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Maren M. Michaelsen[1]

The Hidden Increase in Wage Inequality: Skill-biased and Ability-biased Technological Change

Abstract

This study provides strong evidence for an increase in wage inequality induced by skill-biased technological change in the UK manufacturing industry between 1991 and 2006. Using individual level data from the BHPS and industry level data from the OECD, wage regressions are estimated which identify the effect of innovative activity on wages – the personal innovation wage premium – for university and less educated workers. Innovative activity is defined by R&D expenditure and patent applications to measure innovation input and innovation output, respectively. Using different estimation methods for panel data, such as Fixed effects, Random effects, Mundlak and Hausman-Taylor models, additionally to pooled OLS allows controlling for both industry-specific and individual ability. Using R&D expenditure as a measure for innovative activity additionally provides evidence for ability-biased technological change while patent applications do not support this hypothesis.

JEL Classification: I21, J24, J31, O33

Keywords: Wage inequality; skill-biased technological change; ability-biased technological change; United Kingdom

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1 Introduction

The wage premium for higher education has been well studied for all developed countries and various determinants have been investigated to explain the development in the past decades. In the United Kingdom (UK) there has been a different development of the wage patterns than in other European countries where wage inequality existed but was rather constant. Similar to the U.S. and Canada the wage premium and returns to education increased dramatically in the 1970s and the 1980s (Leuven et al., 2004; Harmon and Walker, 1999; Card and DiNardo, 2002) and for many authors the driving force of this development is skill-biased technological change (SBTC) (Haskel and Slaughter, 2002; Levy and Murnane, 2006).

SBTC is the shift in the demand from low to high-skilled workers induced by technological progress. The increasing efficiency of high-skilled labour and the decreasing demand for low-skilled workers tend to result in higher wages for the high-skilled and decreasing or at least stagnating wages for the low-skilled. For the U.S., Bartel and Sicherman (1999) show that there is strong relationship between wages and technological change in the 1980s and early 1990s. They suggest that the education wage premium in technology-intensive industries can be associated with an increase in the demand for higher educated workers with higher ability. They conclude that variation within the group of higher educated workers with respect to ability has increased. In compliance with these findings, Galor and Moav (2000) developed a growth model in which wage inequality is induced by ability-biased rather than skill-biased technological change. In this model, technological change is responsible for an increase of the demand for high ability. They argue that heterogeneity in skills exists not only between skill groups but also within skill groups which leads to more wage inequality. More recently, a study by Marquis et al. (2011) tries to shed light on the causes of wage inequality in the U.S. in a vintage capital model, showing that technological change is only a minor determinant of wage inequality in the U.S. They suggest that factors such as lack of job-related training at the low end of the skill distribution and increased human capital at the high end of the skill distribution may be driving forces of shifts in the skill distribution, leading to more wage inequality.

However, recent findings for the UK show stagnating education premia. Following Silles (2007), the returns to education did not increase since the 1990s. Purcell et al. (2005) find even decreasing skill premia in the 1990s that arose from higher supply of high skilled workers, among other factors. That would mean that the demand of high skilled workers is saturated by the higher supply so that premia stagnate or even decrease.

In fact, since the beginning of the 1990s, the number of university students increased sharply due to at least two facts: First, the general expansion of the educational system and intensive economic growth which induced young individuals to obtain higher degrees with the aim to earn higher wages in the future and second, the Further and Higher Education Act from 1992. By this act, the polytechnics and colleges that focused on applied education for work and offered credentials that were lower ranked than those from standard universities were changed to 'New Universities'. Thus, the act created a higher supply of university educated workers. It is questionable if the increase in supply of graduates has led to more heterogeneity in qualifications and other human capital related factors, such as ability, among graduates and if this influenced the education-wage pattern. In other words, is there a hidden increase in wage inequality which is only discovered when looking at certain industries?

To investigate this hypothesis and shed more light on the complex wage patterns in the UK, this study estimates the personal innovation wage premium using the British Household Panel Survey (BHPS) for the years 1991 to 2006 and industry level data from the OECD Statistical data base. The study focuses explicitly on the development of wage inequality over time – rather than in levels – in different manufacturing industries taking into account the heterogeneity of innovative activity within the manufacturing sector. As innovative activity related data, such as the amount of R&D expenditure and the number of patent applications, is mostly only available and meaningful for the manufacturing sector this study focuses on manufacturing industries. Both, the SBTC hypothesis and the ability-bias technological change (ABTC) hypothesis will be tested. The SBTC hypothesis will be tested directly using time interactions in the regression models. Employing several panel data estimation techniques, such as Random effects, Fixed effects, and Mundlak and Hausman-Taylor models, to account for different sources of ability-bias allows to indirectly test the ABTC hypothesis.

The contributive features of the study to the existing literature are the following. On the one hand, this is the first study for the UK, which combines data from the BHPS and industry level data on input and output related factors of innovative activity to investigate skill-biased and ability-biased technological change. It is an extension of the study by Bartel and Sicherman (1999), who investigated the 'technological change premium' in the U.S., in at least two respects. First, it uses additional panel estimation models which allow controlling for both individual and industry-specific ability and reduces biases in the estimated premia. Second, by adding time variables to the model it is possible to investigate changes over time and hence, to identify the effects of technological change explicitly. Another new aspect of this study is that it empirically tests the ABTC hypothesis modelled by Galor and Moav (2000) which has not been done so far. The intention of the study is to shed some light on the complicated relationship between technological change and the demand for higher educated workers in times when the number of university graduates has almost doubled within 20 years and reached more than 50% in 2006.

The results show that the graduation wage premium has been high but constant (approximately 30%) during the investigated period according to all estimation methods which may be due to the increased supply of graduates. The personal innovation wage premium however increased significantly by up to 25 percentage points, revealing that the demand for graduates has been higher in innovative industries than in non-innovative industries. This supports the SBTC hypothesis. The effect is found using both indicators for innovative activity. The coefficients of innovative activity measured by R&D expenditure for higher educated workers are smaller when it is controlled for industry-specific and individual ability, indicating that the coefficients are upward biased in the pooled OLS and that the demand for high ability in innovative industries increased. This supports the ABTC hypothesis. Using patent applications as a measure does not support the latter hypothesis though.

The findings have important implications for the future development of wage inequality in the UK. One is that wage inequality between high- and low-educated workers will increase given that demand for graduates in innovative industries increases, i.e. if SBTC continues. The other implication is that wage inequality within the group of high-educated workers will further increase if the number of graduates further increases. The higher number of graduates increases heterogeneity among graduates and reduces the signal of high ability implied by a university degree. The results also relate to the findings about over-education among graduates in the UK (Dolton and Vignoles, 2000; Chevalier, 2000; Chevalier and Lindley, 2009) and the discussion about increasing tuition fees. Hence, the results also contribute to the recent policy debate about public spending on further and higher education.

The paper is organised as follows. The next section presents recent literature on SBTC and ABTC. Section 3 elaborates theoretically the role of innovative activity in the determination of wages and wage differentials. Section 4 explains the estimation methods and the data are described in Section 5. The main empirical results and implications are presented and discussed in Section 6. Finally, Section 7 concludes.

