The effect of routine-biased technical change on wage inequality

Manuel A. Hidalgo-Pérez
Universidad Pablo Olavide

Benedetto Molinari
Universidad de Malaga

This article analyzes the relationship between technology and wage inequality by using systematic data on the U.S. labor market during the 1990s. We focus on the technical change allowing automated machines to replace human labor in some occupational tasks previously performed by workers. By using the results established in the literature, we classify occupational tasks as technology-neutral, technology-substitute and technology-complementary. By clustering workers according to the tasks performed on duty, we show that variations in the prices of technology-complementary tasks explained the observed increase in residual wage inequality in the upper echelon of the wage distribution, whereas variations in the prices of technology-substitute tasks explained the observed reduction of wage inequality in the bottom echelon of the wage distribution. These results conform with the thesis that one of the effects of routine-biased technical change is to hollowing-out the wage distribution.

Questo articolo analizza la relazione fra tecnologia e disuguaglianza salariale utilizzando dati del mercato del lavoro statunitense negli anni '90. In particolare, si concentra sul cambiamento tecnologico che ha permesso a macchine automatizzate (robot) di sostituire il lavoro umano in alcune mansioni precedentemente svolte dai lavoratori. A partire dalle evidenze riportate in letteratura, classifichiamo le mansioni come: neutrali rispetto alla tecnologia, sostituibili, complementari. Raggruppando i lavoratori in base alle mansioni svolte, dimostriamo che variazioni del prezzo delle mansioni complementari alle nuove tecnologie spiegano l'aumento della disuguaglianza salariale osservata nella parte alta della distribuzione dei salari, mentre variazioni del prezzo delle mansioni che sono state sostituite dalla tecnologia spiegano la riduzione della disuguaglianza salariale nella parte più bassa della distribuzione salariale. Questi risultati confermano la tesi secondo cui il routine-biased technical change porta ad una polarizzazione nella distribuzione dei salari.

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Introduction

The evolution of wage inequality during the last 40 years is a debated issue in the literature. The debate was livened up by the observation that wage inequality increased in the U.S. during the 1980s after several decades of relative stability, and it is aimed to understand the determinants of such an increase in inequality. Several authors suggested that continuously growing technological progress, especially in computers and electronically controlled machines and equipment, enhanced firms' demand of skilled workers capable of operating the new technology. Such Skill-Biased Technical Change (SBTC) would raise the wage differential between skilled and unskilled workers, i.e. the *skill premium*, eventually pushing upward wage inequality.

The SBTC hypothesis was later criticized because unable to rationalize several aspects of the dynamics of wages. First, the upward trend of *residual* wage inequality (RWI) – the inequality of wages once controlling for the level of education and experience of workers – was not similar across OECD countries and across time periods, even though ICT innovations and the globalization of trade have been common phenomena to all developed economies during the last 40 years. In particular, Freeman and Katz (1995), Di Nardo, Fortin and Lemieux (1996), Acemoglu (2003) showed that more traditional explanations based on institutional factors, such as differences in the decline of real wages or different rates of de-unionization, or greater commercial openness and trade, played crucial roles in explaining the heterogeneity across countries and the time variation of wage inequality, thus refusing the role of SBTC as key explanation of wage inequality.

Second, Lemieux (2006) showed that a large fraction of the increase in wage inequality observed in the U.S during the 1990s and 2000s was due to a *mechanical* reason rather than to changes in the price of skills. Specifically, he showed that the percentage of workers with more education and experience increased over time, and that these workers are the ones with the greatest within-group wage dispersion. Consequently, the overall wage inequality was dragged upward. Once controlling for changes in the labor-force composition (composition effect), Lemieux found that the increase in wage inequality due to higher skills prices (price effect) only accounted for less than 25% of the observed increase in wage inequality, and that this effect became actually negative in periods other than the 1990s.

Finally, the SBTC hypothesis is in contradiction with the polarization dynamics exhibited by wages. Starting from the 1980s, relative wages increased among high-income workers and decreased among medium-income workers. Consequently, wage inequality increased in the upper echelon of the wage distribution (50th to 90th percentiles) but diminished in the bottom echelon (10th to 50th percentiles). This evidence is challenging the SBTC because an increasing skill premium should strengthen the comparative advantage of (rich) skilled against (poor) unskilled workers, thus implying a monotone increase in inequality across the wage distribution. Overall, the distribution should skew toward the right tail and not polarize as we observe in data. In addition, Goldin and Katz (2008) showed that during the nineteenth and twentieth centuries technical change in manufacturing industries has not only been skill complementary, but also skill substituting, in contrast with the idea of the SBTC hypothesis.

In response to those criticisms, several authors proposed a refined view of the SBTC, arguing that technology is complementary only to some skills whereas is substitute to others (Autor *et al.* 2003)[1]. For example, automated machines (robots) in manufacturing plants replaced blue-collar workers, but at the same time they enhanced the productivity of white-collars workers in charge of the assembly lines. Technological innovations would then push firms to value less workers' skills needed to perform tasks that are replaced by robots and more the sills needed to perform tasks that are complementary to robots. Eventually, the salary of workers performing routine tasks on duty is expected to decline relative to the salary of workers performing either technology-neutral or technology-complementary tasks. The literature on routine-bias technical change (RBTC) also showed that occupational tasks are not randomly distributed across the wage distribution. Occupations consisting mostly of technology-substitute tasks are typically placed in the middle echelon of the wage distribution, whereas occupations consisting mostly of technology-complementary tasks are typically placed in the upper echelon. Hence, RBTC is expected to concurrently depress the remuneration of middle earners and raise that of high earners, thus explaining the polarization dynamics of the wage distribution (Autor *et al.* 2006).

