the relative price for the manual task has to rise substantially to even generate a modest amount of wage polarization.

Table 5: Parameter Values for the Simulations in Figure 1

	Figure 1 (a,b)		Figure 1 (c,d)		Figure 1 (e,f)	
	Left Panel	Right Panel	Left Panel	Right Panel	Left Panel	Right Panel
$\Delta(\pi_A - \pi_R)$	0.35	0.35	0.35	0.35	0.35	0.35
$\Delta(\pi_M - \pi_R)$	0.10	0.10	0.10	0.10	0.30	0.30
$\Delta\pi_R$	-0.05	-0.05	-0.05	-0.05	-0.20	-0.20
$var(s_{Ait})$	3.0	3.0	3.0	3.0	3.0	3.0
$var(s_{Rit})$	1.5	1.5	1.5	1.5	1.7	1.1
$var(s_{Mit})$	1.3	1.3	1.3	1.3	1.0	1.0
$corr(s_{Ait}, s_{Rit})$	-0.5	0.5	0.3	0.3	0.5	0.5
$corr(s_{Ait}, s_{Mit})$	-0.5	0.5	0.0	0.7	0.5	0.5
$corr(s_{Rit}, s_{Mit})$	0.9	0.0	0.0	0.0	0.5	0.5

Notes: Skills are multivariate normal with mean zero. Variances and covariances are given in the table together with the task price changes. The parameter values that differ between the respective left and right panels are highlighted in bold.

A.2 Details on the Derivation of Equations (3)–(5)

Another way of deriving Equation (3) is illustrative: for simplicity consider a case with only two tasks, abstract and routine. Concentrate on a specific worker i first and define

the relative task price and skill as $\tilde{\pi}_{ARt} \equiv \pi_{At} - \pi_{Rt}$ and $\tilde{s}_{ARi} \equiv s_{Ai} - s_{Ri}$. $\Delta \tilde{\pi}_{AR} > 0$, and I_{Ait} is an indicator for working in the abstract task such that $w_{it} = w_{Rit} + I_{Ait}(w_{Ait} - w_{Rit})$. Defining the relative price that makes i indifferent as $\tilde{\pi}_{ARt}^i \equiv -\tilde{s}_{ARi} = -(s_{Ai} - s_{Ri})$, we get:

$$\begin{aligned} w_{i1} - w_{i0} &= \Delta \pi_R + I_{Ai1}(w_{Ai1} - w_{Ri1}) - I_{Ai0}(w_{Ai0} - w_{Ri0}) \\ &= \Delta \pi_R + \begin{cases} \Delta \pi_A - \Delta \pi_R = \tilde{\pi}_{AR1} - \tilde{\pi}_{AR0} & \text{if } I_{Ai0} = 1, I_{Ai1} = 1 \\ \tilde{\pi}_{AR1} + \tilde{s}_{ARi} = \tilde{\pi}_{AR1} - \tilde{\pi}_{ARt}^i & \text{if } I_{Ai0} = 0, I_{Ai1} = 1 \\ 0 & \text{if } I_{Ai0} = 0, I_{Ai1} = 0 \end{cases} \\ &= \Delta \pi_R + \int_{\tilde{\pi}_{AR0}}^{\tilde{\pi}_{AR1}} I_{Ait} d\tilde{\pi}_{ARt}, \end{aligned}$$

which is the two-task analog of (3).

Taking expectations conditional on x_{it} on the top left and bottom of this equation gives result (4): $E(w_{i1} - w_{i0}|x_{it}) = \Delta \pi_R + \int_{\tilde{\pi}_{AR0}}^{\tilde{\pi}_{AR1}} p_A(x_{it}, \tilde{\pi}_{ARt}) d\tilde{\pi}_{ARt}$. Hence, since within tasks the wage gain is constant, the overall gain for a specific worker depends solely on the ‘‘distance’’ of the adjustment that the worker is still in the routine ($\pi_{ARt}^i - \pi_{AR0}$) and already in the abstract ($\pi_{AR1} - \pi_{ARt}^i$) task.

In fact Equation (3) is a little more subtle for the three-task case than the notation used in the main text reveals. Stick with the relative task price and skill notation so that $\tilde{\pi}_{KRt} \equiv \pi_{Kt} - \pi_{Rt}$ and $\tilde{s}_{KRi} \equiv s_{Ki} - s_{Ri}$ for $K \in \{A, M\}$. Holding constant $\tilde{\pi}_{ARt}$ and $\tilde{\pi}_{MRt}$ at $t = 0$ and integrating Equation (2) with respect to π_{Rt} we get

$$w_{it}|_{\pi_{R1}, \tilde{\pi}_{AR0}, \tilde{\pi}_{MR0}} - w_{it}|_{\pi_{R0}, \tilde{\pi}_{AR0}, \tilde{\pi}_{MR0}} = \Delta \pi_R.$$

