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## Closing the Gender Pay Gap and Individual Task Profiles: Women's Advantages from Technological Progress

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# Closing the Gender Pay Gap and Individual Task Profiles: Women's Advantages from Technological Progress

by

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## **Abstract**

In the present paper I provide novel evidence on the formation of the gender pay gap with respect to directly measured job task contents. Using high-quality administrative employment data for Germany, and augmenting these by individual-level task information, I provide detailed evidence on the evolution of task contents and their gender-specific remuneration across and within occupations for both genders. The main finding of the paper is that the formation of the pay gap is substantially driven by the relative prices for non-routine cognitive tasks. Moreover, I document convergence in prices for non-routine cognitive tasks and convergence of tasks contents within occupational groups. The only exception from this general finding constitutes the top of the wage distribution, where the substantial difference in prices for non-routine cognitive tasks is persistent and the pay gap is not narrowing.

JEL-Classification: J16, J24, J31, J62.

Keywords: Gender pay gap, occupational content, task-based approach.

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# 1 Introduction

The narrowing gender pay gap has been documented in most industrialized countries since the 1950s and has attracted much attention in economic literature. Customarily, the decrease in gender-specific pay has been explained by the rising educational level of women, as well as by increases of respective returns to education (Blau and Kahn, 1996). In this paper, I provide analysis of the formation of wage differences between genders that stem from differences in their job contents and relates to substitutability of genders in the production process. This approach has an advantage over the education-based perspective, since raised demand for qualified female labor is itself closely linked to the technological progress and changes in demand for tasks (e.g. see studies for Germany by Fitzenberger and Wunderlich, 2000; Spitz-Oener, 2006). Moreover, as the brain-and-brawn model by Galor and Weil (1996) shows, task contents do not only affect the relative wages of women, but also their labor market participation. Empirical studies also suggest a close link between changes in task contents and the gender-specific pay. Black and Spitz-Oener (2010) document that contents of women's jobs in Germany have disproportionately shifted towards non-routine cognitive tasks, which are shown to be correlated with, on average, higher wages (Spitz-Oener, 2006). For the US, it is also documented that changes in prices for task units contribute to the closing of the gender pay gap: Yamaguchi (2013) shows that up to 40% of the closing of the gender pay gap accounts for falling prices of motor skills.

In this study, I provide a detailed analysis of the formation of the gender pay gap over the quantiles of the wage distribution in Germany between 1986-2004. During this time period, narrowing of the gender pay gap was observed in the middle and at the low end of the wage distribution (Fitzenberger and Wunderlich, 2000) accompanied by the falling gender segregation of occupations. Taken at face value, this evidence suggests that men and women become better substitutes in production, which translates into more equal pay. However, evidence on gender-specific task contents conditional on age, education and occupational groups is lacking in the literature, as well as little is known on the development on gender-specific wage structure with respect to tasks both on the whole and within occupations. The present paper aims to close these gaps in the literature.

So far, the literature has focused on studying task variation at the occupational level or in cross-sections. To study the gender-specific wage formation with respect to tasks in detail, I employ a newly constructed data set that mainly features high-quality administrative panel data (IABS, launched by the German Institute for Employment Research) combined with survey-based information on task contents at the individual level (QSC, German Qualification and Career Survey).<sup>1</sup> The data allows an investigation of the interplay of wages and tasks in great detail, both with respect to gender-specific and occupation-specific variation of tasks. With these detailed data at hand, I am able to make several contributions to the existing empirical literature. Firstly, I employ individual-level task data to provide novel evidence on the differences in average task profiles of men and women, conditional on age, education and occupational group. Secondly, I investigate the evolution of gender-specific prices to task units, in particular, using regression based of the recentered influence function (RIF) and consistent estimation with individual and occupational fixed effects. Thirdly, I apply Firpo-Fortin-Lemieux (FFL) decomposition to analyze the contribution of tasks and prices for task units, along with

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<sup>1</sup>The upcoming study of Fedorets et al. (2013) features a version of individual-level imputation of task profiles to the administrative panel data, for male employees only. For the present study, I expand the imputation procedure to females.

educational controls, to the formation of the gender pay gap. Fourthly, I contribute evidence on the formation of the gender pay gap with respect to job tasks for both the median, and low- and upper-tail of the wage distribution using the recentered influence function (Fortin et al., 2011).

The findings of the paper confirm the existing findings in the literature as well as contribute new evidence obtained from the previously unstudied data variation. Firstly, I find that the closing of the gender pay gap in the period from 1986 to 2004 was concentrated in the middle and the lower part of the wage distribution, which is in line with the findings of Fitzenberger and Wunderlich (2000). Then, I confirm the findings of Black and Spitz-Oener (2010) of observed disproportionate growth of non-routine cognitive tasks and disproportionate decline of routine tasks for women. However, using data variation within occupations reveals that female advantages in terms of task profiles are much less pronounced within occupations. In fact, within occupations one observes convergence of the task profiles of men and women that, itself, points at the high substitutability of genders within occupations. Estimation of relative task prices reveals that relative prices for non-routine cognitive and non-routine manual tasks performed by women grow. Since the mid-nineties, women are higher paid for non-routine manual tasks than men. Prices for non-routine cognitive tasks exhibit convergence over time, with some substantial differences over the wage distribution. At the low-end of the distribution, women's remuneration for non-routine cognitive tasks exceeds those of men. At the median and at the top, convergence of gender-specific returns to non-routine cognitive tasks is observed. On the whole, prices for non-routine cognitive tasks are one of the main components in the formation of the gender pay gap, whose contribution falls with the falling pay gap. Interestingly, at the 75th quantile, the difference in prices for non-routine cognitive tasks has grown which has substantially contributed to the fact that the gender pay gap has not been narrowing at the top of the wage distribution.

The rest of the paper is organized as follows. In section 2, I review the theoretical models that explain wage formation with respect to tasks, as well as the corresponding empirical literature. Section 3 introduces the data set and shortly describes the imputation procedure for the task information. Section 4 discusses the estimation methods (RIF-regression and FFL-decomposition), their limitations and assumptions necessary for consistent estimation of the coefficients of interest. In section 5, I provide detailed analysis of the evolution of the unconditional and conditional gender pay gap, as well as task profiles. Then, relative prices of the task units are estimated and their relation to the gender pay gap is described. I also shortly discuss the performed robustness checks in section 6. Section 7 concludes and discusses the obtained evidence.

## 2 Conceptual Framework and Motivation

Existence of the gender pay gap stems from the fact that men and women constitute imperfect substitutes in the production process. The restricted substitutability can manifest itself in the difference of gender-specific production inputs. However, given equal productivity of genders, the law of one price (equal pay for equal production input) should hold. Otherwise, one could suggest presence of discriminating wage settings that can be hardly isolated from gender-specific productivity in an empirical study. In the following, my argumentation will mainly rely on the differences in production inputs and their respective prices, not discrimination that I cannot directly identify in the data.

Accompanied by the progress of technology over time, the difference in gender pay has been

decreasing (see figure 1 for the years 1986-2004). In particular, these differences are shown to be linked to inequality in job content with respect to skill requirements and job complexity (Korkeamäki and Kyrrä, 2006). Indeed, parallel to the falling gender pay gap, an increase in gender segregation by occupations is observed (figure 2) and the growing share of women in traditionally male occupations is documented (Blau and Kahn, 2000). Thus, the evidence suggests that men and women have, over time, become better substitutes in the labor market (Weinberg, 1998).

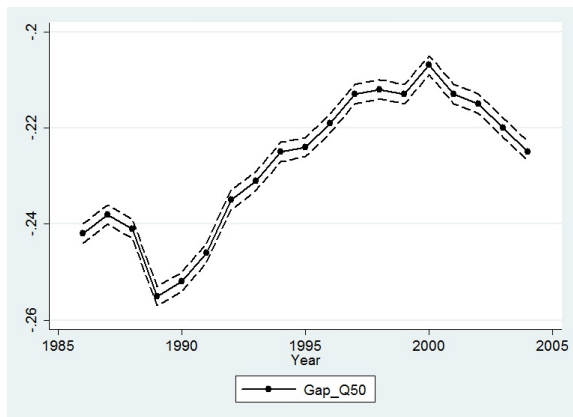


Figure 1: Gender pay gap at the median (with standard error bands). Own calculations based on the IABS data

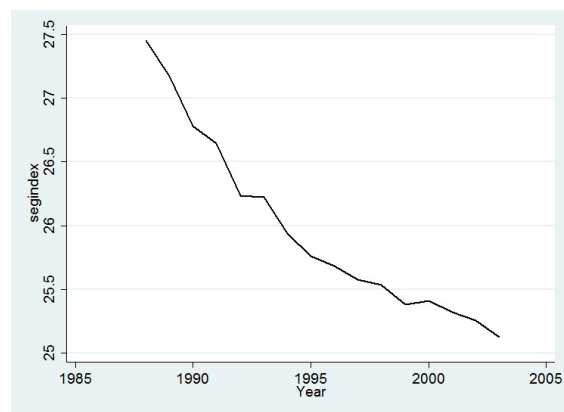


Figure 2: Gender segregation between occupations. Own calculations based on the IABS data.  $I = \frac{1}{2} \sum_{i=1}^n |M_i - F_i|$

In order to study gender-based differences in production inputs, a task-based approach can be applied. The idea behind the task-based approach is based on the representation of job contents by bundles of tasks, which can be broadly classified into routine and non-routine (Autor et al., 2003). By definition, routine tasks are well-codifiable and, therefore, labor performing these tasks can be easily substituted by computers. In the model setup of Autor et al. (2003), exogenous changes in the price for computer capital triggers changes in demanded amounts of different tasks. In particular, a significant decrease in prices for computing power due to technological progress led to replacement of routine labor by capital as a production factor. Thus, labor input experiences a reallocation from routine towards non-routine tasks. The latter can be divided into non-routine cognitive tasks, with strong complementarity to computer input, and non-routine manual tasks, with limited opportunities for substitution by computers or complementarity. Therefore, we observe that demand for routine tasks decreases, whereas demand for non-routine manual and cognitive tasks increases. Given that routine-intensive jobs are placed in the middle of the wage distribution, employment polarization has been documented (Spitz-Oener, 2006; Goos and Manning, 2007; Cortes, 2012).