The presence of technological progress in the form of RBTC and its effect on tasks and employment have been supported by multiple empirical evidence, eventually gathering widespread consensus in the literature. Atalay *et al.* (2018) showed that the arrival of ICTs shifted workers away from routine tasks in

1 In this literature, a task is defined as a unit of work activity that produces output, whereas a skill is worker's endowment of capability to perform a task. See Acemoglu and Autor (2011) for a detailed surveyof the literature on the effects of RBTC hypothesis on employment.

the U.S. labor market during the 1990s, given that new technologies are associated with an increase in non-routine analytic tasks and a decrease in routine cognitive and routine manual tasks. Using the same sample, Gallipoli and Makridis (2018) provided evidence of enhanced productivity growth and employment share of IT intensive occupations. Graetz and Michaels (2018) and Acemoglu and Restrepo (2020) analyzed the displacement effect of robots on workers' tasks performed on-duty in the U.S. manufacturing sector from the beginning of the 1990s to 2007. From a different perspective, Spitz-Oener (2006) asked whether skill requirement in the workplace had been rising in response to technological change. Using a unique database with German administrative data, she showed that occupations required more complex skills in 1999 as compared to 1979, and that changes in skills requirements were most pronounced in rapidly computerizing occupations. Caines *et al.* (2017) found similar evidence for the U.S. In addition, they showed a clear upward trend of relative wages in favor of more skill-complex occupations with respect to less skilled-complex occupations. Regarding employment, several papers showed that the automation of a wide array of occupational tasks previously performed by human labor provoked the hollowing-out of the job distribution when workers were ranked by initial wages, given that routine were typically middle-ranked jobs. Focusing on the sample used in this paper – U.S. during the 1990s – evidence on job polarization have been provided, among others, by Acemoglu and Autor (2011), Goos *et al.* (2014), Acemoglu and Restrepo (2020).

The effect of RBTC on wages are instead unclear. The empirical literature only provided circumstantial evidence. Regarding the U.S., Autor *et al.* (2008) showed that wage inequality increased in the upper echelon and decreased in the bottom echelon of the wage distribution, in line with the predictions of the routinization hypothesis. Fortin and Lemieux (2016) later provided supporting evidence by showing that occupational tasks have been a key determinant of changes in wages at the occupation level. Autor and Dorn (2013) showed that employment and relative wages of routine workers diminished not only relative to technology-complementary occupations, but also relative to low-wage (technology-neutral) manual occupations. Regarding other countries, De La Rica *et al.* (2020) tested the empirical relationship between job tasks and wages in 19 developed countries. They found that an increase in technology-complementary task content of the occupation is related to a significant increase in the wage premium, whereas the opposite is true for routine tasks. Vannutelli *et al.* (2021) found evidence of wage premia for non-routine workers with respect to routine workers in Italy. They also showed that workers' own perceptions about their jobs – whether they are routine jobs and to what extent – can explain wage gaps better than actual occupation characteristics.

Opposite evidence was found by Antonczyk *et al.* (2018) and Naticchioni *et al.* (2014), who did not find evidence of wage polarization for, respectively, Germany and EU, even though Goos *et al.* (2009) found evidence of job polarization in the same samples. Mishel *et al.* (2013) focused on the evolution of wages for 250+ detailed occupations in the U.K., showing that widening wage differentials between technology-substitute and other occupations were too small to support the RBTC hypothesis, even though Goos and Manning (2007) had provided evidence on job polarization in the same sample. Green and Sand (2015) also found mixed evidence for Canada. They showed that wage inequality increased in the upper echelon of the wage distribution, but the increase was monotone across the wage distribution – highest for higher wages, lowest for lower wages – rather than U-shaped as predicted by the RBTC hypothesis. In general, the own advocates of the key role played by RBTC in the labor market admitted that the effect on wages significantly varied across time and countries (Salvatori 2018). As noted by Autor (2015), despite the initial dark forecasts, RBTC eventually appeared to have had milder effect even on employment across developed economies.

This article adds to previous empirical literature by providing a systematic analysis on the effects of RBTC on wage inequality in the U.S. labor market during the 1990s. We exploit the established evidence that some occupational tasks have been replaced by automated machines during the considered sample and, consequently, the price paid by firms for these tasks and associated occupations diminished. Building on this fact, we ask whether lower technology-substitute task prices, and the consequent wage drop for technology-substitute workers, explained the reduction of wage inequality observed in the bottom half of the wage distribution.

Using the same logic, we check whether the higher prices paid by firms for technology-complementary tasks explained the increase in wage inequality observed in the upper half of the wage distribution.

During the last 10/15 years, fast-paced innovations in Artificial Intelligence (AI) and deep learning algorithms made it possible to replace human labor with automated machines in many more tasks than the *routine* tasks considered in the 1990s. This may raise some concern about our sample choice. It may seem that later decades would be better than the 1990s to study the effects of RBTC in the labor market. Nevertheless, recent literature showed that the impact of RBTC in the labor market appears to have been radically different during the first decades of the automation revolution (1980s and 1990s) than during later decades (2000s and 2010s). During these first decades, RBTC was basically associated with the computerization and mechanization, i.e. investment in hardware. As pointed out by Autor *et al.* (2003), this process generated an increase in the demand for non-routine tasks with respect to routine tasks, and it was suspected to lead to an increase in wage inequality especially in the upper part of the wage distribution. Conclusive evidence on this point is still lacking and this article contributes on this aspect of the topic. From the 2000s, everything seems to have changed. Beaudry *et al.* (2016) showed that the job polarization process ended in the year 2000 and since then it began a period of lower relative demand for cognitive labor. According to these authors, the computerization and automation processes that occurred during the 2000s and 2010s can be considered as the consequence of the implementation of a general-purpose technology whose greatest investment was made earlier (i.e. in the sample studied in our article). Such investment generated a greater demand for other types of tasks, not only cognitive vs routine. From this point of view, the competition of workers in such second stage changed from competing for better paying occupations (because more complementary to automated machines), to competing for better paying and more secure jobs because they are located in more 'technological' firms/environment. Our article does not adjust well for an analyze of these later implications of RBTC, which is why we focus on the early sample.

To perform the empirical analysis, we use the May/ORG Census Samples database on wages, supplemented by the U.S. Department of Labor's Dictionary of Occupational Titles (DOT). Workers are grouped according to the usual socioeconomic characteristics and occupations. Then, we analyze the effects of RBTC along two dimensions. First, we perform the reweighing kernel approach of Lemieux (2006) to assess the relative importance of price vs. composition effect. When occupations are included among workers' observable characteristics, the composition effect is shown to contribute less than that reported by Lemieux, whereas the price effect, i.e. changes in the price paid by firms for workers' skills, appears the crucial determinant in explaining the observed changes of wage inequality during the considered sample.