Similarly,

$$\begin{aligned} w_{it}|_{\pi_{R1}, \tilde{\pi}_{AR1}, \tilde{\pi}_{MR0}} - w_{it}|_{\pi_{R1}, \tilde{\pi}_{AR0}, \tilde{\pi}_{MR0}} &= \int_{\tilde{\pi}_{AR0}}^{\tilde{\pi}_{AR1}} I_{Ai}(\tilde{\pi}_{ARt}, \tilde{\pi}_{MR0}) d\tilde{\pi}_{ARt} \\ w_{it}|_{\pi_{R1}, \tilde{\pi}_{AR1}, \tilde{\pi}_{MR1}} - w_{it}|_{\pi_{R1}, \tilde{\pi}_{AR1}, \tilde{\pi}_{MR0}} &= \int_{\tilde{\pi}_{MR0}}^{\tilde{\pi}_{MR1}} I_{Mi}(\tilde{\pi}_{AR1}, \tilde{\pi}_{MRt}) d\tilde{\pi}_{MRt}. \end{aligned}$$

Summing these three expressions gives Equation (3)

$$\Delta w_{it} = \Delta \pi_R + \int_{\tilde{\pi}_{AR0}}^{\tilde{\pi}_{AR1}} I_{Ai}(\tilde{\pi}_{ARt}, \tilde{\pi}_{MR0}) d\tilde{\pi}_{ARt} + \int_{\tilde{\pi}_{MR0}}^{\tilde{\pi}_{MR1}} I_{Mi}(\tilde{\pi}_{AR1}, \tilde{\pi}_{MRt}) d\tilde{\pi}_{MRt}.$$

Taking expectations gives Equation (4):

$$\begin{aligned} E(w_{i1} - w_{i0}|x_{it}) &= \Delta \pi_R + \int_{\tilde{\pi}_{AR0}}^{\tilde{\pi}_{AR1}} p_A(x_{it}, \tilde{\pi}_{ARt}, \tilde{\pi}_{MR0}) d\tilde{\pi}_{ARt} + \\ &\quad + \int_{\tilde{\pi}_{MR0}}^{\tilde{\pi}_{MR1}} p_M(x_{it}, \tilde{\pi}_{AR1}, \tilde{\pi}_{MRt}) d\tilde{\pi}_{MRt}, \end{aligned} \tag{10}$$

where

$$\begin{aligned} p_A(x_{it}, \tilde{\pi}_{ARt}, \tilde{\pi}_{MRt}) &= Pr[s_{Ai} - s_{Ri} > -(\pi_{At} - \pi_{Rt}), \\ &\quad s_{Ai} - s_{Mi} > -(\pi_{At} - \pi_{Mt})], \end{aligned}$$

and similarly for $p_M(x_{it}, \tilde{\pi}_{ARt}, \tilde{\pi}_{MRt})$.

Linearly interpolating (10) (or (4)) by

$$p_A(\pi_t) \approx p_A(\pi_0) + \frac{p_A(\pi_1) - p_A(\pi_0)}{\Delta(\pi_A - \pi_R)} [(\pi_{At} - \pi_{Rt}) - (\pi_{A0} - \pi_{R0})] \quad (11)$$

$$p_M(\pi_t) \approx p_M(\pi_0) + \frac{p_M(\pi_1) - p_M(\pi_0)}{\Delta(\pi_M - \pi_R)} [(\pi_{Mt} - \pi_{Rt}) - (\pi_{M0} - \pi_{R0})].$$

gives equation (5). This contains another approximation on top of the interpolation insofar that one might prefer using $p_A(x_{it}, \tilde{\pi}_{AR1}, \tilde{\pi}_{MR0})$ instead of $p_A(x_{it}, \tilde{\pi}_{AR1}, \tilde{\pi}_{MR1})$ in the first approximation and $p_M(x_{it}, \tilde{\pi}_{AR1}, \tilde{\pi}_{MR0})$ instead of $p_M(x_{it}, \tilde{\pi}_{AR0}, \tilde{\pi}_{MR0})$ in the second, which are not observable in the data. The Monte Carlo simulations in Section A.3 indicate that this is not much of an issue.

A.3 Monte Carlo Simulations for the Estimation Method

This section provides Monte Carlo simulation evidence on the performance of the regression-on-propensities method for identifying the correct task prices. The unobservable skills in Roy-type models are often taken as normally or extreme value distributed (e.g., Heckman and Sedlacek, 1985; Hsieh, Hurst, Jones, and Klenow, 2013). I generate data with observable talents distributed normally and unobservable skills in tasks either distributed normally or type I extreme value.