Changes in demand for tasks are found to have heterogeneous effects across genders. A stylized fact from the empirical literature postulates that women became disproportionately represented in non-routine cognitive jobs, whereas their relative share in routine jobs has disproportionately fallen over time (see figure 5 in appendix C that generally replicates findings of Black and Spitz-Oener (2010) for Germany). Additionally, empirical studies document rising demand for highly educated women (Spitz-Oener, 2006; Lindley, 2012) as well as a strong trend towards skill upgrading amongst women (Fitzenberger and Wunderlich, 2000). These findings show that the composition of the labor force has improved over time, especially concerning skills related to higher wages, which suggests that the supply of qualified labor has

adjusted to the changes in demand for tasks.

Alongside the observed changes in demand for tasks and education, the task-based literature also provides explanations regarding changes in the wage structure. [Firpo et al. \(2011\)](#) empirically show that prices for task units constitute a substantial part of the wage structure and significantly contribute to changes in the wage distribution. [Katz and Murphy \(1992\)](#) also document that rising demand for skills is one of the major forces driving reallocation of labor between sectors and occupations, as well as relative labor prices. In the setup of [Katz and Murphy \(1992\)](#) prices are seen as an endogenous factor determined by changing demands in qualified labor. Endogenous prices are also typical to brain-and-brawn models that predict rising returns to non-routine tasks in response to rising input of computer technology, rising labor market participation of women and, hence, the narrowing of the gender pay gap ([Galor and Weil, 1996](#); [Weinberg, 1998](#); [Rendall, 2010](#)).

Generally, wage structure is found to be a major factor in explaining gender differences in wages ([Blau and Kahn, 1996](#)). In particular, [Yamaguchi \(2013\)](#) estimates a structural model to show that falling prices for motor skills (non-routine manual tasks) explain more than 40% of the narrowing gender pay gap in the US. However, the latter study assumes that the law of one price holds for gender-specific task input, though men and women are likely to be imperfect substitutes in performing same task and, hence, can be differently rewarded (e.g. as shown by [Lindley, 2012](#)).

An overview of the existing studies on the gender pay gap and tasks makes clear that technological progress has triggered fundamental adjustments in both the product and labor markets. Certainly, changes in demand and prices of tasks in the long run are due to general equilibrium effects and must be studied in a dynamic setting ([Galor and Weil, 1996](#); [Rendall, 2010](#)). At the same time, "deep" structural parameters that could describe the triggers of the technological progress and the related adjustment of demand and supply both at the product and the labor market remain undefined. Moreover, [Autor et al. \(2008\)](#) claim that the observed complex pattern of wage and employment adjustments due to technological change do not have a unicausal explanation.

An important issue that remains unstudied both in theoretical models and in empirical applications, is the heterogeneity of gender-specific inputs and pay within and across occupational groups. It is generally recognized that within-occupational differences are substantial to reducing the gender pay gap ([Bayard et al., 2003](#); [Olivetti and Petrongolo, 2011](#)). In the task literature, substantial dynamics of tasks within occupations are also documented ([Black and Spitz-Oener, 2010](#)), though without establishing a direct link to the reduction of the gender pay gap. Moreover, evidence for the UK by [Lindley \(2012\)](#) shows that gender inequality with respect to tasks remains substantial within occupations.

### 3 Data

For the analysis I employ two data sets – the IAB Employment Sample (IABS) and the BiBB/IAB Qualification and Career Survey (QCS). I focus on the time span of 1986-2004, for which both data sets provide comparable data. During this time, both a closing of the gender pay gap and changes in task demands are observed. The IABS is an administrative panel data set launched by the German Institute for Employment Research (IAB). The data set contains detailed daily information on the employment history of employees liable to social security. It includes main individual characteristics (gender, age, state of residence) as well as information



on wages, educational level, occupational group and full- or part-time employment status. QCS is a cross-sectional employee survey that contains survey-based information on tasks that respondents perform in their jobs. QCS provides high-quality information on tasks at the individual level, which is one of its main advantages compared to the widely used DOT or O\*NET data that contain occupational-level task data. Until now, QCS has been widely used in the task-based literature either for cross-sectional analysis (e.g. [Spitz-Oener, 2006](#); [Black and Spitz-Oener, 2010](#)), or merged with panel data (IABS or SOEP) at the level of occupations (e.g. [Gathmann and Schönberg, 2010](#)). I employ a more embrative imputation method regarding tasks using a regression estimation that is based on occupational information alongside gender, age and education. More details on the imputation procedure can be found in appendix A.

The task information from the QCS can be arranged into three broad task groups: routine (R), non-routine cognitive (NRC), and non-routine manual tasks (NRM); for details see table 6 of appendix B. Note that the task categories sum up to one by construction and generally follow the categorization of the seminal paper of [Autor et al. \(2003\)](#). Using these three task categories, an individual task share for categories  $j \in \{\text{non-routine cognitive, routine, non-routine manual}\}$  can be computed based on [Antonczyk et al. \(2009\)](#):

$$TS_{ijt} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ at time } t}{\text{total number of activities performed by } i \text{ over all categories at time } t} \quad (1)$$

These task shares can be interpreted as an approximation of time share spent by each worker to perform tasks in the respective category.

For the imputation procedure, both IABS and QCS were restricted along the same lines. The initial data were restricted to the sample of full-time employed male and female German natives aged between 25 and 55. Moreover, in order to level out the differences in labor market behaviour and incentives of men and women in IABS, I impose further restrictions on "stable" employment histories prior to the year of observation. The latter excludes employees with long inactivity spells (more than 366 days in 2 years), more than one occupational change and long (more than 95 days) interruptions in employment spells.<sup>2</sup> After all restrictions, I am left with a sample of approximately 2.1 million men and 930 thousand women. Additionally, I use employment intensity measured by the fraction of full-time employment in a calendar year as weights in the econometric estimation.

## 4 Empirical Implementation

Aiming at the exercise of decomposing wages at different quantiles of the wage distribution, I build on the empirical estimation based on the recentered influence function (RIF), introduced by [Firpo et al. \(2009\)](#). The main advantage of RIF when working with evidence on quantiles comprises computational efficiency and a possibility to perform both aggregate and detailed decomposition of the differences in the variable of interest between two groups. Virtually, the decomposition method of [Firpo et al. \(2009\)](#) constitutes a generalization of the popular Oaxaca-Blinder decomposition for a broad range of distributional measures. In the subsequent analysis I will estimate the decomposition of log wages at the 25, 50 and 75th quantile (the choice of

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<sup>2</sup>Though these restrictions were crucial for consistent estimation, the overall conclusions drawn from the estimation remain unaffected compared to the sample with "instable" employment history.

quantiles is imposed by data censoring).<sup>3</sup> Moreover, estimation of regression specifications with variables other than real log hourly wages on the left-hand side is conducted using estimation on subsamples that belong to 5-percentage point bands at the 25, 50 and 75th quantiles of the initial wage distribution.

#### 4.1 RIF-Regression

RIF-regressions differ from standard regression methods by featuring recentered influence functions in place of the dependent variable. RIF constitutes a linear approximation of any non-linear distributional statistics  $v(F_Y)$ . In my case, the dependent variables are quantiles of wage distribution  $Q_\tau(F_Y)$ . The recentered influence function (RIF) is defined by the sum of the statistics of interest and the corresponding influence function  $IF(y; v)$ :  $RIF(y; v) = v(F_Y) + IF(y; v)$ . The influence function is an empirical distribution,  $IF = \lim_{\epsilon \rightarrow 0} (v(F_\epsilon) - v(F)) / \epsilon$  with, by definition, a mean of zero:  $\int_{-\infty}^{\infty} IF(y; v) dF(y) = 0$ . Therefore, integrating the RIF along the distribution  $F(y)$  yields the distributional statistics of interest:  $\int RIF(y; v) dF(y) = v(F_Y)$ . Using the law of iterated expectations, the RIF can be re-written for the case of conditional distributions:

$$v(F) = \int \mathbb{E} [RIF(y; v) | X = x] \cdot dF_X(x). \quad (2)$$

In the case of quantiles, the recentered influence function is given by:

$$RIF(y, Q_\tau) = Q_\tau + \frac{\tau - \mathbb{1}\{y \leq Q_\tau\}}{f_Y(Q_\tau)} = c_{1,\tau} \cdot \mathbb{1}\{y > Q_\tau\} + c_{2,\tau}, \quad (3)$$

with  $c_{1,\tau} = 1/f_Y(Q_\tau)$  and  $c_{2,\tau} = Q_\tau - c_{1,\tau} \cdot (1 - \tau)$ . Thus, linearization is performed under the assumption that the relationship between counterfactual proportions and counterfactual quantiles is locally linear. RIF is estimated by computing the sample quantile  $\hat{Q}_\tau$ , and estimating the density at that point using kernel methods. Then, the estimates for  $\hat{Q}_\tau$  and  $\hat{f}(\hat{Q}_\tau)$  are plugged into the equation 2 to obtain estimates of the RIF for each observation. Afterwards, standard (linear) estimation can be performed using specifications with the initial variable of interest  $y$  replaced by the corresponding  $\widehat{RIF}$ . Therefore, estimates of the coefficients of the unconditional quantile regression can be written as:

$$\hat{\gamma}_\tau = \left( \sum_{i \in I} X_i \cdot X_i \right)^{-1} \cdot \sum_{i \in I} \widehat{RIF}(Y_i; Q_\tau) \cdot X_i. \quad (4)$$

Due to local linearization, the time required for computation of  $\hat{\gamma}_\tau$  is considerably lower than in the case of standard estimation methods of quantile regression.

#### 4.2 Firpo-Fortin-Lemieux (FFL) Decomposition

Local linearization also makes RIF-regressions suitable for decompositions of any (non-linear) distributional statistics, very similar to the decomposition procedure proposed by Oaxaca and Blinder for the mean. Analogous to the Oaxaca-Blinder procedure, the overall estimated difference between groups M and W ( $\hat{\Delta}_O^\tau$ , in my case: unconditional wage quantile) can be

<sup>3</sup>In several regression specification, it was necessary to switch from the 75th to 72nd quatile due to the censoring of the wage distribution of women. All output based on the 72nd quantile is respectively marked.



rewritten as a sum of the estimates of wage structure and composition effects (respectively denoted by  $\hat{\Delta}_S^\tau$  and  $\hat{\Delta}_X^\tau$ ):

$$\hat{\Delta}_O^\tau = \underbrace{\bar{X}_M (\hat{\gamma}_{M,\tau} - \hat{\gamma}_{W,\tau})}_{\hat{\Delta}_S^\tau} + \underbrace{(\bar{X}_M - \bar{X}_W) \hat{\gamma}_{W,\tau}}_{\hat{\Delta}_X^\tau}, \quad (5)$$

where the estimates of  $\hat{\gamma}_{M,\tau}$  and  $\hat{\gamma}_{W,\tau}$  are obtained in the separate estimation of equation (4) for the groups  $g = M, W$ :

$$\hat{\gamma}_{g,\tau} = \left( \sum_{i \in G} X_i \cdot X_i \right)^{-1} \cdot \sum_{i \in G} \widehat{\text{RIF}}(Y_{gi}; Q_{q\tau}) \cdot X_i, \quad g = M, W. \quad (6)$$

It should be mentioned that the FFL-decomposition delivers consistent estimates of the aggregate composition and wage structure effect under the common assumptions of ignorability and overlapping support.