Second, we analyze whether occupational tasks are suitable candidates to explain wage inequality. Specifically, we ask whether: (i) changes in the price paid by firms for technology-complementary tasks was a determinant of the higher RWI observed in the upper half of the wage distribution; (ii) changes in the price paid by firms for technology-substitute tasks was a determinant of the lower RWI observed in the lower half of the wage distribution. The results indicate that (i) occupational tasks have a significant effect on RWI and that these effects vary along the wage distribution with signs conforming with the predictions of the RBTC hypothesis. These results are in line with Böhm *et al.* (2019), who developed and estimated a model for prices paid per unit of skill in occupations. Using administrative panel data with detailed occupation codes, they showed that price and employment growth are positively related and that skill prices establish the quantitative connection between occupational changes and the surge in wage inequality.

The rest of the article is organized as follows. In Section 1, we describe data on wages and in Section 2 we describe the distribution of occupational tasks across the wage distribution. Section 3 presents the results of the reweighing analysis, whereas Section 4 reports the estimation of the effects of task groups on residual wage inequality. Last Section concludes.

1. Data

To analyze the U.S. labor market, we use the combined Current Population Survey (CPS) May and Outgoing Rotation Group samples during the 1983-2002 period. This is a comprehensive database often used in this type of studies (Autor *et al.* 2006). In particular, we construct average series of weekly wages by occupations out of individual hourly salary. These series are then used to follow wage inequality across time and different percentiles of the wage distribution. As pointed out by Autor *et al.* and Lemieux (2006), the May/ORG CPS presents some drawbacks, e.g. the treatment of censored wages especially top-coded wages, the existence of allocated or imputed wages for workers who do not respond in the survey, the inability to compare data for 1994 because of changes in sample design. Autor *et al.* (2008) showed that the inclusion of data from the CPS March Issues help to address some of these issues. In the article, we follow their treatment of data and do not address the remaining data issues.

Table 1 reports a set of descriptive statistics on workers included in the CPS survey. Data are for workers aged between 16 and 64 years old, and between 0 and 39 years of working experience. The sample is balanced regarding gender (approximately 50% of males), and slightly unbalanced toward married workers. Regarding tasks, we use an index measuring the presence of each task type in the sample. The values of this index are of particular interest when analyzed across the wage distribution, which we will do in next Section 2. The overall figures reported in Table 1 are mainly useful to assess the relative frequency of task types, with abstract tasks being approximately three times more frequent than manual tasks, and increasing along the considered time interval, whereas routine tasks are four times more frequent than manual task but decreasing over time.

In the following Chart 1, we depict the associated distribution of wages for the initial (blue) and final (red) year of the sample. As apparent from the graph, the frequency of high wages (right hand side of the distribution) appreciably increased during the sample. The mean wage also appears to increase from late 1980s to early 2000s. The overall distribution is less skewed to the right and shows a smaller positive excess kurtosis. Altogether, the evidence suggests that there were not only more high-wage workers at the end of the considered time interval, but also less low-wages and, therefore, the population of low earners was more equal.

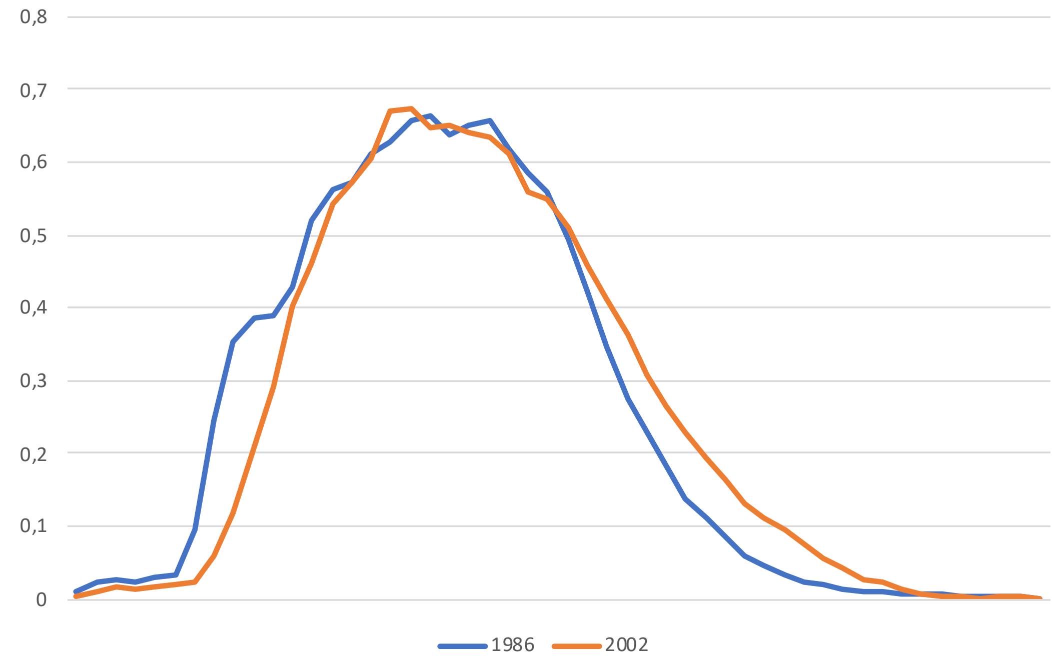
The previous evidence is broadly confirmed in Chart 2, which depicts the growth rate of wages between the initial and final period across wage percentiles, measured in log-changes. Chart 2 provides a clear representation of the largely debated polarization of the wage distribution. Wages whose frequency increased the most are the ones among the 5-19 percentile interval and the 80-95 percentiles interval. The largest reduction instead occurs in the middle echelon of the distribution, i.e. in the 30-59 percentile interval. The empirical finding conforms with the evidence that most of the job losses at that time occurred among middle