Structural estimation of the three-sector Roy model under normality is very demanding. Therefore, I start with a simplified version of the model in Section 2 with only abstract and routine tasks so that (relative) task prices in each sector can be consistently estimated by a Heckman two-step or full-information maximum likelihood regression for the normality case and a logit regression for the extreme value case, respectively. In this two-sector case, the regression-on-propensities (6) reduces to $w_{it} = \alpha_0 + \alpha_1 \bar{p}_A(x_{it}) + \alpha_3 \times 1[t = 1] + \alpha_4 \bar{p}_A(x_{it}) \times 1[t = 1] + \varepsilon_{it}$.⁴² Table 6 reports the simulation results (2000 observations for each period, 2000 replications) for the different estimation methods and under the different distributions with task prices changing by minus 15 log points for the routine task and plus 25 log points for the abstract task.⁴³

One can see in the first panel of the table that the regression-on-propensities as well as the Heckman procedures get close to the true task price changes under normality of the unobservables.⁴⁴ In contrast, the logit estimate possesses a substantial and significant upward bias under the normality assumption so that it is outright misleading.

The standard deviation of the estimates is also of interest. The logit estimates and the Heckman estimates are somewhat more precise than the regression-on-propensities. For the former, one might also be concerned that the standard errors are incorrect when not taking into account that the regressors in (6) are estimated in a first-stage themselves. The average standard error of the estimate reported below the standard deviation of the

⁴²In the regression-on-propensities approach, the probabilities to sort into tasks are estimated using (multinomial) logit regressions, but the results are very similar when using a (multinomial) probit or a linear probability model.

⁴³The task price changes as well as the parameter values for workers' skill distribution are taken as what seems reasonable given the existing empirical evidence.

⁴⁴Unreported full-information maximum likelihood estimation for both tasks at the same time gives similar results to the Heckman ML estimation. However, it often does not converge.

Table 6: Monte Carlo Simulations for the Two-Task Model

		$\Delta\pi_R$ in log points (s.d.)	$\Delta(\pi_A - \pi_R)$ in log points (s.d.)
TRUE		-15.00	40.00
Unobservables	Propensity Regr.	-14.76 (7.22)	39.96 (16.19)
	<i>Avg Std Error</i>	(7.26)	(15.28)
normally	Heckman 2step	-14.86 (4.54)	39.48 (10.69)
distributed	Heckman ML	-14.84 (4.44)	39.30 (10.37)
	Logit	NA	71.06 (11.87)
Unobservables	Propensity Regr.	-14.69 (9.79)	39.67 (21.95)
	<i>Avg Std Error</i>	(9.76)	(21.55)
extreme value	Heckman 2step	-20.76 (7.37)	58.42 (17.81)
distributed	Heckman ML	-20.32 (6.46)	50.80 (14.36)
	Logit	NA	40.26 (8.46)

Notes: The table reports Monte Carlo simulation results of different estimation techniques for the task prices. Data on observable skill components are generated from a multivariate normal distribution with mean 0, abstract variance 1.8, routine 1.3, and covariance 0.5. Data on unobservable skill components are generated from a multivariate normal distribution with mean 0, variance 1, and covariance 0.5 or from a type I extreme value distribution (Gumbel distribution) with independent unobservables. 4000 observations are generated, 2000 for each period, and the simulations were conducted with 2000 replications. Propensity Regr. is the estimation method suggested in Equation (6), Heckman 2step the two step Heckman limited information maximum likelihood estimation for the respective tasks, Heckman ML the corresponding full-information maximum likelihood, and Logit the logit binary choice regression, which can only estimate the relative task price. Note that the parentheses enclose the standard deviation of the estimates in the simulations and not their standard errors. However, for the propensity regression the average estimated standard error is also reported (*Avg Std Error*).

Table 7: Monte Carlo Simulations for the Three-Task Model

		$\Delta\pi_R$ in log points (s.d.)	$\Delta(\pi_A - \pi_R)$ in log points (s.d.)	$\Delta(\pi_M - \pi_R)$ in log points (s.d.)
TRUE		-15.0	40.0	50.0
Unobservables normally distributed	Propensity Regr.	-14.83 (8.31)	39.63 (15.83)	49.66 (19.72)
	<i>Avg Std Error</i>	(8.11)	(15.33)	(19.20)
extreme value distributed	Multin. Logit	NA	73.24 (14.79)	94.10 (13.62)
	Propensity Regr.	-15.25 (13.24)	40.54 (24.92)	50.71 (31.65)
extreme value distributed	<i>Avg Std Error</i>	(13.08)	(24.01)	(30.92)
	Multin. Logit	NA	40.39 (10.23)	50.04 (9.52)

Notes: The table reports Monte Carlo simulation results of different estimation techniques for the task prices. Data on observable skill components are generated from a multivariate normal distribution with mean 0, abstract variance 1.8, routine 1.3, manual 1, and covariance 0.5 between each of these components. Data on unobservable skill components are generated from a multivariate normal distribution with mean 0, variance 1, and covariance 0.5 or from a type I extreme value distribution (Gumbel distribution) with independent unobservables. 4000 observations are generated, 2000 for each period, and the simulations were conducted with 2000 replications. Propensity Regr. is the estimation method suggested in Equation (6) and Multin. Logit the multinomial logit choice regression, which can only estimate the relative task prices. Note that the parentheses enclose the standard deviation of the estimates in the simulations and not their standard errors. However, for the propensity regression the average estimated standard error is also reported (*Avg Std Error*).

estimates suggests that—if at all—there is only a very small down-ward bias here.⁴⁵

In the second panel of Table 6, the unobservable components of skills in tasks are specified as extreme value type I. The regression-on-propensities again comes close to the true value while the Heckman estimates are now severely upward-biased in absolute value. This bias is also highly significant given that the standard deviations in parentheses have to be divided by the square root of the number of replications for the t-test. Given that the specification of the error term is the “correct” one for the logit, this is now close to the true value and precisely estimated.