2 Related literature

While the literature on skill-biased technological change (SBTC) is large and characterised by an ambiguity about the existence and the measurement of SBTC, the strand of the literature that is concerned with ability-biased technological change (ABTC) is rather small, at last because of the complication of measuring the effect of ability on wages and because it is a relatively new topic. In the following, the literature on SBTC change will be summarised and the most influential findings will be discussed. Subsequently, studies concerned with ABTC will be reviewed to setup the framework for the study at hand. Note that the terms *technological change* and *innovation* will be used interchangeably.

In the late 1970s and 1980s there has been the so-called computer revolution in the UK that changed long-run patterns of income distribution. The wages for high skilled workers increased and the wages for low skilled workers decreased. Many authors have found these wage premia especially in innovative industries or firms which exhibit high levels of technological change (Katz and Murphy, 1992; Autor et al., 1998; Haskel and Slaughter, 2002; Levy and Murnane, 2006). Innovative industries are characterised by technological progress, the use of specific IT equipment, the implementation of research and development and a high number of patent applications. In consequence, highly qualified workers are needed to meet the high demands because higher educated workers are known to have a comparative advantage with respect to the adoption and the implication of new technologies (Bartel and Lichtenberg, 1987).

Evidence for SBTC has been found in the 1970s and 1980s. Numerous micro- and macroeconomic studies document the statistical correlation of using new technology and the shift in the level of high skilled employment (Bartel and Lichtenberg, 1987, e.g.) on the one hand and the income distribution (Autor et al., 1998, e.g.) on the other hand. Economic theory and evidence of SBTC is provided by Acemoglu (2002) who models endogenous SBTC, Aghion (2002) who proves Schumpeterian growth theory in relation to wage inequalities and Katz and Murphy (1992) who examine the effect of SBTC on wage differentials in 1992 for the U.S., taking into consideration the fluctuating supply for college graduates between 1963 and 1987. Another study that is taking into account the wage differential and skill-biased technological change is the recent work of Corsini (2008), who estimates a fixed effects model for European countries using (among others) the British Household Panel Survey (BHPS) of the 1990s and the beginning of the 2000s but does not look at changes over time. In the first part of the paper Corsini investigates the correlation of SBTC and wage differentials. He measures the intensity of technological change by R&D expenditure data. The intention is that the higher the rate of R&D expenditures is relative to national GDP, the more intensive the technological progress is in an economy. Corsini (2008) states that SBTC is the driving force of the wage differentials. His interpretation of the result is that skilled workers are more able to adapt to the change of technology and take advantages in periods when technological process is very intensive. Card and DiNardo (2002) provide evidence for the college vs. high school wage gap for the U.S. in the 1980s and 1990s in reference to SBTC. They argue that the rise in wage inequality was an episodic event in the U.S. A recent study by Marquis et al. (2011) tries to shed light on the causes of wage inequality in the U.S. in a vintage capital model. In this model, it can be shown how technological change affects labour demand. They report that technological transition accounts for only 1/20th of the observed increase in wage inequality in the U.S. They suggest that factors such as lack of job-related training at the low end of the skill distribution and increased human capital at the high end of the skill distribution may be more important in the determination of shifts in the skill distribution which then lead to more wage inequality.

Recent findings for the UK also suggest a decline in the wage premium (Silles, 2007; Purcell et al., 2005). Silles (2007) calculates the returns to education for men and women with data from the British General Household Panel (GHP) for the years 1985 to 2003. She computes the returns to years of education using OLS and finds that the returns for men increased slightly over the whole period and the returns for women even declined. With pooled OLS she finds returns to education of 5.7% for men and 8.7% for women[1]. Purcell et al. (2005) postulate that the skill premium has been declining in England. They investigate the education-wage relationship for two graduate cohorts (1995 and 1999) and suggest that at least one reason is the increasing amount of high educated graduates since the 1990s.

Taber (2001) offers an empirical study in which he argues that high college premia in the US in the 1980s are upward biased due to unobserved ability and that the demand for high ability has been increasing. Since the beginning of the 1990s, the number of university students increased sharply due to at least two facts: First, the general expansion of the educational system and intensive economic growth which induced young individuals to obtain higher degrees with the aim to earn higher wages in the future and second, the Further and Higher Education Act from 1992. By this act, the polytechnics and colleges that focused on applied education for work and offered credentials that were lower ranked than those from standard universities were changed to 'New Universities'. Thus, the act created higher supply of university

[1] Detailed studies of returns to education are provided for example by Harmon and Walker (1999), Harmon and Oosterbeek (2000), Card (1999) and Leuven et al. (2004)

educated workers. Presumably, the increase in supply of graduates has led to more heterogeneity in qualifications and other human capital related factors, such as ability, among graduates. Bartel and Sicherman (1999) argue that high-ability high-educated workers sort into industries which are characterised by a high level of technological change. They investigate the education wage premium using individual level data for the U.S. and merge it with industry level data on technological change. As they explicitly look at levels of wage differentials, they are neither able to identify skill-biased nor ability-biased technological change.

The literature on ability-biased technological change is rather scarce but builds on the insights given by studies on skill-biased technological change. Galor and Moav (2000) proposed an economic growth model which suggests that wage inequality exists both between skill groups and within skill groups due to higher variation in ability within the groups of high-educated workers. They suggest that technological change increases the returns to ability and thereby accelerates wage inequality. Andersson et al. (2009) and Stern (2004) explicitly look at the wage premium for scientists. They argue that the relationship between wages and science is characterised by an ability bias and that innovative sectors pay more for high ability.

Finally, the measurement of SBTC and especially ABTC is hampered by the limited availability of appropriate data. Most studies are based on firm or industry data (Bratti and Matteucci, 2005; Haskel and Slaughter, 2002; Dunne et al., 2004; Corsini, 2008) which lacks individual worker characteristics. Only few studies such as Bartel and Sicherman (1999), Stern (2004) and Andersson et al. (2009) are based on individual panel data. Similar to Bartel and Sicherman (1999) this study uses individual panel data and merge industry level data to control for personal, firm and industry characteristics.

3 Theoretical background

In presenting the theoretical background of the determination of wages, a formulation similar to that of Taber (2001) and Griliches (1979) is used. A simple version of the wage equation without subscripts for individuals for the sake of simplicity can be written as

$$w = \beta Edu + \mu_1\theta_1 + \epsilon \tag{1}$$

where w is the wage rate, Edu is the level of education which can either be high ($Edu = hedu$) or low ($Edu = ledu$). The variable θ_1 is an unobserved effect which determines the wage rate and the level of education simultaneously, i.e. education is endogenous. θ_1 is a placeholder for all kinds of unobserved characteristics, such as innate ability, managerial skills, ambition or assertiveness. The literature on the returns to education is mainly concerned with unobserved ability which is correlated with the wage rate and the obtained educational level. It is assumed that more able individuals are more likely to stay in school longer and obtain higher degrees (Card, 1999). In the following, θ_1 is named *individual ability*, but it is left to the interpretation of the reader whether the effect is indeed ability or other related unobservable characteristics that are correlated with both education and the wage rate.

The commonly found wage differential between graduates and less educated workers is defined by

$$
\begin{aligned}
&E\left[w|Edu = hedu\right] - E\left[w|Edu = ledu\right] \\
&= \beta hedu - \beta ledu + \mu_1 \left(E\left[\theta_1|Edu = hedu\right] - E\left[\theta_1|Edu = ledu\right]\right)
\end{aligned} \tag{2}
$$

i.e. the differential can be decomposed into the difference in returns to education $(\beta hedu - \beta ledu)$ and the difference in the returns to ability $(\mu_1 > 0)$ with the induced ability bias $\mu_1 \left(E\left[\theta_1|Edu = hedu\right] - E\left[\theta_1|Edu = ledu\right]\right)$. Hence, an increase in the wage differential is the effect of (a) an increase in the return to education, (b) an increase in the return to unobserved ability or (c) an increase in the ability differential between graduates and lower educated workers.