Table 1. Descriptive statistics

Sample period years	Initial 1986-1988	Final 2000-2002
Workers	440,180	304,912
Gender (males)	52.0%	51.7%
Education		
dropouts	13.8%	11.8%
high school	39.8%	32.0%
prev. to college	23.6%	30.2%
college	22.9%	26.0%
Race (nonwhite)	12.6%	13.4%
Marital status (married)	58.8%	55.0%
Tasks (index value)		
abstract	2.9	3.3
routine	4.3	4.0
manual	1.2	1.1

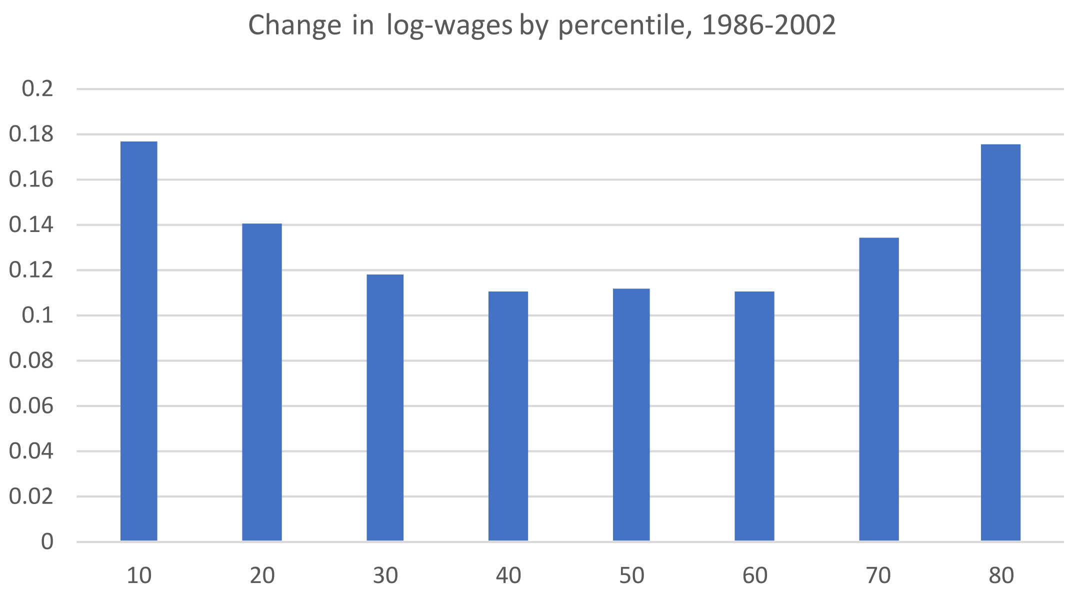
Source: Current Population Survey (CPS) May and Outgoing Rotation Group samples, years from 1983 to 2002

Chart 1. Wage distribution in 1986 and 2002



Source: Current Population Survey (CPS), merged March and May samples, years from 1983 to 2002

Chart 2. Log-change of wages along the wage distribution



Source: Current Population Survey (CPS), merged March and May samples, years from 1983 to 2002

skilled workers, and the contemporaneous reduction in earnings suggests that the labor demand of mid-skilled workers dropped in that period.

Next step in preparing the database has been merging previous data on wages with information on task content of occupations. To this end, we used the Fourth Edition (1977) and Revised Fourth Edition (1991) of the U.S. Department of Labor's Dictionary of Occupational Titles (DOT) to build a map between occupations and tasks. These dictionaries consist in 44 different objective and subjective types of tasks performed by workers in their workplace. All different dimensions of training, skills, skills in the workplace, interest, etc. are evaluated. As a result, each job is stripped down into primary comparable actions (*tasks*). Following Autor *et al.* (2003), we aggregated the original 44 tasks into five groups, namely: (i) EYEHAND, the ability to move hand and feet in coordination with other senses (technology-neutral manual task), (ii) FINGDEX, finger dexterity (technology- substitute routine task); (iii) STS, the ability to set limits, tolerances, or standards of any production process (manual and routine task); (iv) DCP, the ability of direction, control and planning (routine and abstract task); (v) MATH, general education, mathematics, and development (technology-complementary abstract task).

One difficulty arising when working with the DOT is that the different measures of tasks do not have cardinal scales. Autor *et al.* (2003) suggested to solve this problem by transforming the original measures provided by the DOT into percentile values corresponding to the ranking of the distribution of task input in 1960, which allows the variables to provide a logical sequence in the different values they take. The use of 1960 is considered appropriate because it corresponds to a period before the computer revolution.

Another difficulty arises when classifying workers according to the tasks performed on duty. Each occupation comprises a heterogeneous set of tasks. For example, a clerk performs primarily routine tasks such as making copies or performing calculations, but he also performs manual tasks as attending phone calls or abstract tasks as taking minutes of meetings. Executives mostly perform abstract tasks, e.g. organizing firm's business, but they also get involved in routine tasks as checking monthly sales. Such heterogeneity makes difficult to classify occupations in terms of tasks content: no occupation is totally manual or totally routine. To obtain a classification of jobs in terms of tasks, some arbitrary choices have to be taken. For instance, if more than 50% of the tasks involved in an occupation are routine tasks, than the occupation is 'routine'. But why 50% and not maybe 60%? In choosing a classification of occupations it is almost impossible to withdraw subjective elements. We avoided dealing with these issues by performing the empirical analysis directly in terms of tasks. In this way, we did not have to decide whether an occupation is routine or cognitive, but we assessed how changes in what firms pay for different types of tasks affect wages. The resulting database provides a panel of observations at the worker level comprising data on tasks performed on duty, corresponding weekly wage and wage percentile, plus several socioeconomic characteristics. The large number of observations in the survey, together with the pooling strategy (see Section 3), allowed to build narrowly defined cells of homogeneous workers with same education, experience, and occupation, which are used in the following empirical analyses (Sections 3 and 4).