*Assumption 1: Ignorability.* Let  $(G, X, \epsilon)$  have a joint distribution. For all  $x$  in  $X$ :  $\epsilon$  is independent of  $G$  given  $X = x$ . (Where  $G$  denotes groups, here:  $M, W$ .)

*Assumption 2: Overlapping support.* For all  $x \in X$ ,  $p(x) = \mathbb{P}[G = M | X = x] < 1$  and  $\mathbb{P}[G = M] > 0$ .

The latter assumption states that there are no  $x$  in  $X$  that are only observed among the individuals of one group. This assumption is met for my data. For consistent detailed decomposition of the gender pay gap into the contributions of single variables, stronger assumptions than ignorability (independence and strict monotonicity in the random scalar) should be met. Under these assumptions, both  $\hat{\Delta}_S^\tau$  and  $\hat{\Delta}_X^\tau$  can be re-written in terms of the sum of the contribution of each variable  $k \in \{1, \dots, K\}$  to obtain the detailed decomposition. As in the Oaxaca-Blinder decomposition, subcomponents of the detailed decomposition sum up to the aggregate effect:  $\hat{\Delta}_S^\tau = \sum_{k=1}^K \hat{\Delta}_{S,k}^\tau$  and  $\hat{\Delta}_X^\tau = \sum_{k=1}^K \hat{\Delta}_{X,k}^\tau$ . Thus, the decomposition results are easy to interpret as contribution of each variable and price for its units to the composition and wage structure effects.

My first attempt to approach the assumptions for the aggregate and detailed decomposition is to impose the additional sample restrictions on stable career profiles of men and women working in full-time positions (see section 3 for details). This restriction assures that labor market behavior of men and women is comparable in terms of incentives and other unobservable characteristics. Additionally, I employ fixed-effects models (with individual effects and individual plus occupational effects) to tackle in the gender-specific residual wage distribution.

Moreover, Fortin et al. (2011) suggest a reweighted-regression decomposition that helps to obtain consistent estimates of the wage structure and decomposition effect in cases when the conditional mean is a non-linear function. For the present paper, an application of reweighting is necessary, since it can be shown that relationship between tasks and wages is non-linear (based on my own calculations and evidence from Fedorets et al. (2013)). Reweighted composition and wage structure effects are given by:

$$\hat{\Delta}_{S,p}^\tau = \bar{X}_M (\hat{\gamma}_{M,\tau} - \hat{\gamma}_{W,\tau}^C) \quad \text{and} \quad \hat{\Delta}_{X,p}^\tau = (\bar{X}_W^C - \bar{X}_W) \hat{\gamma}_{W,\tau}, \quad (7)$$

where the subsample  $W$  is reweighted to mirror the composition of the subsample  $M$ , so that  $\text{plim}(\bar{X}_W^C) = \text{plim}(\bar{X}_M)$ .

Despite the convincing strengths of the FFL-decomposition, it is subject to several limitations. However, none of these limitations plays a significant role for the present study. Firstly, RIF-

based decomposition requires the ignorability assumption (or in other words, invariance of the conditional distribution), which, in the case of applying the processes over several years, does not yield general equilibrium effects. My analysis, however, relies on the separate estimation of RIF regressions in consecutive cross-sections and two-year panels, which allows for changes of the conditional distribution over time. Secondly, RIF regressions are based on local linearization, which might constitute a problem when measurement errors common to reported wages are present. In the subsequent analysis I employ administrative data with high-quality wage information that are not prone to heaping. Thirdly, RIF-based detailed decomposition are susceptible to the problem of the base group choice, also common to other decomposition methods. As a robustness check, I performed respective Oaxaca-Blinder and FFL-decompositions of contributions of each covariate with different choices of the base and comparison groups. Though, as expected, the estimation results were numerically nonidentical, they indeed delivered very similar qualitative results. Moreover, as the focus of the present paper is on the components of the wage structure, the choice of women being the comparison group seems appropriate as it delivers lower estimates for the wage structure effect.

Though the subsequent analysis does not aim at causal inference, problems of selection should be discussed. In the case of FFL-decomposition, these problems can cause violation of the independence assumption and, consequently, affect consistency of the estimation. The data set employed in the empirical analysis does not contain enough variables to address selection into labor force using the Heckman selection model. However, estimation with fixed effects helps to address selection on observables, time-invariant unobservables, whereas the restriction to locally stable employment histories also considerably reduces the influence on time-variant unobservables.

## 5 Estimation of the Gender Pay Gap

In the following section, I first analyze the evolution of the unconditional and the conditional gender pay gap at different quantiles of the wage distribution between 1986-2004. Then, I describe the dynamics of tasks for the same time span. Introducing tasks as control variables to the wage regression allows me to obtain estimates for the returns to task units. These returns can be interpreted as prices for tasks and are further analyzed on their contribution to the formation of the gender pay gap.

### 5.1 Descriptive Statistics for Men and Women and the Unconditional Pay Gap

Before providing estimations of the gender pay gap, the differences in observable characteristics of men and women should be considered. Descriptive statistics for the time span 1986-2004 (table 7 of appendix D) show that subsamples of men and women are very similar with respect to age, tenure and educational levels (though, men are more likely to have higher education). At the same time, women perform more non-routine cognitive, but less non-routine manual tasks than men; the over-time average share of routine tasks is almost equal between genders. As it is empirically shown that non-routine cognitive tasks are related to higher wages (Spitz-Oener, 2006), it becomes obvious that advantageous task profiles of women with prevailing non-routine cognitive tasks are not directly translated into higher wages, as the unconditional

difference in wages between genders is about 0.3 log points at the median, as well as at the bottom and the top of the wage distribution.

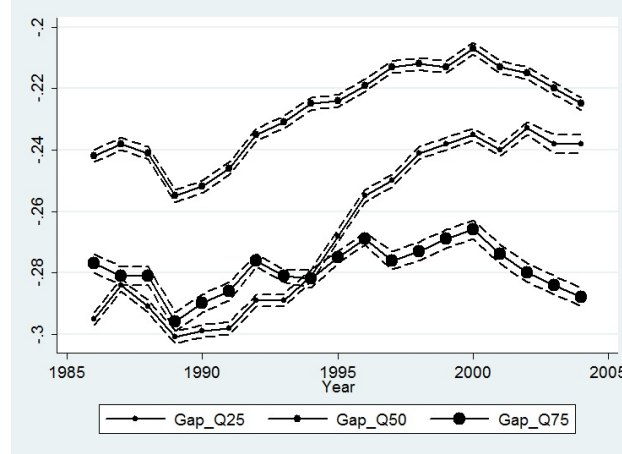


Figure 3: Unconditional gender pay gap at 25th, 50th, 75th quantiles (with standard error bands), 1986-2004

When considering the evolution of the unconditional gender pay gap over time, it becomes apparent that it has been closing at the middle and at the low end of wage distribution (figure 3). Moreover, the most dynamic closing of the pay gap at the median was observed in the 90s; after which we observe a stagnation and even a slight increase in the gap at the median. The gender pay gap at the 25th quantile exhibits a very similar, though more pronounced dynamic. At the 75th quantile, the unconditional gender pay gap is one of the highest and does not decrease with time. The trends in the evolution of the gender pay gap are generally in line with the literature for the German labor market (Fitzenberger and Wunderlich, 2000).

## 5.2 Conditional Gender Pay Gap

In order to control for differences in observable characteristics in the formation of the gender pay gap, I estimate the conditional wage gap using the following regression specification:

$$\text{RIF}(\ln W; Q_{\tau}) = \beta_0 + \beta_1 \text{Female} + \gamma X + \epsilon, \quad \tau = \{25, 50, 75\}. \quad (8)$$

where Female is an indicator variable for women and  $X$  is a set of controls that varies between specifications:

- (1) set of year dummies, age and age squared,
- (2) additionally to (1): dummies for being high- or medium-skilled (low-skilled taken as base category), tenure with the current employer,
- (3) additionally to (2): set of dummies for the current occupation,
- (4) additionally to (2): individual task profiles,
- (5) additionally to (2): set of dummies for the current occupation and individual task profiles.

Table 1 features the estimates of the conditional wage gap for the 25th, 50th and 75th quantiles of wage distribution. Comparing specifications (1)-(5), it becomes apparent that controlling for task profiles yields lower estimates for the pay gap (specification 3 against

1-2). This increase generally confirms the finding of the literature that the structure of female task profiles is positively correlated with wages, that is, females are indeed favored by tasks they perform in their jobs. Such an advantage is negligible when controlling only for the occupation of employment (specification 4). Moreover, including controls both for task profiles and occupation already suggests that positive correlation of female wages and tasks is almost non-existent within occupations. However, comparison of specifications (2) and (4) point to a positive selection of women into occupations at the median and the top of the wage distribution, though conditioning on tasks (cp. specifications 3 and 5) implies the opposite. This pattern is observed in the estimates for all three distributional quantiles. Table 1 shows that tasks are strongly relevant to the formation of the gender pay gap, though their impact is heterogeneous between and within occupations.