A large strand of the literature has found higher wage differentials between workers of different educational or skill levels in firms or industries which exhibit certain features such as large firm size or multinationality. For example, Schmidt and Zimmermann (1991) provide evidence for a positive firm size-wage relationship. Girma et al. (2001) and Taylor and Driffield (2005) show that foreign direct investment increases wage inequality. Borjas and Ramey (1995) show that rising wage inequality can be explained by trade-intensity and Bartel and Sicherman (1999) suggest that technological change induces greater wage differences between high and low skilled workers. Most of these attributes such as technological change, intense patent application behaviour and large investments in R&D, are indicators for the extent of innovative activity of a firm or industry. To account for differences in innovative activity among the industries in which the individuals are employed, the variable $Inn = inn_1, inn_2, ..., inn_\infty$ is added to the above model. Furthermore, it is assumed that there is industry-specific ability, denoted θ_2 which is unobservable:

$$
w = \beta Edu + \gamma Inn + \mu_1\theta_1 + \mu_2\theta_2 + \epsilon \tag{3}
$$

This equation includes the wage differential between different educational levels, different levels of ability and the ability bias as in equation (2) and the wage differential between different rates of innovative activity ($\gamma inn1 - \gamma inn2$), the wage differential between difference in returns to industry-specific ability ($\mu_2 > 0$) and the industry-specific ability bias and can be written as

$$E\left[w|Inn = inn_1\right] - E\left[w|Inn = inn_2\right] \tag{4}$$
$$= \gamma inn1 - \gamma inn2 + \mu_2 \left(E\left[\theta_2|Inn = inn_1\right] - E\left[\theta_2|Inn = inn_2\right]\right).$$

This unobservable industry-specific effect is by assumption a typical random effect that is uncorrelated with the other explanatory variables (as in (Bartel and Sicherman, 1999)).[2] This industry-specific ability could for example be some kind of visual creativity required in the software industry.

Certain jobs require certain skills and abilities. Jobs which are related to innovative activity are likely to require certain skills, such as logical thinking and mathematical knowledge, which allow the possessor the adaption and invention of new technology. A few studies have suggested that positive wage effects of innovative activity are attributed to higher education and advanced skills because high-educated workers are more able to adapt to new technology more easily than less educated workers (Bartel and Sicherman, 1999; Andersson et al., 2009; Stern, 2004). This effect is introduced by the effect of innovative activity, conditional on a high level of education. A third unobservable effect is then plausible to determine the wage rate which is '*innovation ability*' (θ_3) which is correlated with innovative activity and education. Equation (3) expands to

$$w = \beta Edu + \gamma Inn + \delta(Inn|Edu = hedu) + \mu_1\theta_1 + \mu_2\theta_2 + \mu_3\theta_3 + \epsilon \tag{5}$$

Innovation ability is assumed to be the ability to invent or develop a new product which is likely to be specific to high education. This does not imply that low educated workers cannot have good ideas for a new product or the improvement of an existing product. Rather the implementation is more likely to be pursued by a higher ranked, normally higher educated, co-worker who consequently will receive the wage gain from the original idea.

An increase in the wage differential between high and less educated workers can now be due to the concepts (a), (b), (c) explained above, or due to (d) an increase in the return to high education attributed to innovative activity (δ), (e) an increase in the return to innovation ability (μ_3) or (f) an increase in the innovation ability

[2] Note that this assumption is necessary for the application of a GLS model as will be explained in the next section.

bias. Furthermore, the equation implies that the group of university graduates is differentiable into those with higher ability and those with lower ability.

The hypothesis is that not only education is associated with the adoption and invention of new technology but also innate ability. A high level of ability enables a worker to adapt to new technology more easily than with a low level of ability and hence, makes him more productive. If this is the case, those individuals should receive higher wages, imposing a wage differential between high-educated individuals with low ability and high-educated individuals with high ability. This hypothesis is based on recent findings on the development of wage differentials in the UK. While increasing wage differentials have been found in the 1970s and 1980s in the UK, more recent studies on wage differentials have found stagnating wage differentials between educational levels (Silles, 2007; Purcell et al., 2005). Presumably, the steadily increasing number of university graduates is responsible for this change. A plausible assumption is that it is unlikely that the additional number of individuals who attended universities in the recent past are equally well endowed with innate ability as the former smaller number of university students. This means that heterogeneity with respect to ability increased within the group of university graduates and a university degree in itself cannot serve as a signal of high ability anymore. As a consequence, those university graduates with lower ability will sort into low paid jobs while highly able graduates sort into higher paid jobs where other skills than those obtained at university are equally or even more important.

In line with these considerations is the hypothesis of skill-biased technological change. If the wage differential between graduates and less educated workers is increasing over time and is correlated with innovative activity, this suggests that skill-biased technological change exists. Furthermore, if there is an (additional) increasing premium for workers with high ability associated with innovative activity, this implies that ability-biased technological change is present. The investigation of these hypotheses requires the investigation of wage patterns over time. This is done by adding time variables (T) to equations (3) and (5). The next section explains this procedure in more detail and elaborately describes the estimation methods used.

4 Estimation techniques

The static relationship between innovative activity of the employing industry and individual wages can be estimated as formulated in equation (3). Adding subscripts for individual i, working in industry j at time t and additional individual controls, such as socio-economic and workplace characteristics summarised in X and an overall constant α, (3) becomes

$$w_{ijt} = \alpha_{ij} + \beta Edu_i + \gamma Inn_{jt} + \lambda X_{ijt} + \theta_{1i} + \theta_{2j} + \epsilon_{ijt} \tag{6}$$

with θ_1 and θ_2 being time-invariant and λ represents the coefficient vector of X. Accordingly, equation (5) becomes

$$w_{ijt} = \alpha_{ijt} + \beta Edu_i + \gamma Inn_{jt} + \lambda X_{ijt} + \delta(Edu * Inn)_{ijt} + \theta_{1i} + \theta_{2j} + \theta_{3ij} + \epsilon_{ijt} \tag{7}$$

where θ_3 is also time-invariant. Estimating the equations using pooled Ordinary Least Squares (OLS) will result in efficient but biased estimates. The coefficient on the education variable (β) will be upward biased because it is endogenous (it is correlated with unobservable ability θ_1). Moreover, the coefficient on the interaction term between innovative activity and education will be upward biased due to endogeneity (it is correlated with unobservable 'innovation ability' θ_3). The solution to this kind of bias would be the estimation of a Fixed effects (FE) model in which all variables are time-demeaned. By time-demeaning, the unobserved time-invariant effects, such as ability, drop out of the regression equation and the estimation gives unbiased results of the endogenous regressors. However, the variable on education also drops out because it is time-invariant by definition[3]. In the first part of the study in which the static relationship is estimated other estimation methods are necessary.