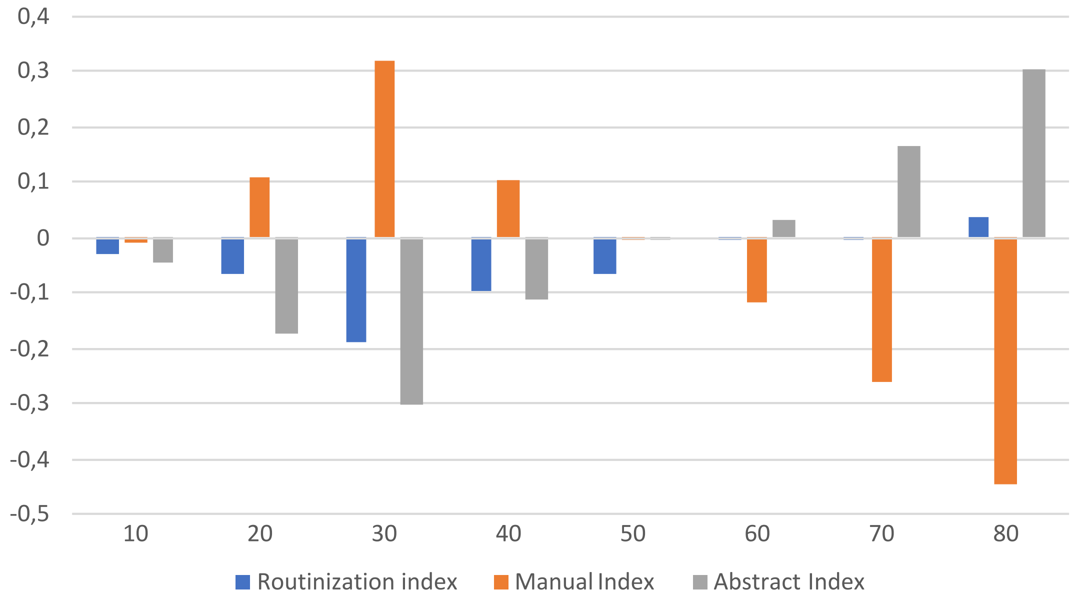
As final remark, note that the classification of tasks used in this article cannot be straight-forwardly mapped into the standard 'manual/routine/abstract' jobs classification often used in the literature on job polarization. This occurs because the group STS appear in-between manual and routine tasks, and DCP in-between routine and cognitive tasks. According to Autor and Dorn (2013), the five-groups classification has the advantage to wash out statistical noise from data by identifying the categories of manual, routine, and cognitive tasks with a narrower definition than other empirical strategies. Moreover, this empirical strategy has the advantage to facilitate the comparison of the results with the literature that studied the evolution of tasks content along the skill distribution (Autor *et al.* 2003).

2. Tasks distribution

In next sections, we use occupational tasks to track the effects of RBTC on wages. As mentioned before, the relationship between technical change and tasks has been established and supported with multiple evidence in the literature, both theoretical and empirical. Thus, we take for granted some assumptions about tasks: (i) RBTC replaces routine tasks thus negatively affecting their price; (ii) RBTC complements abstract tasks thus positively affecting their price; (iii) RBTC has no effect on manual tasks thus leaving their price unaffected.

There are, however, some other features of occupational tasks that are crucial in the light of our analysis, and thus we want to check them in our sample data. In Section 3, we will be working under the assumption that the intensity of tasks varied along the sample differently for the different groups of tasks. In Section 4, we claim that RBTC affect in opposite directions wage inequality in the bottom

Chart 3. Tasks distribution along the wage distribution



Source: Authors calculations using merged March/May CPS with DOT data. Years from 1983 to 2002

than in the upper echelon of the wage distribution. If these conditions hold, we should observe that the intensity of occupational tasks indeed vary in time and, in particular, that technology-complementary tasks increase, especially in the upper echelon of the wage distribution, and technology-substitute tasks decrease, especially in the bottom echelon of the wage distribution.

Chart 3 depicts the percentage variations of tasks intensities along the sample period. To summarize tasks in relation to their degree of substitutability with RBTC, we created three synthetic tasks indexes, based on the intensity that each occupation has on the different five groups of tasks defined above[2] The percentage variations represented in the chart indicate how each meta-group of tasks was represented among workers' duties from late 1980s to early 2000s. In general, they conform with the assumptions on RBTC. The presence of technology-substitute tasks decreased throughout the sample, and this effect was strongest among wage percentiles 30th and 40th. The presence of technology-complementary tasks increased among wage percentiles 70*th* and 80*th* and decreased among lower percentiles. Manual tasks seem to have replaced the loss of routine and abstract tasks in the bottom echelon of the wage distribution. These effects are not surprising in the light of the evidence on job polarization, given that RBTC has been shown to reduce routine-jobs employment in the middle of the wage distribution and increase abstract and manual jobs in the tails of the distribution. Whether the effect of technology also hit prices in another question, on which we hinge in the next two sections.

3. Price and composition effect: the role of tasks

In this section, we estimate an extended version of the kernel reweighing approach proposed by Lemieux (2006). This approach decomposes wage inequality into two separate functions: inequality due to the dispersion in the returns to skills, and inequality due to the heterogeneity of workers' characteristics. Changes in wage inequality can be caused either by changes in the *remuneration* of workers' characteristics, or by changes in the *distribution* of workers' characteristics, or both. In particular, growing wage inequality can be determined not only by higher skill premia, but also by increases in the share of workers with characteristics that intrinsically imply higher wages dispersion like education.

To properly assess the effect of skill-premia on

2 The indices represented in Chart 1 are created using the formulas: $rout_i = \ln(sts_i * finger_i)^{1/2} - ln(ehf_i) - \ln(math_i * dcp_i)^{1/2}$, $man_i = ln(ehf_i) - ln(sts_i * finger_i)^{1/2} - ln\,(math_i * dcp_i)^{1/2}$, $abstr_i = ln\text{-}(math_i * dcp_i)^{1/2} - ln(ehf_i) - ln\text{-}(sts_i * finger_i)^{1/2}$.

wages, Lemieux's suggests simulating a counterfactual change in the wage distribution when the composition of labor-force is held constant, thereby isolating the so-called *price effect*, i.e., the effect of changes in the remuneration of workers' skills, from the *composition effect*, i.e., the effect of changes in the composition of the labor force. As argued by Lemieux, if the share of workers with higher wage dispersions increased, then we would observe increasing wage dispersion even with constant skill premia. Eventually, he showed that workers' average education and experience grew during the postwar period, and that the group of more educated/experienced workers have higher wage dispersion. Thus, he showed that changes in the composition of the labor force played a key role in determining wage inequality since late 1980s explaining most of the observed changes in wage inequality.