Table 1: Conditional Gender Pay Gap 1986–2004,  $N = 3058336$ , RIF based on real log hourly wages

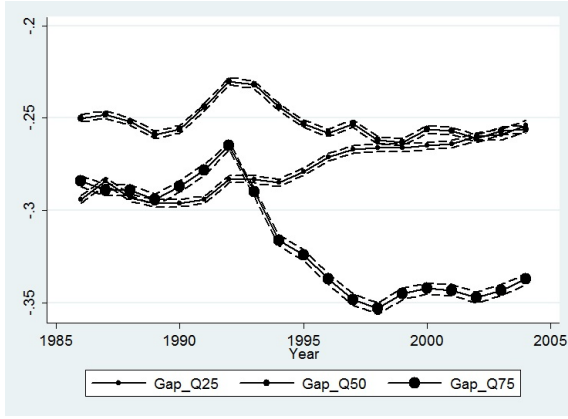
	(1)	(2)	(3)	(4)	(5)
Gap Women-to-Men, 25th quantile	-0.257*** (0.001)	-0.245*** (0.001)	-0.281*** (0.001)	-0.238*** (0.001)	-0.235*** (0.001)
Adjusted $R^2$	0.113	0.155	0.174	0.279	0.280
Gap Women-to-Men, 50th quantile	-0.210*** (0.000)	-0.189*** (0.000)	-0.254*** (0.000)	-0.222*** (0.001)	-0.219*** (0.001)
Adjusted $R^2$	0.098	0.182	0.245	0.330	0.331
Gap Women-to-Men, 75th quantile	-0.258*** (0.001)	-0.216*** (0.001)	-0.325*** (0.001)	-0.283*** (0.001)	-0.279*** (0.001)
Adjusted $R^2$	0.079	0.228	0.313	0.390	0.390
Additional covariates:					
Year	Yes	Yes	Yes	Yes	Yes
Age, Age <sup>2</sup>	Yes	Yes	Yes	Yes	Yes
Educational level		Yes	Yes	Yes	Yes
Tenure with employer		Yes	Yes	Yes	Yes
$TS_{NRC}$ & $TS_{NRM}$			Yes		Yes
Current occupation				Yes	Yes
Standard errors in parentheses; * $p < 0.05$ , ** $p < 0.01$ , *** $p < 0.001$					

In order to illustrate the evolution of the conditional gender pay gap, I chose specifications (3) and (5) to estimate gender pay gap in consecutive cross sections (figure 4).

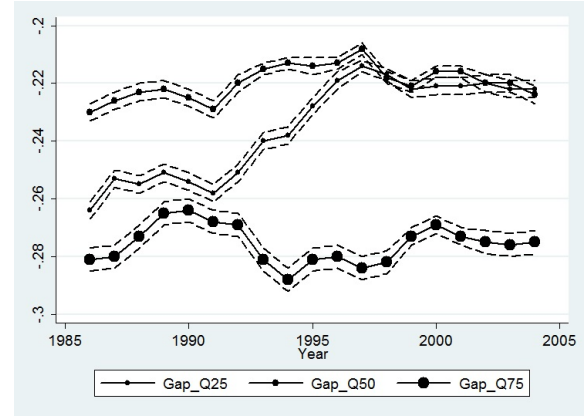
On the whole, the observed pattern of the conditional gender pay gap does not differ much from its unconditional counterpart. Closing of the gender pay gap is most pronounced at the 25th quantile of the conditional wage distribution. In contrast, the gender pay gap exhibits growth at the 75th quantile.

### 5.3 Development of Relative Task Shares

Empirical evidence of the task-based literature has focused on explaining the closing of the gender pay gap with changes in the composition of performed tasks that favored women more than men. Using the QCS data, I am able to reproduce the finding of [Black and Spitz-Oener \(2010\)](#) that women have experienced a disproportional increase of non-routine cognitive tasks



(a) Controls: age, education, tenure, task profiles



(b) Controls: age, education, tenure, task profiles, occupational group

Figure 4: Conditional gender pay gap at 25th, 50th, 75th quantiles (with standard error bands), 1986-2004

in their job contents, whereas their share of routine tasks has disproportionately fallen (see figure 5 in appendix C). At first glance, these results seem to suggest a decrease of the gender pay gap. However, it is unclear how task shares would evolve when conditioning on education, age and tenure. Empirical evidence on differences in task profiles conditional on occupations is absent. Moreover, there is evidence from the UK that women do not experience task-related advantages within broad sectors (Lindley, 2012).

In order to estimate differences in relative task shares, I perform separate OLS estimations of task shares  $TS_j$ ,  $j = \{NRC, R, NRM\}$  regressed on different sets of control variables:

$$TS_j = \beta_0 + \beta_1 \text{Female} + \gamma X + \epsilon, \quad (9)$$

where Female is an indicator variable for women and  $X$  is a set of controls that varies between specifications:

- (1) set of year dummies, age and age squared,
- (2) additionally to (1): dummies for being high- or medium-skilled (low-skilled taken as base category) and tenure with the current employer,
- (3) additionally to (2): set of dummies for the current occupation.

Separately estimated conditional mean differences in task profiles are featured in table 2. Specifications (1) and (2) show that in the period of 1986 to 2004 women were employed in jobs with, on average, higher shares of non-routine cognitive tasks and lower shares of routine and non-routine manual tasks. Interestingly, this finding holds between occupational groups, but not within them (specification 3). Within occupations women exhibit even lower shares of non-routine cognitive tasks and higher shares of routine tasks than men. Though the coefficient for female indicator is negative in all specifications for non-routine manual tasks, its magnitude is much lower within occupations. The estimation makes clear that female advantages in task profiles that have been found in the literature until now, are not observed within occupational groups. Including interactions of the independent variables with the indicator (tables 8, 9 and 10 in appendix D) for women provides a similar conclusion about females' advantageous task profiles on the whole, but not within occupations.

Table 2: Conditional Task Profiles 1986–2004,  $N = 3058336$ , OLS

	(1)	(2)	(3)
Dependent var: Non-routine cognitive task share $TS_{NRC}$ :			
Female	0.102*** (0.000)	0.121*** (0.000)	-0.033*** (0.000)
Adjusted R-squared	0.100	0.304	0.844
Dependent var: Routine task share $TS_R$ :			
Female	-0.028*** (0.000)	-0.038*** (0.000)	0.044*** (0.000)
Adjusted R-squared	0.125	0.222	0.644
Dependent var: Non-routine manual task share $TS_{NRM}$ :			
Female	-0.074*** (0.000)	-0.083*** (0.000)	-0.010*** (0.000)
Adjusted R-squared	0.046	0.136	0.814
Additional covariates:			
Year	Yes	Yes	Yes
Age, Age <sup>2</sup>	Yes	Yes	Yes
Educational level, Tenure		Yes	Yes
Current occupation			Yes
Standard errors in parentheses; * $p < 0.05$ , ** $p < 0.01$ , *** $p < 0.001$			

In order to shed light on the dynamics of conditional task profiles, I analyze specifications 2 and 3 at the quantiles of the wage distribution by year. For this exercise, I define 5-percentage points bands at the wage quantiles of interest (25th, 50th and 75th) and use OLS to estimate mean task shares for men and women separately by year and quantile of the wage distribution. Mean differences in task shares at quantiles are displayed in figures 6 and 7 of appendix C. The results clearly state that the dynamics of conditional task profiles generally follows the trends of the unconditional profiles. However, the changes in task profiles within occupations exhibit these changes at a much lower magnitude. Indeed, one observes relative growth in both non-routine tasks and a decrease in the routine tasks, but these changes cannot be qualified as disproportionate growth. Rather, one could speak of levelling out the initial disproportions in task shares that are present in the beginning of the analyzed time span. Interestingly, this finding is robust across quantiles of wage distribution and might be related to the growing substitutability of men and women within occupations.

Comparison of unconditional and conditional task shares points towards the fact that the closing of the gender pay gap is mainly carried out by the differences between occupations that have favored women.

## 5.4 Gender-Specific Returns to Tasks and Their Contribution to the Pay Gap

Alongside gender differences in endowments, gender-specific wage determination and wage inequality can be explained by wage structure, defined as "prices set for various labor market skills and the rents received for employment in particular sectors of the economy" (Blau and Kahn, 1996). In order to approach the question of possible gender-specific differences in returns to task units, I estimate separate wage regressions for men and women:



$$\text{RIF}(\ln W; Q_\tau) = \beta_0 + \beta_1 \text{TS}_{NRC} + \beta_2 \text{TS}_{NRM} + \gamma X + \epsilon, \quad \tau = \{25, 50, 75\}. \quad (10)$$

where  $X$  is a set of controls varying across specifications. I report estimates for the following sets of variables in  $X$ : (1) age, age squared, education, tenure, (2) age, age squared, education, tenure and occupational groups, (3) age, age squared, education, tenure and individual fixed effects, (4) age, age squared, education, tenure and individual times occupation fixed effects.

A remark should be made about the exclusion of one task category (as NRC, R and NRM share sum up to one by construction). Performing robustness checks with different combinations of tasks showed a qualitatively stable picture of the evolution of task prices and their contributions to the gender pay gap. However, choosing routine tasks as the excluded category in the regression analysis yields several advantages. Firstly, the estimates are easily interpretable using the brain-and-brawn framework that focuses only on non-routine cognitive and manual tasks and almost disregards the routine tasks. The study of [Yamaguchi \(2013\)](#) also focuses on these task categories. Secondly, exclusion of a task category which exhibits a declining share over time has the advantage that the estimated relative prices for the other two categories can be seen as lower bound of estimates for relative task prices. This is the case both because the quantity of the routine tasks diminishes, as well as because of the secondary general equilibrium effect that leads to relative price decrease for the included task categories.

The resulting estimates of relative task prices for NRC and NRM for specifications 1-4 are depicted in figures 8, 9, 10 and 11, together with the corresponding standard errors. Figures 8 and 9 additionally contain the contribution of relative task prices to the formation of the gender pay gap based of the Firpo-Fortin-Lemieux decomposition for quantiles of wage distribution.

Conditional task prices in figure 8 substantially contribute to the formation of the gender pay gap. For all quantiles, the role of the task prices diminishes over time, though at the 75th quantile it remains at a high level. Gender-specific prices for non-routine cognitive tasks converge over time. Moreover, at the 25th quantile women receive a substantially higher remuneration of same task units since the mid-nineties. The evolution of task prices for manual tasks is also more advantageous for women. Since the mid-nineties they are significantly higher remunerated for NRM tasks. It is worth noticing that the role of the prices for non-routine cognitive tasks in the formation of the gender pay gap gains importance at the high end of wage distribution.

For the sake of comparison, the right panels of figures 8 and 9 contain the contribution of the returns to education to the gender pay gap. It is apparent that the role of tasks in the formation of the gender pay gap is more important than those of education, as the contribution of tasks is both higher in magnitude and exhibits more dynamics over time.

A similar patterns can be observed for relative task prices within occupations (see figure 9). Convergence of prices is detected at the 25th and the 50th quantile, though contributions of task prices to the formation of the pay gap is about zero. At the high end of the wage distribution, convergence of price estimates is seen only for the non-routine manual tasks. Relative prices for non-routine cognitive tasks diverge from the mid-nineties onwards, favoring men. This translates into the growing relevance of task prices in the formation of the gender pay gap.