A method that is able to account for the bias that results from industry-specific ability (θ_2) is the Random effects model (RE). Under the estimation of a RE model the individual specific effects are assumed to be i.i.d. which is assumed for θ_2. The coefficients in the RE model are estimated via Generalised Least Squares (GLS) and is consistent and efficient given the correlation between the individual effects and the explanatory variables imply no correlation between the explanatory variables and the error term. As pointed out before, θ_1 and θ_3 are correlated with the explanatory variables *education* and the interaction term which induces correlation between the error term and these regressors. Hence, the RE model can solve the problem of industry-specific effects but cannot account for the individual-specific ability-bias. Furthermore, a Hausman test suggests that a FE model is appropriate.

One solution is the method proposed by Mundlak (1978). He proposed to estimate a RE model which allows for correlation between the explanatory variables and the individual fixed effects because the individual effects are a linear combination of the

[3] All individuals who obtained a university degree after or while having worked in the manufacturing industry are deleted from the sample to avoid bias from 'latecomers'.

time averages of all the explanatory variables such that

$$\theta_{1i} = \pi_1 \bar{X_{ij}} + u_{1i} \tag{8}$$

and

$$\theta_{3ij} = \pi_3 \bar{X_{ij}} + u_{3ij} \tag{9}$$

where $\bar{X}$ is a vector of all time-demeaned explanatory variables and u is the i.i.d. disturbance term. Practically, this means estimating equation (6) and (7) including $\pi_1 \bar{X_{ij}}$ and $\pi_3 \bar{X_{ij}}$. As the Mundlak model (MU) also accounts for industry-specific unobserved effects because it uses the GLS estimator, it gives estimators which are unbiased and more consistent and efficient than the OLS and RE estimates.

Another possibility to account for individual correlated effects in panel data is the approach proposed by Hausman and Taylor (1981). The Hausman-Taylor (HT) model makes an explicit distinction between exogenous and endogenous explanatory variables. Adopting this distinction, the presented model can be written as

$$w_{ijt} = \alpha_{ijt} + \lambda_1 X_{1ijt} + \lambda_2 X_{2ijt} + \varphi_1 Z_{1ijt} + \varphi_2 Z_{2ijt} + \theta_{1i} + \theta_{2j} + \theta_{3ij} + \nu_{ijt} \tag{10}$$

where X_1 is a vector of time varying exogenous, i.e. uncorrelated with the individual unobserved effects, variables and includes Inn. X_2 is a vector of time varying variables which can be correlated with the error term, for example $(Inn|Edu = hedu)$. Z_1 is a vector of time-invariant regressors which are uncorrelated with the unobserved effects and Z_2 is a vector of time-invariant endogenous regressors, such as Edu. ν is the remaining idiosyncratic error term. The HT model is an instrumental variable model with the advantage that it does not require model-external instruments. These are usually difficult to find because they underlie strong assumptions. The model uses X_1 and Z_1 as their own instruments, uses deviation from the mean of X_2 $(X_2 - \bar{X}_2)$ as instruments for X_2, and Z_2 is instrumented by the individual means of X_1, namely $\ddot{X}_1$. The model is identified as long as there are at least as many time-varying exogenous regressors as time-invariant endogenous regressors. The model is based on the random effects transformation, i.e. the HT instrumental variable estimator is a GLS estimator. As mentioned before, the GLS estimator is consistent and efficient if all regressors are uncorrelated with the idiosyncratic error term ν and only a subset of regressors is correlated with the unobservable fixed effects (Cameron and Trivedi, 2005). The HT approach usually leads to very high coefficients of education variables. Hence, the interpretation on the education coefficients will be made carefully, if at all.

Furthermore, this study is less concerned with the level of wage differentials but more with the development of wage differentials over time. To allow the coefficients to vary over time, time period dummy variables are included in the model and multiplied with the education variable, the variable which measures innovative activity and the interaction term of both. This step enables to explicitly test the SBTC hypothesis. If the wage differential between graduates and less educated workers has increased over time and if the differential is associated with higher levels of innovative activity, i.e. if there is a personal innovation premium, this suggests that SBTC has been prevalent. Moreover, if the coefficients resulting from the models in which it is possible to account for individual time-invariant unobserved effects are lower than the coefficients from models where the coefficients on education are likely to be upward-biased, this indicates that ability is driving the large wage premia for graduates in innovative industries and that there is a sorting of highly educated and highly able individuals into innovative industries. This would support the ability-biased technological change hypothesis.

5 Data

This study uses the first sixteen waves of the British Household Panel Survey (BHPS) from 1991 to 2006. The BHPS is a nationally representative random sample of about 5,500 British households, containing approximately 10,000 interviewed individuals. The survey provides a rich source of socioeconomic information on household and individual level (Taylor et al., 2007). For the presented investigation it contains the required data on educational attainment of individuals, their income and the industry affiliation of their job classified at national Standard Industrial Classification (SIC 80/SIC 92), as well as a large number of personal socio-economic and job characteristics. The investigation is restricted to the manufacturing industry as data that relates to innovative activity is mainly available for the manufacturing sector and is also mostly reasonable in this sector.

Industry level data, i.e. the amount of R&D expenditure, the number of patent application and the value of production output, is extracted from the OECD StatsExtract website[4], where industries are classified at the International Standard Industrial Classification (ISIC 2 and 3.1). All four classifications are standardised to one classification which resulted in 8 two-digit industries (see Table 3 in the Appendix). The remaining manufacturing industries are (1) Food, Beverages and Tobacco, (2) Textiles and Leather, (3) Wood, Paper, Publishing, (4) Chemicals, Coal, Plastics, (5) Non-metallic Minerals, (6) Basic Metals, (7) Machinery and Equipment and (8)

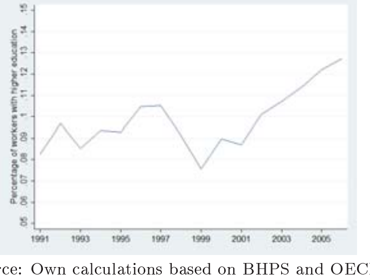
[4] http://stats.oecd.org/index.aspx

Other Manufacturing industries. The information on patent applications based on the International Patent Classification (IPC) has also been made consistent with the developed classification.

The sample used[5] is an unbalanced panel of male and female workers aged 20 to 64. Only individuals that are salaried in the private sector and are not self-employed are included. The final sample contains about 14,000 person-year-observations over 16 years (1991-2006).

The dependent variable is log real hourly wage. It is calculated using usual gross pay per month (a derived variable that measures usual monthly wage or salary payment before tax and other deductions in current main job for employees) divided by usual standard weekly hours. Wages are then deflated by the consumer price index (CPI) to the base year 1991.

Figure 1: Share of Graduate Workers

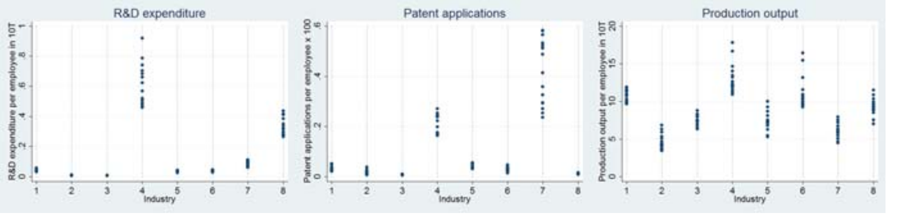


Source: Own calculations based on BHPS and OECD data.