However, Lemieux's kernel reweighing exercise did not account for occupations or occupational tasks. We show that including them among workers' characteristics actually reverse the results. Intuitively, if a cell of homogeneous workers is defined only by education, experience, and gender – i.e. the variables used by Lemieux –, then it will contain workers performing different tasks. If in addition RBTC affects tasks prices either positively or negatively, depending on whether they perform technology-complementary or technology-substitute tasks, then in a cell with different task-types the higher prices for technological-complementary tasks will average out the effect of lower prices for technological-substitute tasks, thus maintaining stable wage dispersion within the cell. We recall that in the kernel reweighing analysis the wage variance is imputed either to the composition effect or to the price effect. If wages within cells of workers are stable, all the variation of wages is imputed to the composition effect. The price effect is thus downward biased and the effect of RBTC obscured.

To unravel the actual effect of RBTC, we repeat Lemieux's analysis maintaining occupations constant in the reweighing analysis. In other words, we define cells of homogeneous workers with the same education, experience, and occupation. Then, we measure wage inequality within cells by using the variance of OLS residual errors obtained from a set of Mincer-type wage regressions, in which worker's wage is explained by gender, education, age dummies, their cross products, and occupations. Because some of the 6,700 cells of homogeneous workers defined by these characteristics have only a limited number of observations, we construct a pseudo-panel by pooling the years 1986–1988 as initial period and the years 2000–2002 as final period. Then, we estimate wage variance in the initial and final period and compare the growth rates of overall versus composition-adjusted wage variances.

The following Table 2 summarize the results. The first panel reports the overall, residual, and composition-adjusted wage variance in absolute terms in the initial and final sample periods, together with their percentage changes. Composition-adjusted wage variance is obtained from residual wage variance by combining the actual price function with the composition function of a pre-sample year (1983) using fixed weights. The second panel reports the same statistics computed separately for wages above and below the median wage.

From Table 2 we learn that controlling for the composition effect does not reduce the increase in wage variance observed during the sample. The change in composition-adjusted wage variance is even larger than that of residual wage variance, suggesting that the main force driving the increase in wage inequality was the price effect and not the composition effect. In fact, changes in workers' observable characteristics appear to mitigate the increase in wage dispersion during the considered sample. Once we keep the labor-force composition constant, the price effect implies an increase in wage dispersion (+10.3%) bigger than the increase in overall wage dispersion (8.4%). This evidence suggests that changes in the remuneration of workers' unobservable characteristics were large. However, the analysis remains silent on why these changes occurred, or whether it was indeed technological progress in the form of RBTC the key determinant of these changes. This point will be the object of the next section.

Finally, by inspecting the last two lines of Table 2, we learn that the price effect had a key role in explaining wage inequality on the left-hand side of the wage distribution, whereas price and composition effects are equally important in shaping the right-hand side of the distribution. This result conforms with Autor *et al.* (2008), who showed that wage inequality in the U.S. during the 1990s changed in opposite directions above and below the median wage.

Table 2. Wage variance

	Overall wage variance	Residual wage variance	Composition-adjusted residual wage variance
1986/1988	0.290	0.175	0.175
2000/2002	0.315	0.180	0.194
change (in %)	+8.4%	+2.8%	+10.3%
Percentiles		Variations in levels	
below 50th	-0.016	-0.010	-0.010
above 50th	0.020	0.023	0.016

Note: *Overall wage variance* is computed as the variance among individual wages. *Residual wage variance* is computed as the variance among residual wages, in which residuals come from the regression of wages on workers' education, age and the intensity of occupational task groups as defined in Section 2. *Composition-adjusted wage variance* is computed with the reweighing kernel approach described in Lemieux (2006) using 1983 as base year.

Source: merged March/May CPS with DOT data. Years from 1983 to 2002

4. Residual wage inequality and tasks

In this section, we test whether changes in the remuneration of occupational tasks are suitable candidates to explain wage inequality. To do so, we pursue a two-step estimation strategy. In the first step, we perform a set of Mincerian wage regressions in which wages are explained by gender, education, age dummies − age is used as proxy of worker's experience −, their cross products, and occupations. We repeat the estimation for the initial and final period. As in the kernel reweighing analysis of the previous Section 3, we pool years 1986, 1987, 1988 to build the wage distribution in the initial period, and the years 2000, 2001, 2002 for the final period. Then, we compute the sum of squared residuals for each cell of workers defined in the wage regressions, $V_{i,t}$. That is, the dispersion of wages among workers that are homogeneous in terms of gender, education, age, and occupations. In the second step, we regress the growth rate of residual wage variance from the initial to the final period on tasks intensities for the five groups of tasks as defined in Section 1[3].

Formally, we denote ehf_i, fgx_i, sts_i, dcp_i, $math_i$ the intensity of, respectively, EYE-HAND, FINGDEX, STS, DCP, MATH in cell i, and estimate by OLS the specification

$$\Delta V_i = \alpha + \beta_1 ehf_i + \beta_2 fgx_i + \beta_3 sts_i + \beta_4 dcp_i + \beta_5 math_i + \Theta X_i + \varepsilon_i \quad (1)$$

where $\Delta V_i = \log(V_{i,end}) - \log(V_{i,init})$ is the log-change of wage variance and X_i is a vector of control variables with coefficients Θ. In the specification (1), the coefficients β_j *for* $j \in (1, ..., 5)$ measure the effects of task prices on wage dispersion. That is, within-group wage inequality in the terminology of related literature. The estimation of (1) is repeated four times. First, using the whole wage distribution; second, using only the left tail of the distribution (wages below the 30th percentile); third, using the middle echelon of the distribution (wages from the 30th to the 60th percentile), fourth, using only the right tail of the distribution (wages above the 60th percentile). Each estimation is then repeated twice, either including or not several control variables that related literature indicated as possible co-explanatory variables of wage inequality. That is, membership in a union, marital status, and race (Firpo *et al.* 2011).