Table 7 reports the results (again 2000 observations for each period and 2000 replications) from the three task model of Equation (6), with the price for the manual task rising by 35 log points. The structural estimation of the three-sector Roy model under normality is too demanding to implement and thus it is left out here. Under both distributions of the unobservables, the regression-on-propensities recovers the parameters well, albeit not very precisely in the extreme value case. The multinomial logit performs well under the “correct” extreme value distribution, but it is again outright wrong under normality.

⁴⁵In the empirical results of the main text, the first-stage multinomial choice regression and the second stage wage regression are bootstrapped together in order to deal with this potential problem. In addition, one might be concerned that there is attenuation bias in the regression-on-propensities due to sampling variation in the first-stage estimates. The results in Table 6 and 7 do not suggest any such bias to be substantial.

Finally, simulations with different parameter values and with other distributions of the unobservables—such as extreme value type II, the skew normal, chi-square, uniform, and the gamma distribution—were also conducted. The Heckman and the logit performance varied while the regression-on-propensities estimation generally got close to the true parameters. These results are available upon request.

B Empirics

B.1 Detailed NLSY Sample Construction

I use data from the National Longitudinal Survey of Youth (NLSY) cohort of 1979 and 1997. The strength of the NLSY is that it provides detailed information about individuals' background and test scores in addition to education and labor market outcomes.

Individuals' labor market outcomes are evaluated at age 27 with the NLSY79 birth cohorts of 1957–64 reaching that age in 1984–92 and the NLSY97 birth cohorts of 1980–82 reaching it in 2007–09. Table 8 summarizes how the sample restrictions, attrition, and labor market participation reduce the sample size from 6,403 to 3,054 and from 4,599 to 1,207 males in the NLSY79 and the NLSY97, respectively. I restrict the sample to individuals who participated in the Armed Services Vocational Aptitude Battery of tests (ASVAB) in the first survey year. This restriction is necessary because the ASVAB provides measures of different dimensions of talent for each individual that are comparable over the two cohorts.

Table 8: From the Full NLSY to the Analysis Sample

	NLSY79 (Birthyears 1956-1964)	NLSY97 (Birthyears 1980-1984)
Reason for exclusion		
Total males	6,403	4,599
Excluded oversampled white and older arrivers in U.S. than age 16	4,585	4,599
Birthyear > 1982	4,585	2,754
Type of attrition		
Ought to be present with ASVAB at age 27	4,585	2,754
No ASVAB excluded	4,299	2,081
%	94	76
Not present at age 27 excluded	3,939	1,737
%	86	63
Conditioned on working		
Excluded who report no or farm occupation, self-employed, and those with no wage income	3,054	1,207

Notes: The table reports how the analysis sample is constructed from the full NLSY 1979 and 1997, and where observations are lost or need to be dropped.

The participation in ASVAB is substantially lower in the NLSY97 than the NLSY79 where almost everyone participated.⁴⁶ Moreover, sample attrition at age 27 is higher in the NLSY97 than the NLSY79 and overall only 63 percent of the NLSY79 participated in ASVAB and are also present at age 27. This problem is known (e.g. [Altonji, Bharadwaj, and Lange, 2012](#); [Aughinbaugh and Gardecki, 2007](#)) and the attrition and non-test-participation rates in the data closely line up with those reported in the study by [Altonji, Bharadwaj, and Lange \(2012, henceforth ABL\)](#). The only difference is that ABL consider outcomes at the younger age of 22 and thus have slightly lower attrition rates.

In their paper, ABL note that the higher attrition rate in the NLSY97 may be partly due to NLSY97 respondents being first interviewed at ages 12–16 versus ages 14–21 for the NLSY79 and thus had more time to attrit. ABL further extensively examine the potential non-randomness of attrition and non-test-participation and its likely impact in biasing important labor market outcomes. [Aughinbaugh and Gardecki \(2007\)](#) do a similar exercise but focus on social and educational outcomes. Both studies find evidence that attrition is not random with respect to youths' outcomes and their backgrounds. However, [Aughinbaugh and Gardecki \(2007\)](#) conclude that attrition from the NLSY97 does not appear to affect inference when estimating the three outcomes at age 20 that they are considering and ABL decide that the differences between non-attriters and the whole sample are not forbidding.