Graduates are those who obtained a university degree, measured by a dummy variable. Figure 1 represents the development of the relative supply of graduates between 1991 and 2006 in the sample. Production output, patent applications and the amount of R&D expenditure per industry are divided by the number of employees in the respective industry, i.e. the industry levels of the indicator variables are per employee values. All monetary indicators are deflated using the same index as for deflating wages. The innovation indicators – R&D expenditure and patent applications – and also production output which serves as a control variable, are plotted in Figure 2. It can be seen that only two industries have high R&D expenditures and only two apply for patents regularly. Figure 4 shows the correlation between graduates' hourly wages and innovative activity which is positive for both indicators.

[5]The data used were extracted using the Add-On package PanelWhiz v2.0 (Nov 2007) for Stata. PanelWhiz was written by Dr. John P. Haisken-DeNew (john@panelwhiz.eu). The PanelWhiz generated DO file to retrieve the BHPS data used here and any PanelWhiz plugins are available upon request. Any data or computational errors in this paper are my own. Haisken-DeNew and Hahn (2006) describe PanelWhiz in detail.

Figure 2: Variation in Indicators



Source: Own calculations based on OECD data.

Furthermore, Figures 5 and 6 show the development of average wages in industries which are innovative, meaning they have a high level of R&D expenditure and a high level of patent applications, respectively. A high level of a certain activity means that the activity is greater than the average in the whole manufacturing sector. It can be seen that according to both indicators the mean wages are higher if the level of innovative activity is high. Also, wage growth is higher. Descriptive statistics can be found in Table A1[6] for all time periods separately. The time periods are $t_1 = 1991 - 1994$, $t_2 = 1995 - 1998$, $t_3 = 1999 - 2002$ and $t_4 = 2003 - 2006$ (and $t'_4 = 2003 - 2005$ in the case of patents as there is currently no more recent data available). The amounts of R&D expenditure per employee and the value of production output per employee have increased over the whole investigation period. Solely the amount of patent applications per employee has decreased only in the last period after it had increased significantly.

6 Results

Levels

The results are presented in two different tables, one for each of the innovation indicators, including the OLS, RE, Mundlak and Hausman-Taylor results. Separate tables for the fixed effects results are presented and discussed later as they are not directly comparable with the other estimation results. We start looking at the impact of R&D investments per employee in levels. Table 1 shows the effect of R&D expenditure on wages for graduates and less educated workers combined and then separately when the interaction term of R&D expenditure and the education variable is included. In all regressions the indicator variables measure the semi-elasticity between wages and innovative activity.

According to the OLS results, higher education, i.e. having a university degree, is

[6] All tables are generated using the user written ESTOUT command in STATA 11/SE. See Jann (2004)

Table 1: Pooled OLS and Panel Regressions for Indicator: R&D Expenditure

	OLS		Random Effects		Mundlak		Hausman-Taylor	
Higher Education	0.205***	0.132***	0.321***	0.274***	0.313***	0.291***	0.634***	0.572***
	(0.011)	(0.017)	(0.021)	(0.027)	(0.021)	(0.032)	(0.113)	(0.114)
R&D exp.	0.199***	0.172***	0.144***	0.127***	0.102***	0.085***	0.104***	0.086***
	(0.017)	(0.017)	(0.026)	(0.026)	(0.030)	(0.030)	(0.018)	(0.019)
HE×R&D exp.	–	0.269***	–	0.180***	–	0.202**	–	0.208***
		(0.041)		(0.062)		(0.084)		(0.050)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14247	14247	14247	14247	14247	14247	14247	14247
R^2	0.455	0.457	0.408	0.410	0.410	0.411	–	–
Chi^2	–	–	3300	3370	3431	3482	4155	4179

Note: Standard errors in parentheses. *,** and *** denote significance level of 1%, 5% and 10% respectively. 18 regional dummies, 9 occupational and 15 year dummies included. This table is a comprised version of Table A3.

rewarded with a wage premium of 21% which is statistically significant at the 1% level. The graduation premium is even higher when controlling for unobserved effects: the RE model estimates a premium of 32%, Mundlak 31% and Hausman-Taylor 63%. A much higher premium resulting from the HT model has been found as well by Hausman and Taylor (1981) and should be interpreted with care. Interestingly, all other estimated coefficients, even those which are endogenous, do not differ to the coefficients estimated with the other models. The coefficient of R&D expenditure is 20% in the OLS regression model, 14% in the RE model and 10% in the Mundlak and HT models. A coefficient of 0.21 implies that an increase in R&D expenditure per employee per year in average industries by 10,000 GBP leads to an increase of the average wage of all workers by 21%. Seeing that the whole manufacturing sector spends on average 2,060 GBP per employee per year on R&D between 1991 and 2006, this impact can be considered being large. When the interaction term between R&D expenditure and graduation is included, the base R&D expenditure regressor, which now measures only the effect of R&D expenditure on less educated workers, drops by 2 percentage points in all estimation models. The base education coefficient drops even more in all models. The interaction term measures the effect of an increase in R&D expenditure for graduates only and thus estimates the wage premium differential for additional R&D expenditure – the personal innovation wage premium – between graduates and less educated workers. It is 27% according to OLS, 18% in the RE model, and 20% and 21% in the Mundlak and HT models, respectively. The results suggest, that graduates profit much more from R&D expenditure than less educated workers. Furthermore, controlling for industry-specific ability and individual-specific ability lowers the interaction term by 7%-points and raises the graduation coefficient significantly. This suggests that OLS results for the effect of R&D expenditure for graduated workers are upward biased due to ability, implying a sorting process of high-ability high-educated workers into jobs or industries which are R&D intensive.

As Bartel and Sicherman (1999) have mentioned, R&D expenditure is an input related factor for technological change, while the use of patents is an output related factor. In their study, they find a higher impact of input related factors of technological change on wages than of output related factors. The measure of patents in the presented investigation is the amount of patent applications per employee. A measure of patent applications compared to patent use as in Bartel and Sicherman (1999) is a more precise measure of innovative activity because it covers more inventions of a new product or process rather than the grants of patents only[7]. Still, the here used measure of patent applications can also be considered as an output based factor of technological change and is a measure of innovative activity. Table A2 shows that the correlation coefficient between R&D and patent applications is rather small (18.9%) but significant. As there is a correlation between all the indicators and production output, all regression equations include production output as an additional regressor.

Table 2: Pooled OLS and Panel Regressions for Indicator: Patent Applications

	OLS		Random Effects		Mundlak		Hausman-Taylor	
Higher Education	0.213***	0.191***	0.326***	0.301***	0.325***	0.316***	0.692***	0.658***
	(0.012)	(0.015)	(0.022)	(0.024)	(0.022)	(0.028)	(0.125)	(0.125)
Patents	0.232***	0.214***	0.129***	0.109***	0.097***	0.075***	0.106***	0.084***
	(0.020)	(0.021)	(0.025)	(0.026)	(0.028)	(0.029)	(0.019)	(0.020)
HE×Patents	–	0.182***	–	0.224***	–	0.255***	–	0.262***
		(0.068)		(0.075)		(0.085)		(0.065)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13564	13564	13564	13564	13564	13564	13564	13564
R^2	0.454	0.454	0.406	0.406	0.407	0.407	–	–
Chi^2	–	–	3102	3148	3135	3176	3732	3754

Note: Standard errors in parentheses. *,** and *** denote significance level of 1%, 5% and 10% respectively. 18 regional dummies, 9 occupational and 14 year dummies included. This table is a comprised version of Table A4.