The reduced-form specification (1) imposes few structures on the underlying model and isconsistent with a large family of models postulating the effect of RBTC on wage inequality. This effect has been rationalized in the literature mostly using the Roy (1951) model. (e.g. Autor and Hendel 2013). In this model, a worker's wage is defined as the price paid by firms for tasks times the intensity of tasks performed on duty by the worker, plus some idiosyncratic components. Tasks prices are interpreted as equilibrium prices in labor market for tasks, in which RBTC shifts the labor demand (Acemoglu and Restrepo 2019). This affects wage

3 Each variance $V_{i,t}$ is also weighted by the sum of individual weights of the workers belonging to the cell, as assigned from the MAY/ORG CPS depending on the representativeness of each worker in the labor- force population. This estimation strategy ensures that all available information is efficiently used, but no observation is over-weighted with respect to its original sample weight.

determinants and, in turn, changes wage inequality.

By expressing the wage equation in logs, a Roy model with tasks can be formulated as

$$\omega_{i,j,t} = \delta_n + \gamma_j + \sum_{k=1}^{K_n} \left(p_{k,j,t} + \alpha_{n,k,t} + T_{k,t}\right) \quad (2)$$

where $\omega_{n,j,t}$ is the log-wage of individual $n \in N$ working in firm j at time t, δ_n and γ_j are fixed effects capturing, respectively, idiosyncratic worker's and firm's effects, K_n is the number of tasks performed by n, $p_{k,j,t}$ is the price of task k paid by firm j at time t, and $a_{n,k,t}$ measures worker's n efficiency in performing task k at time t. $T_{k,t}$ indicates the different tasks, whose classification is obtained by breaking down occupations into primary comparable actions (tasks). When the analysis hinges on workers' skills and not on tasks (e.g. Böhm *et al.* 2019; Böhm 2020), the formulation of the Roy model (2) can be further refined by assuming that efficiency units $a_{n,k,t}$ are functions of workers' skills. Formally,

$$\alpha_{n,k,t} = \pi_{0,k} + \sum_{h=1}^{H} \left(\pi_{h,k} S_{n,h,t}\right) \quad (3)$$

where coefficients $\pi_{n,h,k}$ measure the value of skill h in performing task k, $\pi_{0,k}$ are time- invariant common coefficients that depends on the intrinsic characteristics of the task, and $S_{n,h,t}$ indicates workers' innate skills that usually are unobservable to the econometrician.

Equations (2)–(3) formulate the Roy model with tasks in a very general way. In practice, all papers that attempt to estimate some model predictions must impose restrictive assumptions For instance, many papers assume that skills and therefore effectiveness units are time-invariant ($a_{n,k,t} = a_{n,k}$). Others that the law of one price holds and thus all firms pay equally the same task ($p_{k,j,t} = p_{k,t}$), even though few papers acknowledge this assumption (Fortin and Lemieux 2016). Others assume no firm-specific effect ($\gamma_j = 0$), even though the point is highly debated in the literature (Song *et al.* 2019, Autor *et al.* 2020). In this article, we do not impose restrictive assumptions, but we use workers' variability to get rid of the idiosyncratic components. In the first step estimation, we compute wage variance among workers with same observable characteristics, i.e. $V_{n\in\vec{N}_i}(\omega_{n,j,t})$ where the vector $\vec{N}$ is formed by a partition of the population N into i cells of homogeneous workers. Then, we compute variance difference between initial and final period, i.e. $\Delta V_i(\omega) = V_i(\omega_{j,1}) - V_i(\omega_{j,0})$, which nets out time-invariant fixed effects. In the second-step regressions, we use task intensities as regressors to explain the observed average variations in wage variances, i.e., specification (1).

This strategy has the advantage not to impose structure on the model, but it has two shortcomings. First, it only assesses the effect of tasks on within-group wage inequality. So, it does not use efficiently data information and the estimation power is reduced. However, Böhm *et al.* (2019) argued that between-occupations wage inequality underestimates the impact of shifting occupational demand on wage inequality. Thus, our estimation loses power, but it does not suffer from this bias. Second, because effectiveness coefficients, $a_{i,k,t}$, and task prices, $p_{k,j,t}$, enter multiplicative in the model above, then a reduced-form estimation of (1) cannot disentangle between the channels through which RBTC affects wages. That is, whether RBTC operates in the labor market by changing task prices, or by affecting the complementarity between human labor and tasks, and thus the effectiveness coefficients.

Few more remarks on the empirical analysis are worth mentioning. As noted by Autor and Hendel (2013), tasks cannot be directly included into Mincerian wage equations because they are not exogenous fixed regressors like education or gender, given that workers' self-select into jobs in which they are most productive in terms of tasks, given their skills. This implies that OLS is inconsistent unless the estimation controls for occupations. We do this by including occupations in the first-step regression, and then estimating the effects of tasks in the second step. This solution comes at the cost that we can only analyze the effect of tasks on the variance and not the *level* of wages. Finally, the resulting two-step approach is akin to the one proposed by Firpo *et al*. (2018). The difference is that they use quantile regressions, thus focusing on the effect of tasks across the wage distribution, whereas we focus on the average effect. Also, by using the OB decomposition they can focus on wage gaps to measure inequality, whereas use wage variance to measure inequality.