Moreover, ABL carefully select the samples of NLSY79 and NLSY97 to make them comparable to one another and compute weights that adjust for attrition and non-test-participation on observable characteristics. I closely follow their procedures for constructing my own sample.⁴⁷ First, immigrants who arrived in the United States after age 16 are excluded from the NLSY79. This is done because the scope of the NLSY97 (age 12–16) also doesn't include older than age 16 arrivals. Second, I exclude the economically disadvantaged whites and military supplemental samples from the NLSY79 because they were discontinued early on in the survey and thus don't provide labor market outcomes at age 27 (or for ABL's purposes). [Table 8](#) reports that 1,818 observations are dropped by making these restrictions to the sample. For each individual the observation that is closest to 27 years and 6 months of age is retained and labor market and final educational outcomes are measured from this observation.

ABL use a probit model to adjust the NLSY79 and NLSY97 base year sample weights to account for attrition and non-test-participation according to several observable characteristics, such as parental education, parental presence at age 14, indicators by birth-year, urban and SMSA residence status, indicator variables for race and gender, and an interviewer coded variable describing the attitude of the respondent during the interview. I also employ a probit model to adjust weights for attrition and non-test-participation and use the same specification and variables as ABL apart from leaving out parental presence

⁴⁶According to the NLSY97 technical sampling report ([Moore, Pedlow, Krishnamurty, and Wolter, 2000](#)), nonrespondents to the ASVAB include ineligible, refusals, breakoffs, and computer crashes, as well as individuals who are too ill or handicapped or with a language barrier. [Moore, Pedlow, Krishnamurty, and Wolter \(2000\)](#) find that this is higher among metropolitan youths, non-whites, males, and 16 year olds. They argue that there is a substantial impact of nonresponse only if the proportion of nonrespondents is high and if the differences between respondents and nonrespondents are high. Sampling weights, as used in this study, can account for differences in response rates between observable characteristics like the ones mentioned above.

⁴⁷Thus, for more information on the sample construction and for statistics on the effects of attrition, please refer to ABL in addition to the description provided here. I would like to thank Prashant Bharadwaj for providing me with their data and do-files.

at age 14. Alternatively, a fully stratified set of indicators for birthyear, year, sex, and race, as employed by the Bureau of Labor Statistics for weighting, yields very similar results.⁴⁸ As ABL do in their paper, I proceed from this point with the assumption that, after attrition weighting, the two NLSY samples are representative of the population of young Americans that they are supposed to cover. These samples have the size of 3,939 and 1,737 individuals in the NLSY79 and the NLSY97, respectively.

I follow Lemieux (2006), who uses CPS Outgoing Rotation Group data, in how I compute wages and in defining the sample of working individuals (henceforth labor supply). Hourly wages reported for the current main job are used and normalized to 1979 real values by adjusting with the PCE deflator provided by the St. Louis Federal Reserve Bank.⁴⁹ While Lemieux (2006) removes outliers with 1979 real hourly wages below \$1 and above \$100, I remove the high wages from \$40 onward because the NLSY wage data is very inaccurate for values above this threshold.

Finally, in order to condition on working individuals, all individuals who report not to be self-employed, and who are employed in a non-farm, non-fishing and non-forestry occupation according to the Census 1990 three-digit occupation classification are left in the sample. This leaves me with an analysis sample of 3,054 and 1,207 males in the NLSY79 and NLSY97, respectively (compare table (8) again). As in Lemieux (2006), all of those individuals are weighted by the number of hours that they work per week on top of the sample weights that are adjusted for test-participation and attrition.

B.2 Task Price Estimates for Females

This section reports the task price estimates for females. As in the main text, regression 6 is run on predicted task probabilities from a first-stage multinomial logit in the NLSY sample and on actual choice frequencies for discrete demographic cells in the Census/ACS sample.

Table 9 reports the results. In the first row of Panel A the task prices for 27 year old females between the NLSY79 and the NLSY97 move in the opposite direction of what is predicted by RBTC. The relative price for the abstract and the manual task fall substantially, while the price for the routine task rises. The same happens when college dummies are controlled for in the second stage wage regression in the third row of Panel A.

The reason for this unexpected result should be that the identification Assumptions 1–2.b are violated or that RBTC is dominated by other forces for females. One identification violation that was already mentioned in the main text may be on the first-stage Assumption 1, as in the (unreported) multinomial logit regression the mechanical talent for females is unrelated to task choice in the NLSY79, but it predicts that the abstract task will not be chosen in the NLSY97. Therefore, the three talents do not strongly and consistently predict task choices in the two NLSYs for females.⁵⁰ Row two of Panel A supports this suspicion, as the direction of the task price estimates reverses and moves in the initially expected direction when a college dummy is included in the first-stage choice

⁴⁸I thank Steve McClaskie and Jay Zagorsky for providing me with the official attrition-adjusted sample weighting program for the NLSY.