The effect of patent applications on wages in levels is documented in Table 2. When the interaction term is not included the coefficients are very similar to the R&D results. The premium for being higher educated is almost exactly the same as in the table above. The coefficient for patent applications is 23% according to the pooled OLS regression. This means that an increase in patent applications by 0.01 per employee per year increases the average hourly wage by 23%. In other words, applying for one more patent per year increases a worker's wage on average by 0.23%. This is also an mentionable effect, as the manufacturing sector applied for about 1 patents per year per 1000 employees between 1991 and 2005. The inclusion of the interaction term of patent applications and graduation also changes the coefficients of the base regressors in a similar way as the inclusion of the R&D expenditure interaction term does. The coefficients of the interaction term are large and highly

[7]Note that some industries, such as the software industry, do not apply for patents regularly.

significant. However, the coefficient of the interaction term itself is higher, between 22% and 26%, when controlling for individual unobserved heterogeneity, than in the OLS regression (18%). This implies that the application of patents is less correlated or even negatively correlated with ability than R&D expenditure, but still suggests the favour of higher education in the relation to innovative activity.

Changes over time

The previous results have shown that there is a significant and large personal innovation premium for all workers averaged over the period 1991-2006. The concern of this study is to look at the development of the personal innovation premium over time to allow inference to be made about skill-biased and ability-biased technological change. Therefore time period dummies are included in the regressions and multiplied with the effects of interest, i.e. the innovation indicator, the education variable and their interaction term.

Table 3: Pooled OLS and Panel Regressions with Time Interactions for Indicator: R&D Expenditure

	OLS		Random Effects		Mundlak		Hausman-Taylor	
R&D expenditure								
1991-1994	0.261***	0.244***	0.109***	0.114***	0.020	0.039	0.041	0.049
	(0.035)	(0.036)	(0.042)	(0.043)	(0.049)	(0.051)	(0.030)	(0.031)
1995-1998	0.268***	0.234***	0.179***	0.179***	0.118***	0.129***	0.120***	0.126***
	(0.034)	(0.035)	(0.037)	(0.037)	(0.042)	(0.043)	(0.028)	(0.029)
1999-2002	0.203***	0.187***	0.143***	0.141***	0.098***	0.100***	0.090***	0.094***
	(0.024)	(0.025)	(0.028)	(0.029)	(0.032)	(0.033)	(0.022)	(0.022)
2003-2006	0.129***	0.081***	0.124***	0.095***	0.090***	0.063*	0.091***	0.070***
	(0.024)	(0.024)	(0.029)	(0.029)	(0.032)	(0.033)	(0.020)	(0.021)
Higher Education								
1991-1994	0.214***	0.153***	0.289***	0.295***	0.283***	0.270***	0.744***	0.747***
	(0.023)	(0.042)	(0.029)	(0.044)	(0.028)	(0.047)	(0.124)	(0.124)
1995-1998	0.205***	0.127***	0.278***	0.270***	0.269***	0.244***	0.738***	0.733***
	(0.021)	(0.032)	(0.029)	(0.043)	(0.029)	(0.044)	(0.123)	(0.123)
1999-2002	0.222***	0.162***	0.356***	0.341***	0.349***	0.319***	0.843***	0.836***
	(0.018)	(0.029)	(0.025)	(0.032)	(0.025)	(0.038)	(0.123)	(0.123)
2003-2006	0.180***	0.050	0.358***	0.268***	0.351***	0.249***	0.852***	0.772***
	(0.021)	(0.035)	(0.031)	(0.050)	(0.031)	(0.054)	(0.123)	(0.124)
HE× R&D expenditure								
1991-1994	–	0.264**	–	-0.018	–	-0.134	–	-0.036
		(0.126)		(0.121)		(0.134)		(0.099)
1995-1998	–	0.375***	–	0.048	–	-0.049	–	-0.001
		(0.106)		(0.132)		(0.152)		(0.092)
1999-2002	–	0.219***	–	0.060	–	0.025	–	0.006
		(0.072)		(0.075)		(0.092)		(0.069)
2003-2006	–	0.372***	–	0.253***	–	0.241***	–	0.200***
		(0.067)		(0.084)		(0.093)		(0.061)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14247	14247	14247	14247	14247	14247	14247	14247
F	273	261	–	–	–	–	79	74
p	0.000	0.000	0.000	0.000	0.000	0.000	–	–
R^2	0.454	0.456	0.407	0.408	0.411	0.415	–	–
Chi^2	–	–	3250	3426	3420	3714	3894	3920

Note: Standard errors in parentheses. *,** and *** denote significance level of 1%, 5% and 10% respectively. 18 regional dummies, 9 occupational and 15 year dummies included. Charcatersitics inlcude prodiction output by industry, a female dummy, tenure tenure squared, two firmsize dummies, a dummy for union membership, a dummy for being married, having kids, self-rated healh and three age dummies.

Table 3 shows the estimated coefficients for the innovation indicator R&D expenditure. The OLS results are very different to those from the other models: Without the interaction term, the effect of higher R&D expenditure on wages is decreasing over time and the graduation premium is more or less constant over time. In the other models, R&D expenditure first jumps from being small in the first period (insignificant in Mundlak and HT model) and then drops continually but stays large in the end (between 9% and 12% in 2003 to 2006) and is statistically significant. When including the interaction term multiplied with the time period dummies the base R&D expenditure coefficients stay the same in size in all but the last period, where it is smaller of about 2 to 4 percentage points, depending on the model. The base graduation regressors shrink in the OLS model through including the interaction term but stay the same in the other models. Only in the last period, the higher education premium is much smaller than in the regression without the interaction term. To summarise, the inclusion of interaction terms in the regressions reduces the coefficients of the base variables only in the last period, which is puzzling at first sight. This puzzle can be explained by looking at the coefficients of the interaction terms. In all three models which control for unobserved effects the interaction term increases from a negative but insignificant value in the first period to a positive but insignificant value in the third period and is large and significant in the last period. This suggests that graduates did not gain from innovative activity in the 1990's but do significantly in the new millennium. This is strong evidence for skill-biased technological change. Additionally, both industry-specific ability and individual ability seem to be rewarded more with higher R&D expenditure. The results show an ability bias in the R&D expenditure-graduation variable, as the coefficients in the models which control for unobserved ability are much smaller than the coefficients from the OLS regressions. This implies that the UK manufacturing industry is characterised by both skill-biased technological change and ability-biased technological change.