Concerning specifications 3 and 4, it should be mentioned that inclusion of individual fixed-effects differences out all time-invariant components. In particular, this leads to an insignificant gender pay gap in all years. Taking account of individual fixed effects captures invariant components of individual productivity, including productivity in performing particular tasks. Introducing individual times occupational fixed effects captures individual productivity within

particular occupations. Specification 3 yields consistent estimates of relative task prices under the assumption of invariant individual productivity within 2 years. Specification 4 imposes a stronger assumption on invariant individual productivity within occupations. The estimation full results of estimation including fixed effects can be found in appendix C, figures 10 and 11.

## 6 Robustness Checks

In order to test the stability of the obtained results, various robustness checks were performed. First, the formation of the gender pay gap conditional on tasks and other covariates was estimated for the mean of the wage distribution using the Tobit analysis (due to the censoring of the wage variable) and the corresponding Oaxaca-Blinder decomposition. The quality of the results remained unchanged.

Second, the overall picture was checked on stability of samples with and without the restriction on the stable employment histories. Different ways of restricting careers to make labor market behaviour of men and women more comparable, also did not provide qualitatively different results.

Third, the robustness checks by taking different combinations of the included and base categories for the estimation of the relative task prices was performed. In all cases, prevailing relevance of the non-routine cognitive tasks over years and quantiles remained a strongly pronounced result.

## 7 Conclusion

The goal of the present paper is to provide comprehensive evidence on the evolution of the gender pay gap in Germany with a focus on gender-specific task inputs. The main advantage of applying the task-based approach to the analysis of the gender pay gap is that it allows the direct comparison of the job contents between men and women. Moreover, tasks and returns to them are directly involved in the formation of wages. In contrast, parameters of education that have been widely used in the literature mirror the supply of skills and have no straightforward relation to the parameter of the demand for skills. Though education is correlated with the evolution of tasks, it can be also seen as a response of the supply side to the shifts in the demand for tasks. Therefore, in the analysis I focus on the role of tasks in the formation of the gender pay gap, but also introduce educational levels as a control variable. The econometric analysis has shown that job tasks are closely related to the formation of the gender pay gap. Moreover, the contribution of the returns to tasks to the formation of the gender pay gap is substantially higher than the contribution of educational controls.

Just as [Black and Spitz-Oener \(2010\)](#), I find substantial changes in the relative content of job tasks over time that favor women. However, this evidence is almost non-existent at the occupational level, exhibiting a mere convergence of gender-specific job tasks within occupations. This finding points at the growing substitutability of genders within occupations. The assumed comparative advantage of women in performing non-routine cognitive tasks seems to be translated into females being employed in occupations that require higher inputs of these tasks. Yet, within occupations, the task profiles of women do not exhibit overproportionate shares of non-routine cognitive tasks. This evidence suggests the existence of different selection mechanisms with respect to job content on the whole and within occupations.

For the formation of the gender pay gap, the returns to task units play a substantially more important role than task inputs themselves. At the middle and the low-end of the wage distribution, the observed convergence of relative task prices over time translates into their falling contribution to the gender pay gap. Moreover, stagnation of the gender pay gap at the top of the distribution is accompanied by diverging gender-specific prices for task units and their increasing contribution to the gender pay gap. The chosen empirical design does not, however, answer the question of why relative task prices in occupations diverge at the top of the wage distribution, but not at the low end and the median. Alongside the possible discrimination of women in high-paying jobs, there are other possible explanations to the observed differences in task prices. Due to the rising specificity of inputs in high-paying jobs, it is more likely that men and women actually perform different tasks within the broad group of non-routine cognitive tasks, which gives rise to the differences in returns to these tasks. Gender-specific heterogeneity of tasks within the task categories can also stem from unobserved heterogeneous shifts in the respective demand and supply. The incidence of higher inequality at the top of the wage distribution is in line with the findings of [Autor et al. \(2008\)](#).

On the whole, the findings of the present paper are very robust. Though the presented evidence stems from a reduced-form estimation, it points towards an increasing level of gender substitutability in production over time, especially within occupations. Except for the top of the wage distribution in occupations, the evidence suggests that the law of one price for gender-specific task units is observed.

## A Data and Imputation Procedure

This appendix features a summary of an appendix appearing in the current draft of [Fedorets et al. \(2013\)](#) that employs the same data sources and a very similar imputation procedure for the subsample of men. For the purposes of the present study, I exclude individual wages from the imputation procedure and perform it separately for men and women.

### A.1 Data

The main data source for the present study is the IAB Employment Sample (IABS) launched by the German Institute for Employment Research of the Federal Employment Service. The data contains a 2 percent representative sample of all individuals for which social insurance is compulsory. The employment histories are recorded on a daily basis and contain individual-level information on wages, educational level, occupational group and full- or part-time employment status along with selected individual characteristics (gender, age, state of residence). The panel structure of this data set allows detailed analysis of wage dynamics. As these data do not contain any information on tasks, I use regression analysis to impute the lacking task data from the QCS.

QCS is an employee survey launched by Federal Institute for Vocational Education and Training (BiBB) together with the Institute for Employment Research (IAB). This data set includes the four cross-sections of QCS launched by BiBB and IAB in 1979, 1985/86, 1991/92 and 1998/99, as well as the later wave of the "Working-Population Survey" launched by BiBB and the Federal Institute for Occupational Safety and Health (BAuA) in 2006. QCS is a rich data set that has been widely used in the task-based literature as it contains individual-level information of activities that respondents perform in their jobs alongside other characteristics such as occupation of employment, gender, age, qualification, wages. The individual-level task information contained in QCS is seen as its main advantage over the common US data sources on tasks.<sup>4</sup> The task data from the QCS is, until now, either used in their initial cross-sectional form, or as a basis for calculation of task intensities at occupational level and their further merger with other data sets (IABS or GSOEP). Yet the latter procedure allows for panel data analysis, it destroys variation of tasks within occupations. [Fedorets et al. \(2013\)](#) and the present paper employ imputation using regression analysis that helps to maintain initial task variation within occupational groups.

Based on the time span covered by IABS and QCS, I am able to perform the imputation procedure for the years from 1986 to 2004.

### A.2 Calculation of Task Shares in QCS

The questionnaires of QCS for different years contain sets of questions on activities that respondents perform in their jobs in the form of either binary variables, or a Lickert scale (that is commonly re-scaled to a binary variable). Table 6 illustrates how the reported activities are assigned into three task categories: non-routine cognitive (NRC), routine (R) and non-routine manual (NRM).

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<sup>4</sup>The widely used Dictionary of Occupational Titles (DOT) and O\*NET include task information at occupational level. Individual-level task data from the Princeton Data Improvement Initiative are now available as a single cross-section of 2008.

Following [Antonczyk et al. \(2009\)](#) and after necessary sample restrictions, an individual-level share of each of the three categories is calculated for each cross-section:

$$TS_{ijt} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ at time } t}{\text{total number of activities performed by } i \text{ over all categories at time } t}$$

Thus,  $TS_{ijt}$  approximates the share of working time that individual  $i$  spends on task  $j$  at time  $t$ . Table 4 documents evolution of task categories for men and women over time. As expected, the share of routine tasks falls for both men and women over time.

Table 3: Average task intensities in QCS by year and gender

	1986	1992	1999	2004
Men				
NRC tasks	38%	37%	43%	47%
R tasks	37%	35%	32%	26%
NRM tasks	24%	27%	24%	26%
Women				
NRC tasks	31%	29%	36%	40%
R tasks	50%	51%	40%	25%
NRM tasks	18%	19%	22%	34%

### A.3 Imputation of Task Shares in IABS

These task indices (individual task profiles) were then imputed from QCS to IABS data. Firstly, the calculated task shares were regressed on a set of variables regressed on employee's characteristics (130 occupational groups, age, qualification as well as interaction terms) using separate OLS estimation for genders as well as different QCS waves (1986, 1991, 1998 and 2006). The set of the predictors was chosen to be available both in QCS and IABS, and the data sets were restricted along the same lines. In order to avoid task shares that are bigger than one or negative, a truncation of misfitting values is performed.

Secondly, the estimated single coefficient of the predicting variables were interpolated for the analyzed time span of 1986-2004 using linear weights according to the following rule:

$$\hat{\beta}_{x(ijt)}(t) = \frac{t_1 - t}{t_1 - t_0} \hat{\beta}_{x(ijt)}(t_1) + \frac{t - t_0}{t_1 - t_0} \hat{\beta}_{x(ijt)}(t_0),$$

where  $t$  indicates a year of the time span 1986-2004 with  $t_0$  and  $t_1$  being the most close years out of the available QCS waves (1986, 1991, 1998 and 2006).

Thirdly, the interpolated coefficients were used to predict the individual task profiles in IABS based on the same set of predictors.

Such an imputation procedure constitutes an approximation of task shares for further empirical analysis and captures natural correlation of individual task profiles with other individual characteristics. In order to control for quality of the imputing procedure, the following measures were taken (detailed tables can be found in [Fedorets et al. \(2013\)](#)):

- The distributions of the predicting variables in QCS and IABS were thoroughly investigated and found to be roughly equal.

- The distribution of the initial task shares in the QCS and the fitted values both in the QCS and IABS were compared. The imputation procedure proved to be more precise for men than for women, though in both cases the dynamics of relative task shares were identical. The possible deviations of the absolute task shares is tackled by using yearly dummies in cross-sectional analysis.

Table 4: Average predicted task intensities in IABS by year and gender

	1986	1992	1999	2004
Men				
NRC tasks	40%	38 %	47%	49%
R tasks	37%	36%	31%	27%
NRM tasks	23%	26%	23%	24%
Women				
NRC tasks	43%	40%	66%	65%
R tasks	45%	46%	15%	13%
NRM tasks	12%	14%	20%	22%

- In order to prove the importance of including variables other than occupation into the imputational procedure, additional imputation based only on occupations was performed. Comparing the variations of the initial task shares to their fitted values based on the two imputation procedures, one can conclude that, though about half of the variation in tasks comes from occupations, additional covariates (such as age and gender) help to reach almost the total variation in the initial variable (see table 5 below).

Table 5: Standard deviation in the original task categories, as well as in task categories predicted by occupations with and without additional covariates. Calculations using the QCS data for the subsample of men.