⁴⁹Source: "Personal Consumption Expenditures: Chain-type Price Index (PCECTPI)", accessed 2012-8-14, <http://research.stlouisfed.org/fred2/series/PCECTPI>

⁵⁰The pseudo R-squared in the choice regressions for females is also substantially lower than for males in table 11.

regression. Overall, the results on the task prices in the NLSY are therefore inconclusive.

Table 9: Estimated Task Prices in the NLSY and Census/ACS Sample—Females

		$\Delta(\pi_A - \pi_R)$ in log points (s.e.)	$\Delta(\pi_M - \pi_R)$ in log points (s.e.)	$\Delta\pi_R$ in log points (s.e.)
Panel A (NLSY): 1984/92 to 2007/09	Baseline	-52.9 (21.4)	-88.7 (38.8)	48.7 (14.1)
	1st-stage college	19.1 (15.1)	26.9 (32.8)	-2.1 (10.9)
	2nd-stage college	-60.6 (21.1)	-53.9 (36.5)	36.9 (13.2)
Panel B (Census/ACS): OLS on Demogr. Cells (Baseline)	1979-1989	12.5 (5.2)	-28.6 (12.0)	2.2 (3.5)
	1989-1999	4.8 (3.5)	2.2 (8.1)	8.2 (2.6)
	1999-2007	1.5 (4.2)	-23.4 (8.9)	-0.8 (3.3)
	1989-2007	6.2 (5.2)	-23.4 (11.4)	-7.4 (4.0)
Panel C (Census/ACS): OLS on Demogr. Cells (Educ, Age, Region Cntrls)	1979-1989	14.8 (13.4)	12.1 (15.6)	-8.4 (6.0)
	1989-1999	-2.8 (12.4)	-25.3 (14.0)	15.5 (5.9)
	1999-2007	-23.5 (9.7)	-43.6 (9.3)	6.8 (4.6)
	1989-2007	-17.3 (16.2)	-63.3 (16.1)	19.6 (7.5)

Notes: Panel A of the table presents estimated task price changes for females in the NLSY sample. The three rows correspond to the specifications reported in the first three rows in Table 3 for males. Panels B and C present task price change estimates in the Census/ACS sample for females baseline and with main effects for education, age, and region category, respectively. These correspond to panels A and C of Table 4 for males. Standard errors in parentheses next to the coefficients.

Panels B and C of Table 9 report the results for females in the Census/ACS sample, which are again not clearly supportive of RBTC. First, the estimated relative price of the abstract task rises by around 12–15 log points during the 1980s, but it stagnates (Panel B) or even falls when controlling for main effects (Panel C) in the 1990s and 2000s. Moreover, the relative price for the manual task falls substantially in both specifications over the last two decades. Only in the 1980s, when controlling for main effects in Panel C, do the estimated relative prices for the abstract and the manual task rise as is predicted by RBTC.⁵¹

The results reported for females in Table 9 as well as for males in Table 4 in the main text are in line with [Acemoglu and Autor \(2011\)](#). Using the same data as in Table 9 panels B and C, [Acemoglu and Autor \(2011\)](#) find that, while for males initial specialization in abstract and manual tasks predicts higher wage growth over the last decades, the results for females are rather inconclusive. As explained in Section 3.1, the author’s view is that this is because the demand and supply of skills for females has changed quite drastically for reasons which come on top of RBTC or which even dominate it during this period.

C Additional Figures and Tables

⁵¹All of the task price estimates in panels A–C are similar when adjusting for the change in real value of the minimum wage as in the main text.

Table 10: Male Employment in the NLSY with Respect to Average Demographics, Early, and Contemporary Skill Determinants

	NLSY79	NLSY97
Nbr of observations	3,054	1,207
Percentage of observations	71.60	28.40
<i>Demographics</i>		
Age	27.00	27.00
White	0.80	0.72
Black	0.13	0.14
Hispanic	0.06	0.14
<i>Early skill determinants</i>		
AFQT	167.31	167.65
Low AFQT Tercile	0.34	0.33
Middle AFQT Tercile	0.33	0.34
High AFQT Tercile	0.33	0.32
Math Score (NCE)	50.45	50.73
Verbal Score (NCE)	50.26	50.49
Mechanical Score (NCE)	50.41	50.69
Illicit Activities (NCE, Measured 1980)	49.98	50.01
Precocious Sex (NCE, Measured 1983)	49.91	50.24
Mother's Education (Years)	11.86	13.11
Father's Education (Years)	10.83	13.09
<i>Contemporary skill determinants</i>		
High School Dropout (HSD)	0.12	0.07
High School Graduate (HSG)	0.43	0.58
Some College (SC)	0.20	0.06
College Graduate (CG)	0.19	0.24
Advanced Degree (AD)	0.06	0.04
North East	0.22	0.17
North Central	0.29	0.25
South	0.32	0.35
West	0.17	0.21

Notes: The table shows average demographics and skill proxies in the NLSY79 and NLSY97 for all males weighted by hours worked. NCE indicates variables in the population (including non-workers) are standardized to "normal curve equivalents" with mean 50 and standard deviation 21.06. This is done when absolute values of these variables cannot be compared over the two cohorts.