The impact of patent applications on wages over time is slightly different to the impact of R&D expenditure. Equally is the development of the graduation variable, both when the interaction term between patent applications and higher education is not included and when it is included (Table 4). The patent coefficients decrease continually between 1991 and 2006 but are still significant in all periods. Only the patent coefficient in the first period is slightly smaller when the interaction term is included. This drop is balanced out by the coefficient of the interaction term in the first period. In both the RE and the HT models, more patent applications raise the wage for graduate workers significantly. In the next period, the coefficients are significant, while they increase again from the second to the third period and are highest in the last period. This implies that the skill-bias has already been there with respect to patent applications, then seemingly disappeared and then appeared again and increased since about the year 2000. The result can also, but less strongly,

Table 4: Pooled OLS and Panel Regressions with Time Interactions for Indicator: Patent Applications

	OLS		Random Effects		Mundlak		Hausman-Taylor	
Patents								
1991-1994	0.320***	0.289***	0.237***	0.202***	0.159**	0.132*	0.206***	0.160***
	(0.060)	(0.063)	(0.062)	(0.064)	(0.068)	(0.070)	(0.046)	(0.049)
1995-1998	0.330***	0.326***	0.219***	0.218***	0.187***	0.191***	0.196***	0.187***
	(0.047)	(0.050)	(0.042)	(0.044)	(0.044)	(0.046)	(0.034)	(0.036)
1999-2002	0.217***	0.196***	0.145***	0.132***	0.120***	0.108***	0.127***	0.117***
	(0.029)	(0.030)	(0.027)	(0.029)	(0.030)	(0.032)	(0.023)	(0.024)
2003-2005	0.163***	0.148***	0.077**	0.048	0.050	0.013	0.062**	0.033
	(0.038)	(0.040)	(0.038)	(0.039)	(0.040)	(0.043)	(0.029)	(0.031)
Higher Education								
1991-1994	0.217***	0.188***	0.289***	0.256***	0.287***	0.260***	0.794***	0.744***
	(0.023)	(0.034)	(0.028)	(0.038)	(0.028)	(0.039)	(0.137)	(0.137)
1995-1998	0.208***	0.203***	0.281***	0.280***	0.279***	0.288***	0.793***	0.776***
	(0.021)	(0.027)	(0.029)	(0.035)	(0.029)	(0.035)	(0.136)	(0.136)
1999-2002	0.225***	0.192***	0.361***	0.342***	0.359***	0.353***	0.901***	0.880***
	(0.018)	(0.023)	(0.026)	(0.029)	(0.026)	(0.035)	(0.136)	(0.135)
2003-2005	0.196***	0.180***	0.373***	0.339***	0.371***	0.353***	0.924***	0.882***
	(0.024)	(0.031)	(0.031)	(0.035)	(0.031)	(0.039)	(0.136)	(0.136)
HE× Patents								
1991-1994	–	0.297	–	0.361*	–	0.334	–	0.482***
		(0.205)		(0.217)		(0.248)		(0.152)
1995-1998	–	0.049	–	0.037	–	0.025	–	0.141
		(0.158)		(0.140)		(0.150)		(0.120)
1999-2002	–	0.222**	–	0.150**	–	0.169**	–	0.130*
		(0.098)		(0.074)		(0.081)		(0.079)
2003-2005	–	0.143	–	0.288**	–	0.346***	–	0.298***
		(0.135)		(0.128)		(0.128)		(0.096)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13564	13564	13564	13564	13564	13564	13564	13564
F	257	238	–	–	–	–	72	67
p	0.000	0.000	0.000	0.000	0.000	0.000	–	–
R^2	0.452	0.453	0.406	0.406	0.407	0.410	–	–
Chi^2	–	–	3064	3167	3110	3256	3516	3540

Note: Standard errors in parentheses. *,** and *** denote significance level of 1%, 5% and 10% respectively. 18 regional dummies, 9 occupational and 14 year dummies included. Charcatersitics inlcude prodiction output by industry, a female dummy, tenure tenure squared, two firmsize dummies, a dummy for union membership, a dummy for being married, having kids, self-rated healh and three age dummies.

be interpreted as skill-biased technological change in the UK manufacturing industry. Different to the R&D results, using patent applications finds no evidence for ability-biased technological change. However, as mentioned earlier, measuring innovation output in terms of patent applications is a worse measure for innovative activity than R&D expenditure. Bartel and Sicherman (1999) also found stronger evidence of wage premia for higher educated workers when using innovation input-related factors compared to output-related factors.

Furthermore, fixed effects regressions are estimated which eliminate the effect of unobserved effects correlated with education completely. However, as the obtained educational level is time-invariant, it drops out of the regression equation. Multiplying time period dummies allows looking at the change of the graduation premium over time. Table A5 presents the coefficients of the graduation regressor. It shows that the graduation premium was not significantly different in the second period compared to the first period. In the third and the fourth period the premium is 10 and 12 percentage points higher than in the first two periods. This validates the results that have been found using the other models. Table A6 shows the development of the personal innovation premium for graduate workers (interaction term) and on average. Similar to what has been seen before, the personal innovation premium for higher educated workers increases significantly and the average innovation premium decreases over time. Hence, also the fixed effects regression results support the skill-biased technological change hypothesis. They are not allow drawing conclusions about ability-biased technological change.

As further robustness checks, all models have been estimated including both R&D expenditure data and patent application data and their interaction terms simultaneously. The coefficients do not change qualitatively and results do not lead to different conclusions than with estimating separate models. Furthermore, all models including R&D expenditure data are estimated for the period 1991 to 2005 instead of 1991 to 2006 for better comparison with the patent data results. We can neglect the concern that the year 2006 may be responsible for the large coefficients estimated for the last period.

7 Conclusion

A large strand of the literature has tried to shed light on the complex wage patterns and the increasing wage inequality between graduates and less educated workers in recent decades in the UK. Many authors have shown that wage inequality can partly be explained by industry and firm characteristics, especially by innovative activity and technological change (Katz and Murphy, 1992; Autor et al., 1998; Haskel and Slaughter, 2002; Levy and Murnane, 2006; Bartel and Sicherman, 1999). As most studies focus on the U.S., this paper concentrates on the UK. It contributes to the existing literature in many ways. First, it extends the study by Bartel and Sicherman (1999), who investigated the 'technological change premium' in the U.S., in at least two respects. One is the use of additional panel data estimation methods namely Mundlak and Hausman-Taylor models, which allow controlling for both individual and industry-specific ability and reduces biases in the estimated premia. The other is the inclusion of time variables to the model, making it possible to investigate changes over time and hence, to identify SBTC explicitly. Second, a new aspect of this study is that it indirectly tests the ABTC hypothesis modelled by Galor and Moav (2000) empirically, which has not been done so far. Furthermore, the study can shed some light on the complicated relationship between technological change and the demand for university graduates in times when the share of university graduates has almost doubled within 20 years and reached more than 50% in 2006.

The results provide strong evidence for skill-biased technological change in the UK manufacturing industry between 1991 and 2006. Using individual level data from the British Household Panel Survey (BHPS) and industry level data from the OECD statistical database, wage regressions are estimated which identify the effect of innovative activity on wages for university educated workers compared to less educated workers. Innovative activity is defined by two indicators, namely the amount of R&D expenditure and the number of patent applications, which measure innovation input and innovation output, respectively. Using different estimation methods for panel data, such as Fixed effects, Random effects, Mundlak and Hausman-Taylor models, additionally to pooled OLS regressions allows controlling for both industry-specific ability and individual ability which are correlated with earnings as well as with education and thus lead to an upward bias of the graduation premium. The results for the wage differentials in levels show that an increase in innovative activity, irrespective of the used indicator, raises wages for graduates much more than less educated workers' wages. For example, additional R&D expenditure of 10,000 GBP per employee per year raises wages for graduated workers by up to 27%-points. The effect is smaller but still large and statistically significant when controlling for ability. This implies an ability-bias in the estimation of the personal innovation premium for graduates. Including time period dummies in the regressions allows for looking at the development of the premia over time. As the innovation premium for graduates increased significantly over time by up to 25 percentage points, while it does not for less educated workers, the results provide evidence for skill-biased technological change. Using R&D expenditure as a measure for innovative activity additionally provides evidence for ability-biased technological change, while patent applications are not supporting this hypothesis. This is evidence that there is indeed a hidden increase in wage inequality which cannot be detected at an aggregate level.