	Abstract	Routine	Manual
1986			
SD: Orig. BiBB info	0.138	0.073	0.082
SD: Pred. by Occ & X	0.133	0.060	0.078
SD: Pred. by Occ	0.101	0.037	0.067
1992			
SD: Orig. BiBB info	0.160	0.078	0.092
SD: Pred. by Occ & X	0.157	0.073	0.088
SD: Pred. by Occ	0.126	0.055	0.077
1999			
SD: Orig. BiBB info	0.145	0.084	0.067
SD: Pred. by Occ & X	0.142	0.081	0.063
SD: Pred. by Occ	0.118	0.069	0.050
2006			
SD: Orig. BiBB info	0.153	0.068	0.093
SD: Pred. by Occ & X	0.149	0.065	0.087
SD: Pred. by Occ	0.124	0.055	0.072



## B Assignment of Tasks into Categories

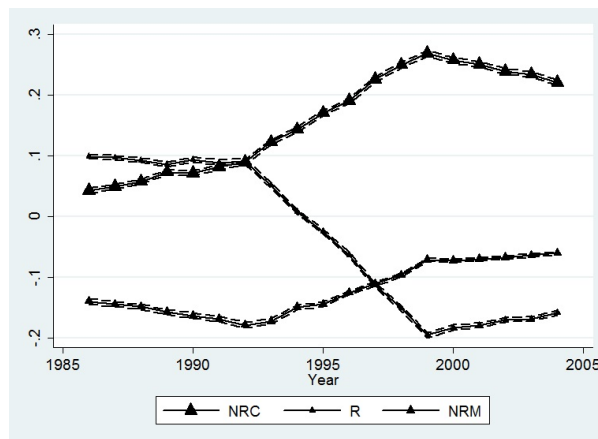
This appendix features a table from [Fedorets et al. \(2013\)](#) that describes assignment of activities from the QCS questionnaire into task categories. A very similar classification with 5 task categories can be found in [Spitz-Oener \(2006\)](#).

Task categories	Tasks
Non-routine cognitive (NRC)	<b>Human resources management:</b> recruiting, negotiating, prescribing rules, instructing. <b>Research and development:</b> researching, analyzing, evaluating, construction, designing, developing. <b>Public relations:</b> marketing, publishing, acquisition, presenting, consultation, lobbying. <b>Management and organisation:</b> purchasing, sales, coordinating, planning, legal interpretation. <b>Education:</b> teaching, training.
Routine (R)	<b>Accounting and controlling:</b> calculating, bookkeeping, archiving, sorting, correction. <b>Quality management:</b> measuring, monitoring, quality checks. <b>Production:</b> producing, packaging, loading, transporting, sending, operate machines.
Non-routine manual (NRM)	<b>Maintenance:</b> repairing, renovation, servicing machines, restoring. <b>Construction:</b> building, installing. <b>Hotel and restaurant:</b> serve, accommodating, catering. <b>Other Services:</b> cleaning, security, care.

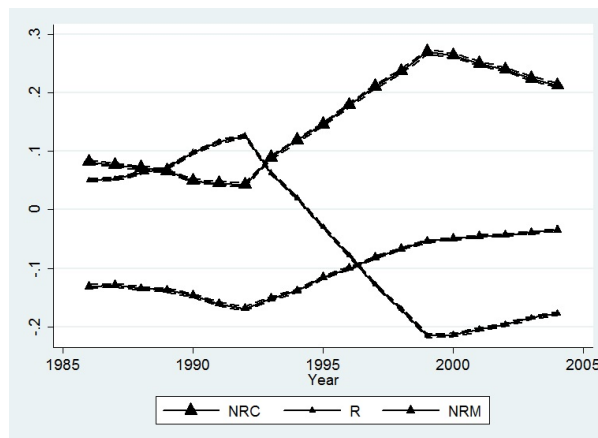
## C Figures

Figure 5: Unconditional mean relative task profiles (women-to-men) at different quantiles of the wage distribution (with standard error bands), 1986-2004

(a) 25th quantile:



(b) at 50th quantile:



(c) at 75th quantile:

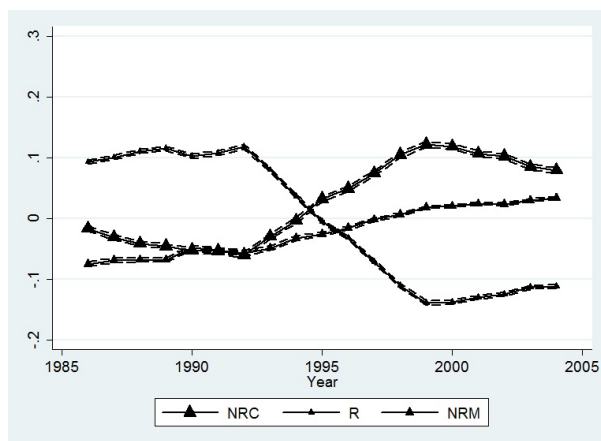
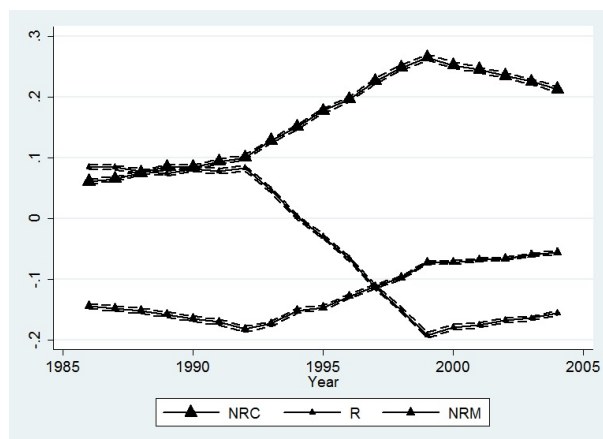
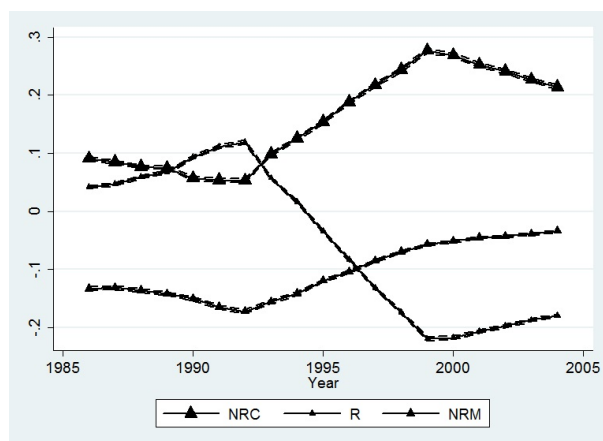


Figure 6: Mean relative task profiles (women-to-men) at different quantiles of the wage distribution, conditional on age, education, tenure (with standard error bands), 1986-2004

(a) 25th quantile:



(b) at 50th quantile:



(c) at 75th quantile:

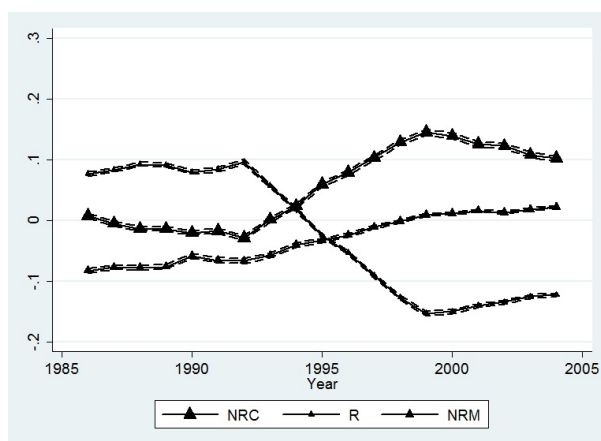
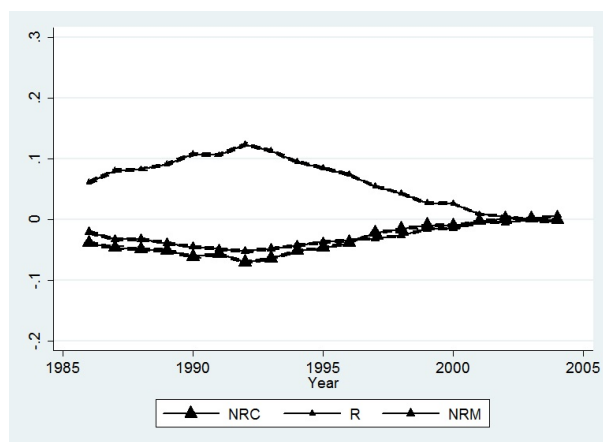
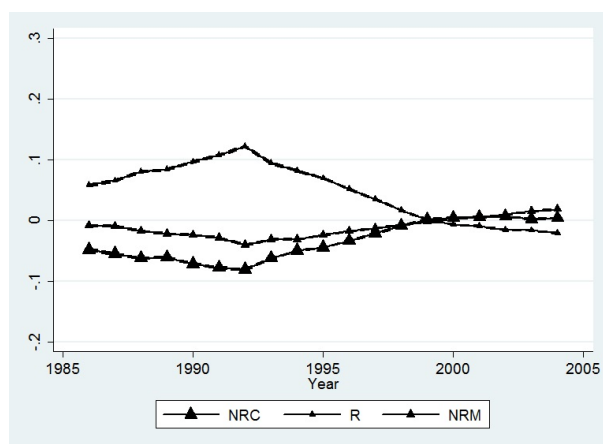


Figure 7: Mean relative task profiles (women-to-men) at different quantiles of the wage distribution, conditional on age, education, tenure and occupation (with standard error bands), 1986-2004

(a) 25th quantile:



(b) at 50th quantile:



(c) at 75th quantile:

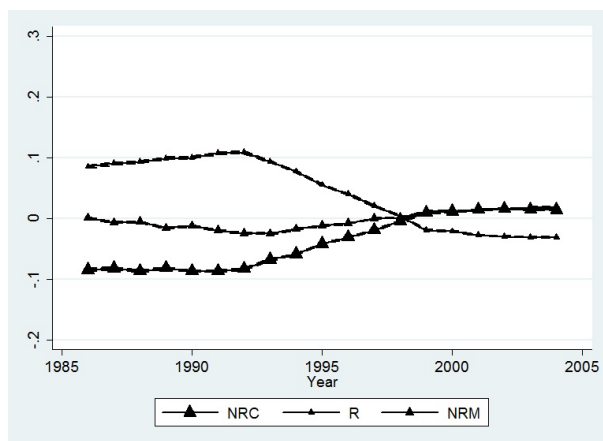
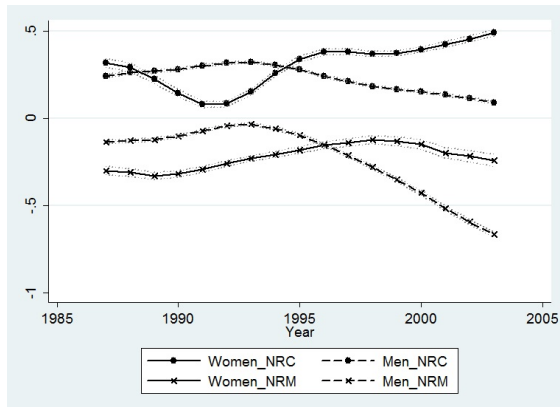
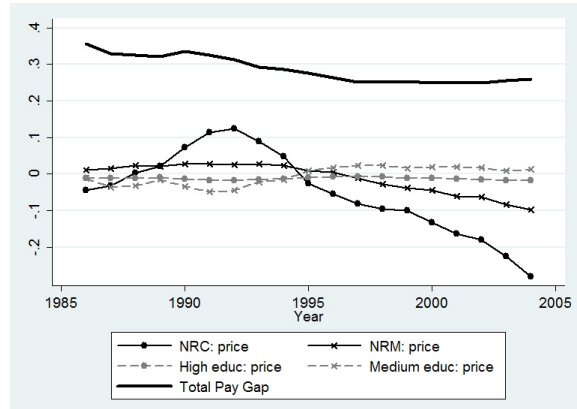


Figure 8: Prices for task units (conditional on age, education, tenure) and total contribution of task prices to formation of the gender pay gap (with standard error bands), 1986-2004

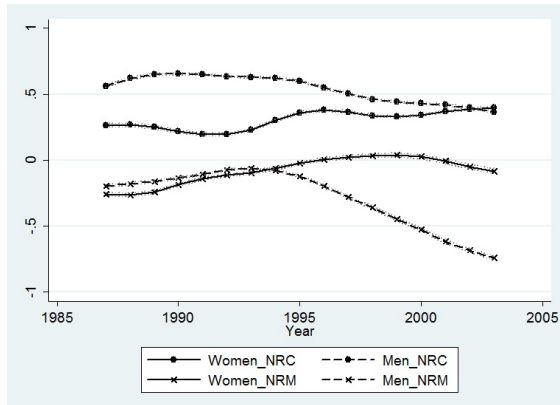
(a) 25th quantile: Gender-specific task prices



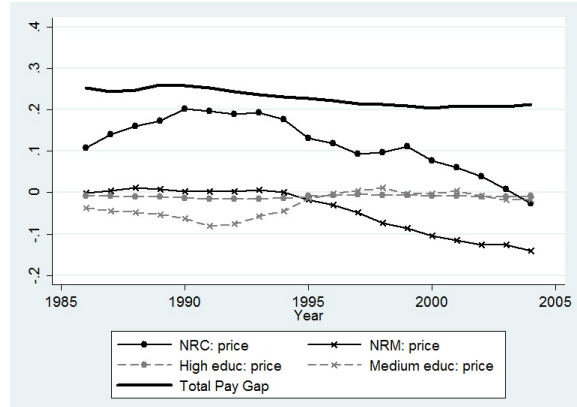
(b) Total contribution of task prices to pay gap



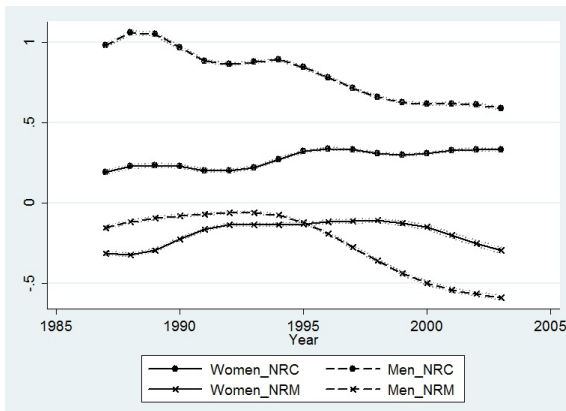
(c) at 50th quantile: Gender-specific task prices



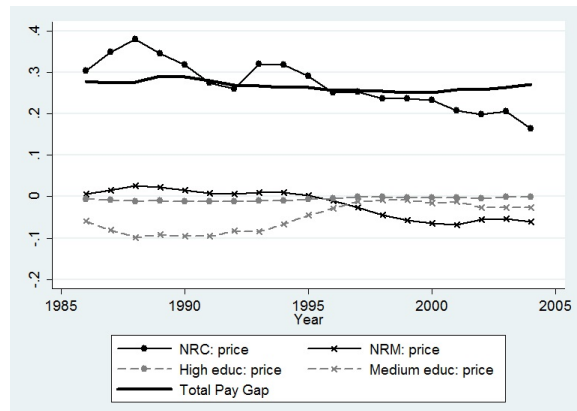
(d) Total contribution of task prices to pay gap



(e) at 72nd quantile: Gender-specific task prices



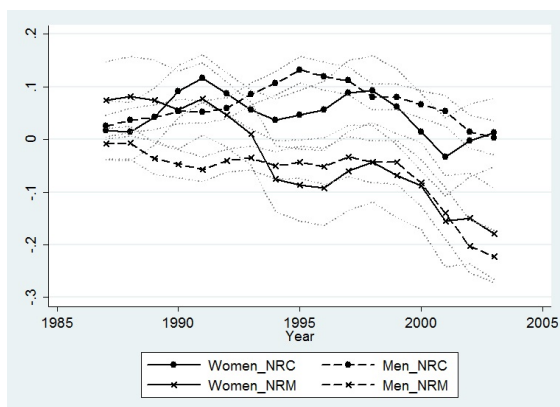
(f) Total contribution of task prices to pay gap



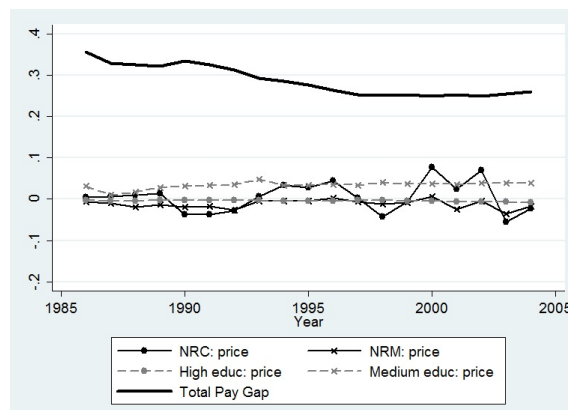
Gray-coloured lines refer to contributions of returns to education and are displayed for the sake of comparison.

Figure 9: Prices for task units (conditional on age, education, tenure, occupation) and total contribution of task prices to formation of the gender pay gap (with standard error bands), 1986-2004

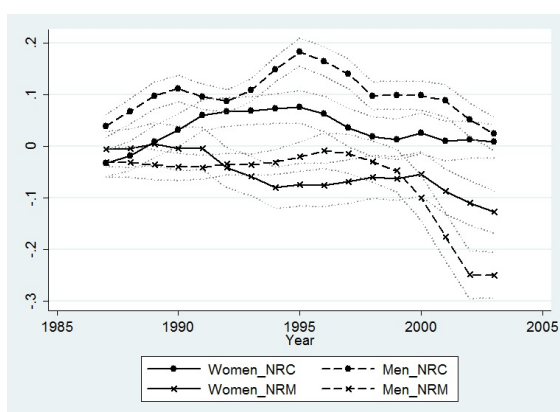
(a) 25th quantile: Gender-specific task prices



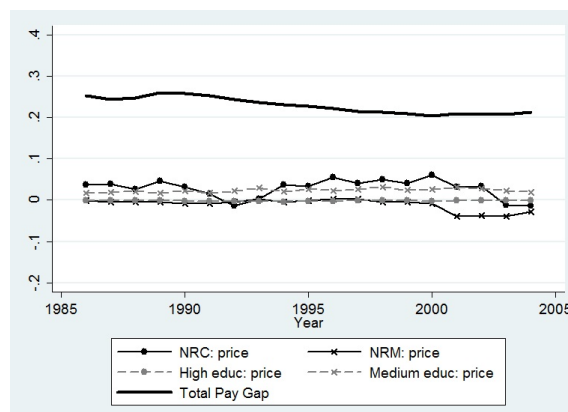
(b) Total contribution of task prices to pay gap



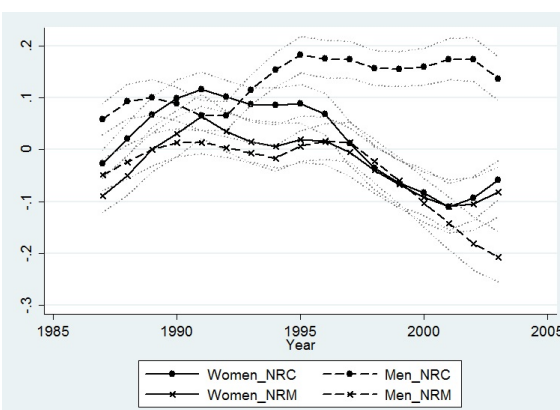
(c) at 50th quantile: Gender-specific task prices



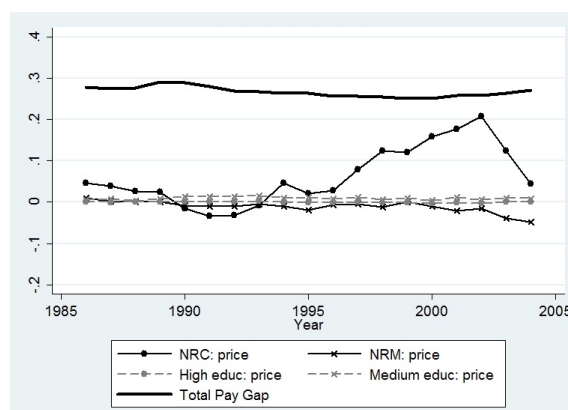
(d) Total contribution of task prices to pay gap



(e) at 72nd quantile: Gender-specific task prices



(f) Total contribution of task prices to pay gap

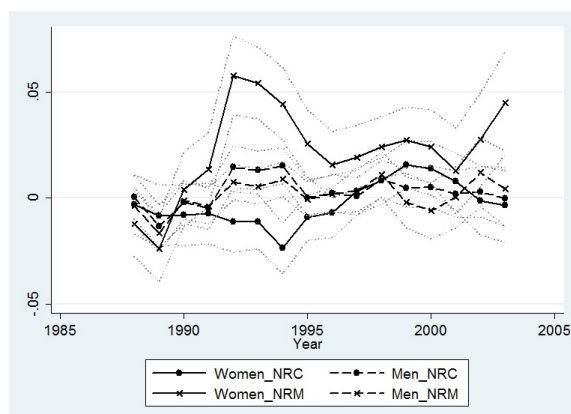


Gray-coloured lines refer to contributions of returns to education and are displayed for the sake of comparison.