Table 11: Sorting into Tasks in the NLSY, Multinomial Logit Regressions

	(1)	(2)	(3)	(4)
	NLSY79	NLSY79	NLSY97	NLSY97
Abstract				
Constant	-4.024*	-1.710*	-3.176*	-1.384*
black	0.235	0.159	-0.152	-0.106
hispa	0.03	-0.031	-0.472	-0.456
Math (NCE)	0.047*		0.034*	
Verbal (NCE)	0.023*		0.032*	
Practic (NCE)	-0.014*		-0.019*	
Middle Math Tercile		1.144*		0.441
High Math Tercile		2.315*		1.426*
Middle Verbal Tercile		0.207		0.670*
High Verbal Tercile		0.750*		1.445*
Middle Mechanic Tercile		-0.269		-0.258
High Mechanic Tercile		-0.552*		-0.618*
Illicit Activities (NCE)		-0.009*		-0.003
Precocious Sex (NCE)		-0.004		-0.006
Manual				
Constant	-1.689*	-1.608*	-1.339*	-2.053*
Black	0.636*	0.762*	0.473*	0.658*
Hispanic	0.201	0.243	-0.216	-0.114
Math (NCE)	-0.002		-0.009	
Verbal (NCE)	0.018*		0.021*	
Practic (NCE)	-0.023*		-0.017*	
Middle Math Tercile		-0.381*		-0.07
High Math Tercile		0.128		-0.395
Middle Verbal Tercile		0.342		0.27
High Verbal Tercile		0.471		0.790*
Middle Mechanic Tercile		-0.319		-0.281
High Mechanic Tercile		-0.908*		-0.608
Illicit Activities (NCE)		-0.002		0.013
Precocious Sex (NCE)		-0.003		-0.003
Pseudo R-Squared	0.132	0.123	0.114	0.112
N	2936	2936	1210	1210

Notes: Each column presents the results from a multinomial logit regression of task choice on demographics and talent proxies. The omitted group is the routine task. The first column uses only linear test scores in the NLSY79. The second column, which is the specification to estimate task propensities in the following, uses terciles of test scores and adds measures of risky behavior. The last two columns repeat these estimations for the NLSY97. Not to overload the table, significance at the five percent level is indicated by a single *.

Table 12: Male Employment in the Census/ACS with Respect to Education, Age, and Region by Year

	1979	1989	1999	2007
Nbr of observations ('000)	2,589	2,834	3,158	667
<i>Share of Education Group (%)</i>				
High School Dropout	25	15	13	12
High School Graduate	32	33	31	30
Some College	23	29	30	31
4 year College	12	15	17	18
Graduate Degree	7	8	9	9
<i>Share of Age Group (%)</i>				
16-24	27	22	19	20
25-39	38	42	38	35
40-54	24	26	33	33
55-64	11	10	9	12
<i>Share of Region (%)</i>				
Northeast	22	21	19	18
Midwest	27	24	24	23
South	32	33	35	35
West	19	21	22	23

Notes: The table shows education, age, and region groups' shares of employment in the Census/ACS sample as constructed by [Acemoglu and Autor \(2011\)](#). A full interaction of these groups yields 80 demographic cells for the task price estimation.

Figure 6: The distributions of employment and wages for males age 27 in the NLSY and the CPS (1984/92 to 2007/09)