The estimation results are reported in Table 3. Several insights are worth noting and we explore them in turn. The estimations performed using the whole distribution reveal that the group of tasks with the largest coefficient is routine analytic, which is also the only significant and *positive* coefficient. Routine manual

Table 3. The effects of occupational tasks on the growth of RWI

	Percentiles							
	all		below 30th		30th-60th		above 60th	
Non-routine manual	0.007	0.006	0.016**	0.016**	0.004	0.004	-0.006	-0.006
	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.009)	(0.009)
Routine manual	-0.018*	-0.019*	-0.021*	-0.021*	-0.003	-0.004	-0.021**	-0.021**
	(0.010)	(0.010)	(0.013)	(0.013)	(0.012)	(0.012)	(0.010)	(0.010)
Routine cognitive	0.002	0.001	-0.011***	-0.011***	-0.004	-0.005	0.014***	0.014***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Non-routine interactive	-0.003	-0.003	-0.011*	-0.010*	-0.003	-0.003	0.002	0.002
	(0.004)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
Non-routine analytic	0.062***	0.065***	0.078***	0.078***	0.060***	0.062***	0.031***	0.032***
	(0.007)	(0.007)	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.008)
Union member		-0.218***		-0.203**		-0.116**		-0.061
		(0.067)		(0.089)		(0.053)		(0.054)
Non-white		0.028		0.032		-0.027		-0.019
		(0.078)		(0.053)		(0.057)		(0.072)
Married		0.043		-0.043		-0.017		-0.006
		(0.061)		(0.045)		(0.043)		(0.054)
Constant	-0.324***	-0.339***	-0.356***	-0.362***	-0.351***	-0.364***	-0.184***	-0.189***
	(0.036)	(0.037)	(0.041)	(0.041)	(0.041)	(0.042)	(0.039)	(0.040)
N. of groups	6,815	6,815	5,557	5,557	6,307	6,307	5,785	5,785

Source: merged March/May CPS with DOT data. Years from 1983 to 2002

is the largest negative and significant coefficient, followed by non-routine interactive. The remaining coefficients (non-routine manual and routine cognitive) are non-significant. In the estimations performed using the lower echelon of the distribution – wages below the 30^{th} percentile –, the coefficient of manual tasks is significant and positive, and the one of routine cognitive is significant and negative. Note that both routine tasks appear negative and significant in this estimation, whereas manual and analytic tasks appear to have positive impact on RWI.

In the estimations performed using the middle and top percentiles – the percentiles interval 30^{th}–60^{th} and above 60^{th} –, no coefficient is significant except for analytic tasks. Note that only in the estimation that uses high wages the introduction of controls changes the significativeness of coefficients. In general, although the point estimates do not differ much among sub-samples, their significance do. However, because of cell weights and the different content of tasks in the different percentiles, no relationship can be established between whole sample coefficients and sub-samples coefficients.

Previous results generally conform with the predictions of the RBTC hypothesis. Non-routine analytic technology-complementary tasks seem to have pushed upward wage inequality during the considered sample, while routine manual tasks that are technology-substitute appeared to have had the opposite effect. Manual tasks (technology-neutral) had a mild effect on the overall distribution, but a positive effect on inequality in the bottom echelon, in line with the idea that their wage differential with routine jobs diminished due to the negative effect of technological progress on the price of routine tasks (Autor and Dorn 2013), and therefore routine and manual workers' wages became more equal. A question that remains open is what happens to those workers displaced from routine intermediate jobs. The limited evidence available from birth cohort data suggests that they can either move up to high-wage cognitive jobs, or down to low-wage manual jobs, with younger and better qualified workers more likely to make the former transition, but more evidence on this transition is needed.

Final remarks

In this article, we provide empirical evidence on the effects of RBTC on wage inequality. We show that technical change pushed upward wage inequality among high earners in accordance with the evidence provided by Piketty and Saez (2003; 2006). Also, it appears to have pushed downward wage inequality among low earners. This last evidence can be explained by a twice effect of technical change on routine labor. First, by lowering the remuneration of routine tasks, it reduced the wage differential between initially richer routine workers and initially poorer manual workers. Second, by inducing a migration of some routine workers toward other occupations, it reduced the variance of salaries for this group of workers, which resulted in lower wage inequality in the middle echelon of the wage distribution. We leave to future research the analysis to disentangle between these two operating channels, whether one or both were in place at that time, and the assessment on their relative importance in explaining observed wage inequality.

Overall, our analysis of the U.S. wage distribution during the 1990s reveals differential wage growth at different points in the distribution. If confirmed, RBTC appears to reward a certain type of high earners as compared to mid and low earners. If maintained for enough time, such dynamics would generate a polarization pattern of labor income that can be dangerous for social stability. The consequences of a continuous loss of purchasing power for middle earners eventually can cripple the founding pillars of modern economies. On the one hand, it can impair the functioning of democracy by polarizing political parties, each wing chasing the more populated peripheries of the electorate. On the other hand, polarization fosters social unrest from groups that are more and more divergent in terms of consumption, wealth, and affluence. If RBTC were confirmed to be the key determinant of such polarizing pattern, then a strong call would arise for balancing policies. First, there would be a demand for educational policies to develop, or at least maintain, intermediate levels of education provision, or to encourage individuals to reach such levels of attainment. It is necessary for individuals to receive the education and training required to prepare them for the mid-earning occupations that exist now. Such education will also need to provide learners with flexible skills, to enable them to face future further changes. Second, there would be a demand for fiscal policy to finance the enhanced educational needs of the population. At the same time, implementing fiscal policy as taxes levied on automated capital would partially offset the economic benefit of replacing human labor with automated capital, thus slowing the transition, and allowing households to adapt with training and education to the changing labor market. As a byproduct, the inevitable reduction of investment.

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Manuel A. Hidalgo-Pérez
mhidper@upo.es

Tenured researcher at the Department of Economics of Pablo de Olavide University (Sevilla, Spain). His main filed of expertise is Applied Economics and his research focused on labor market and its relationship with technological change. He is also a Senior Economist at ESADE-EcPol.
Recent publications: Costa, Garcia-Cintado, and Hidalgo-Pérez, *Political cycles in Latin America: more evidence on the Brazilian economy*, Latin American Economic Review (2021), and *Labor demand and ICT adoption*, in Spain Telecommunications Policy (2016).

Benedetto Molinari
bmolinari@uma.es

Assistant professor at the Department of Economic Theory and History of University of Malaga, and Research Fellow at the Rimini Center of Economic Analysis (RCEA). His main research interests are Dynamic Macroeconomic Theory, Fiscal Policy, Applied Time-series, Macro-Labor and Technical Change.
Recent publications: *Public Debt Frontier: A Python Toolkit for Analyzing Public Debt Sustainability*, Sustainability 13 (2021); *The Government in SNA-Compliant DSGE Models*, The B.E. Journal of Macroeconomics, forthcoming (2021); *Advertising and Aggregate Consumption: A Bayesian DSGE Assessment*, The Economic Journal (2018).