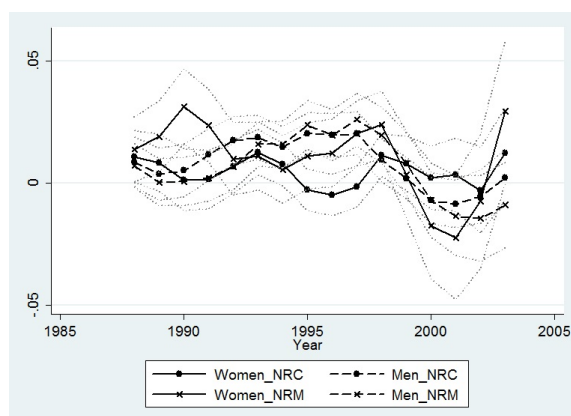


Figure 10: Prices for task units (conditional on age, qualification with individual fixed effects) and total contribution of task prices to formation of the gender pay gap (with standard error bands), 1986-2004

(a) 25th quantile: Gender-specific task prices



(b) at 50th quantile: Gender-specific task prices



(c) at 75th quantile: Gender-specific task prices

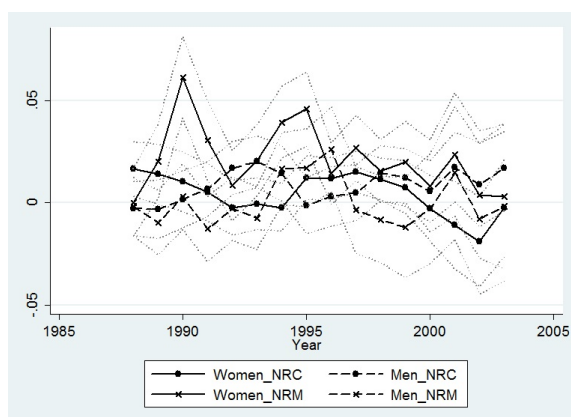
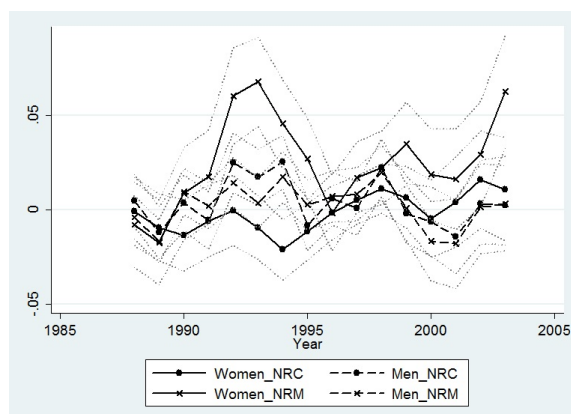
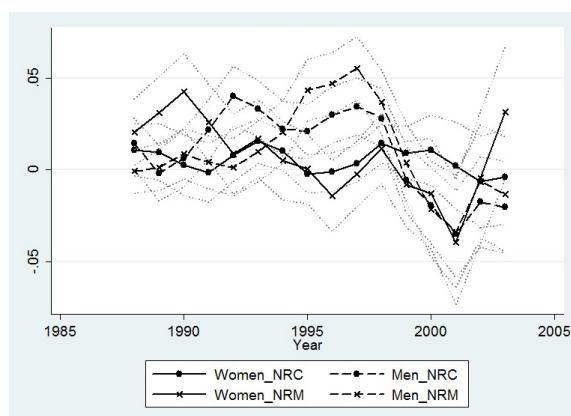


Figure 11: Prices for task units (conditional on age, qualification with individual · occupation fixed effects) and total contribution of task prices to formation of the gender pay gap (with standard error bands), 1986-2004

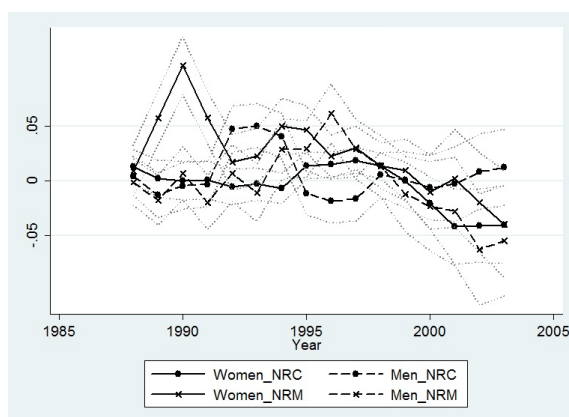
(a) 25th quantile: Gender-specific task prices



(b) at 50th quantile: Gender-specific task prices



(c) at 75th quantile: Gender-specific task prices



## D Descriptive Statistics

Table 7: Descriptive statistics for the subsamples of men and women, 1986–2004

	Men		Women	
Log hourly wage : 25th quantile	2.36		2.07	
Log hourly wage : 50th quantile	2.55		2.32	
Log hourly wage : 75th quantile	2.81		2.54	
Low-skilled : mean	0.062		0.068	
Medium-skilled : mean	0.812		0.863	
High-skilled : mean	0.126		0.069	
Non-routine cognitive tasks : mean (s.d.)	0.443	(0.243)	0.543	(0.221)
Routine tasks : mean (s.d.)	0.327	(0.168)	0.298	(0.237)
Non-routine manual tasks : mean (s.d.)	0.230	(0.170)	0.159	(0.152)
Tenure with current employer : mean (s.d.)	10.99	(6.593)	10.74	(6.260)
Observations	2131143		927193	

Table 8: Conditional Profile of Non-Routine Cognitive Tasks 1986–2004,  $N = 3058336$ 

Dependent Var: $TS_{NRC}$ :	(1)	(2)	(3)	(4)	(5)
Female	0.097*** (0.000)	0.526*** (0.007)	0.389*** (0.006)	0.470*** (0.006)	0.071*** (0.003)
Age		0.030*** (0.000)	0.020*** (0.000)	0.022*** (0.000)	0.013*** (0.000)
Age · Female		-0.019*** (0.000)	-0.010*** (0.000)	-0.015*** (0.000)	-0.003*** (0.000)
Age <sup>2</sup>		-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Age <sup>2</sup> · Female		0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Medium-skilled			0.191*** (0.001)	0.196*** (0.001)	0.083*** (0.000)
Medium-skilled · Female			-0.002* (0.001)	-0.018*** (0.001)	-0.030*** (0.000)
High-skilled			0.526*** (0.001)	0.525*** (0.001)	0.185*** (0.000)
High-skilled · Female			-0.160*** (0.001)	-0.155*** (0.001)	-0.006*** (0.001)
Tenure				-0.002*** (0.000)	-0.001*** (0.000)
Tenure · Female				0.007*** (0.000)	0.003*** (0.000)
Adjusted R-squared	0.091	0.103	0.312	0.318	0.846
Additional covariates:					
Year	Yes	Yes	Yes	Yes	Yes
Current occupation					Yes
Standard errors in parentheses; * $p < 0.05$ , ** $p < 0.01$ , *** $p < 0.001$					

Table 9: Conditional Profile of Routine Task 1986–2004,  $N = 3058336$ 

Dependent Var: $TS_R$ :	(1)	(2)	(3)	(4)	(5)
Female	-0.025*** (0.000)	-0.211*** (0.006)	-0.099*** (0.005)	-0.172*** (0.005)	0.045*** (0.004)
Age		-0.013*** (0.000)	-0.008*** (0.000)	-0.010*** (0.000)	-0.004*** (0.000)
Age · Female		0.008*** (0.000)	0.003*** (0.000)	0.008*** (0.000)	0.000* (0.000)
Age <sup>2</sup>		0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Age <sup>2</sup> · Female		-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)
Medium-skilled			-0.118*** (0.000)	-0.122*** (0.000)	-0.067*** (0.000)
Medium-skilled · Female			-0.040*** (0.001)	-0.026*** (0.001)	0.005*** (0.001)
High-skilled			-0.283*** (0.001)	-0.282*** (0.001)	-0.120*** (0.000)
High-skilled · Female			0.015*** (0.001)	0.010*** (0.001)	-0.018*** (0.001)
Tenure				0.001*** (0.000)	0.001*** (0.000)
Tenure · Female				-0.006*** (0.000)	-0.004*** (0.000)
Adjusted R-squared	0.120	0.126	0.224	0.231	0.647
Additional covariates:					
Year	Yes	Yes	Yes	Yes	Yes
Current occupation					Yes
Standard errors in parentheses; * $p < 0.05$ , ** $p < 0.01$ , *** $p < 0.001$					

Table 10: Conditional Profile of Non-Routine Manual Task 1986–2004,  $N = 3058336$ 

Dependent Var: $TS_{NRM}$ :	(1)	(2)	(3)	(4)	(5)
Female	-0.071*** (0.000)	-0.316*** (0.005)	-0.291*** (0.005)	-0.299*** (0.005)	-0.117*** (0.002)
Age		-0.017*** (0.000)	-0.012*** (0.000)	-0.012*** (0.000)	-0.009*** (0.000)
Age · Female		0.011*** (0.000)	0.007*** (0.000)	0.007*** (0.000)	0.003*** (0.000)
Age <sup>2</sup>		0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Age <sup>2</sup> · Female		-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Medium-skilled			-0.073*** (0.000)	-0.075*** (0.000)	-0.017*** (0.000)
Medium-skilled · Female			0.043*** (0.001)	0.044*** (0.001)	0.025*** (0.000)
High-skilled			-0.243*** (0.001)	-0.243*** (0.001)	-0.065*** (0.000)
High-skilled · Female			0.146*** (0.001)	0.146*** (0.001)	0.025*** (0.000)
Tenure				0.001*** (0.000)	-0.001*** (0.000)
Tenure · Female				-0.001*** (0.000)	0.002*** (0.000)
Adjusted R-squared	0.042	0.047	0.144	0.145	0.815
Additional covariates:					
Year	Yes	Yes	Yes	Yes	Yes
Current occupation					Yes
Standard errors in parentheses; * $p < 0.05$ , ** $p < 0.01$ , *** $p < 0.001$					



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