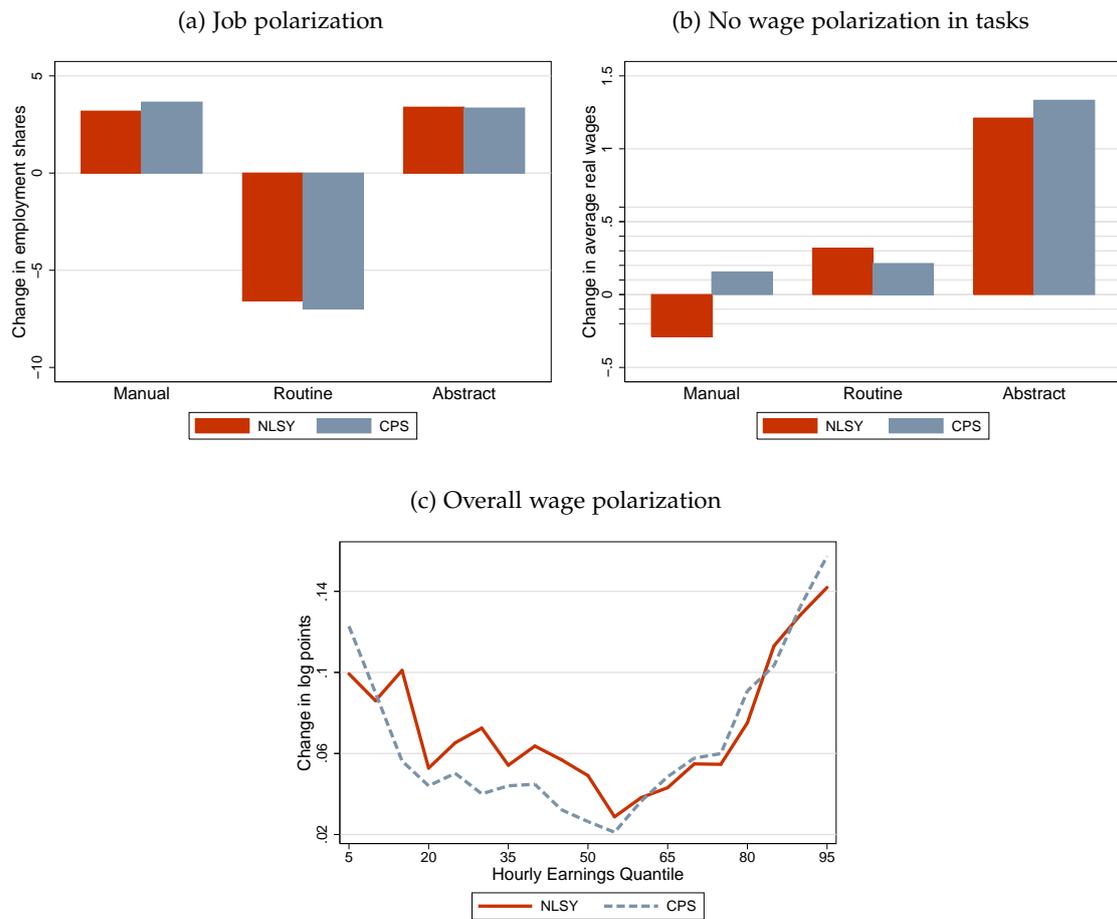
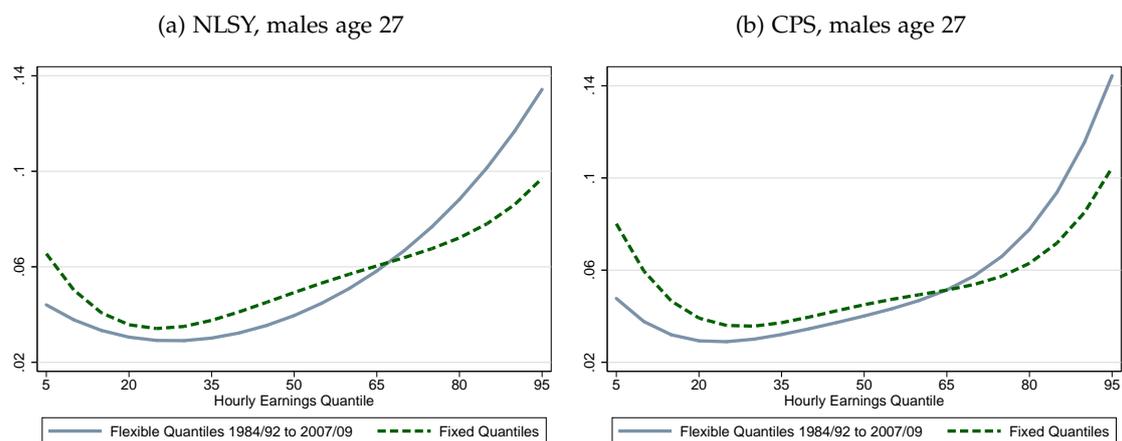
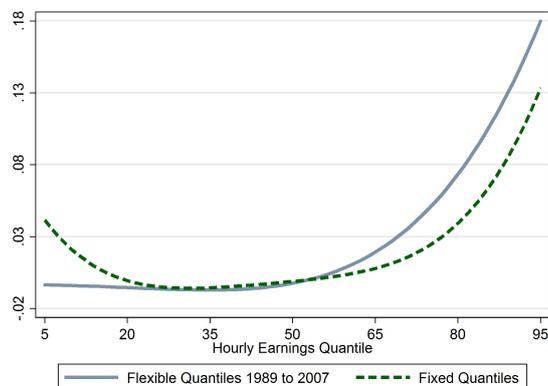


Figure 7: Smoothed predicted change in the wage distribution due to changing task prices, flexible and fixed quantiles



(c) CPS, males all ages (as in Acemoglu and Autor, 2011, Figure 9b)



Notes: The solid line depicts the predicted change in log real wages along the quantiles of the wage distribution due to estimated changes in task prices. The dashed line depicts the same predicted change when individuals are fixed at their original quantiles in the wage distribution. The lines are smoothed because for the predicted under fixed quantiles the individuals who correspond to these quantiles exclusively determine their change. This would make the predicted change very spiky. Smoothing is done using the predicted values from a fourth order polynomial regression of average wage changes on the quantiles.