The findings have important implications for the future development of wage inequality in the UK. One is that wage inequality between high- and low-educated workers will increase given that demand for graduates in innovative industries increases, i.e. if SBTC continues. The other implication is that wage inequality within the group of high-educated workers will further increase if the number of graduates further increases. It can easily be concluded that those graduates with the highest ability have sorted into jobs which are associated with a high rate of innovative activity. The results also relate to the findings about over-education among graduates in the UK (Dolton and Vignoles, 2000; Chevalier, 2000; Chevalier and Lindley, 2009).

An increase in the number of graduates has been an explicit policy goal by the British government. By 2010 it wanted to raise the share of university educated to 50% which has been achieved. However, this has led to a new policy debate about tuition fees in 2010. To be able to finance higher education, the current coalition government has proposed to raise the limit for tuition fees from 3,290 GBP to 9,000 GBP from 2012 (The Economist, 2010). Given that the expansion of the higher education system in the last decades has disproportionally benefited people from richer family backgrounds than those from poorer family backgrounds (Blanden and Machin, 2004), perspectives for people from poorer families decrease. The gain from technological change will also in future be reserved for rich people, boosting their wealth and accelerating economic and social inequality.

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Appendix

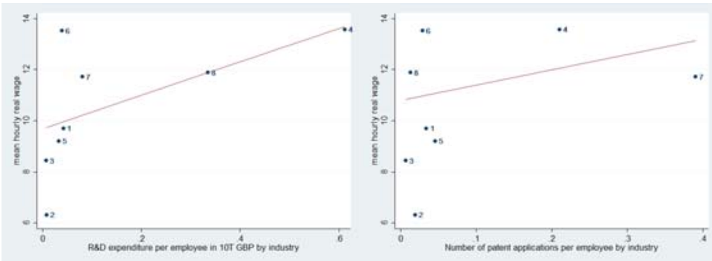
Figure 3: List of Industries

Standardisation of ISIC rev.2, ISIC rev. 3, SIC 92 and SIC 80

ISIC-Rev. 2	**ISIC-Rev. 3**	**Standardised Industry Classification**	**SIC 92***	**SIC 80**
3 Manufacturing	**D Manufacturing**	**1. Manufacture of Food, Beverages and Tobacco**	**D. Manufacturing**	**4 Other manufacturing Industries**
31 Manufacture of Food, Beverages and Tobacco	**15** Manufacture of food products and beverages		**DA(15,16)** Manufacture of food products, beverages and tobacco	**41/42** Food, drink & tobacco manufacturing industries
	16 Manufacture of tobacco products			
32 Textile, Wearing Apparel and Leather Industries	**17** Manufacture of textiles	**2. Manufacture of Textile, Wearing Apparel and Leather Industries**	**DB (17,18)** Manufacture of textiles and textile products	**43** Textile industry
	18 Manufacture of wearing apparel; dressing and dyeing of fur		**DC (19)** Manufacture of leather and leather products	**44** Manufacture of leather & leather goods
	19 Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear			**45** Footwear & clothing industries
33 Manufacture of Wood and Wood Products, Including Furniture	**20** Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	**3. Manufacture of Wood and Wood Products, Including Furniture, Paper and Paper Products, Printing and Publishing**	**DD (20)** Manufacture of wood and wood products	**46** Timber & wooden furniture industries
34 Manufacture of Paper and Paper Products, Printing and Publishing	**21** Manufacture of paper and paper products		**DE (21,22)** Manufacture of pulp, paper and paper products; publishing and printing	**47** Manufacture of paper & paper products; printing & publishing
	22 Publishing, printing and reproduction of recorded media			
35 Manufacture of Chemicals and Chemical, Petroleum, Coal, Rubber and Plastic Products	**23** Manufacture of coke, refined petroleum products and nuclear fuel	**4. Manufacture of Chemicals and Chemical, Petroleum, Coal, Rubber and Plastic Products**	**DF (23)** Manufacture of coke, refined petroleum products and nuclear fuel	**11** Coal extraction & manufacture of solid fuels
				12 Coke ovens
	24 Manufacture of chemicals and chemical products		**DG (24)** Manufacture of chemicals, chemical products and man-made fibres	**13** Extraction of mineral oil & natural gas
				14 Mineral oil processing
				15 Nuclear fuel production
	25 Manufacture of rubber and plastics products		**DH (25)** Manufacture of rubber and plastic products	**25** Chemical industry
				26 Production of man-made fibres
				48 Processing of rubber & plastics
36 Manufacture of Non-Metallic Mineral Products, except Products of Petroleum and Coal	**26** Manufacture of other non-metallic mineral products	**5. Manufacture of other non-metallic mineral products**	**DI (26)** Manufacture of other non-metallic mineral products	**24** Manufacture of non-metallic mineral products
37 Basic Metal Industries	**27** Manufacture of basic metals	**6. Manufacture of basic metals**	**DJ (27,28)** Manufacture of basic metals and fabricated metal products	**22** Metal manufacturing
				31 Manufacture of metal goods not elsewhere specified
38 Manufacture of Fabricated Metal Products, Machinery and Equipment	**28** Manufacture of fabricated metal products, except machinery and equipment	**7. Manufacture of Fabricated Metal Products, Machinery and Equipment**	**DK (29)** Manufacture of machinery and equipment not elsewhere classified	**32** Mechanical engineering processing equipment
	29 Manufacture of machinery and equipment n.e.c.			**33** Manufacture of office machinery & data
39 Other Manufacturing Industries	**30** Manufacture of office, accounting and computing machinery	**8 Other Manufacturing Industries**	**DL (30,31,32,33)** Manufacture of electrical and optical equipment	**34** Electrical & electronic engineering
	31 Manufacture of electrical machinery and apparatus n.e.c.			
	32 Manufacture of radio, television and communication equipment and apparatus			
	33 Manufacture of medical, precision and optical instruments, watches and clocks			**37** Instrument engineering
	34 Manufacture of motor vehicles, trailers and semi-trailers		**DM (34,35)** Manufacture of transport equipment	**35** Manufacture of motor vehicles & parts thereof
	35 Manufacture of other transport equipment			**36** Manufacture of other transport equipment
	36 Manufacture of furniture; manufacturing n.e.c.		**DN (36,37)** Manufacturing not elsewhere classified	**49** Other manufacturing industries
	37 Recycling			

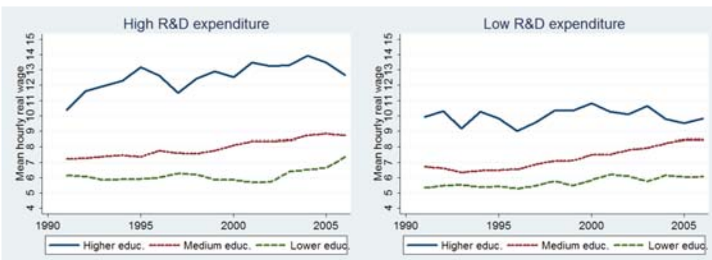
* SIC92 is given at the 4 digit level in BHPS. The numbers in brackets are the first two numbers of each classified group.

Figure 4: Linear Fit of Hourly Wages and Innovation Indicators for Higher Education



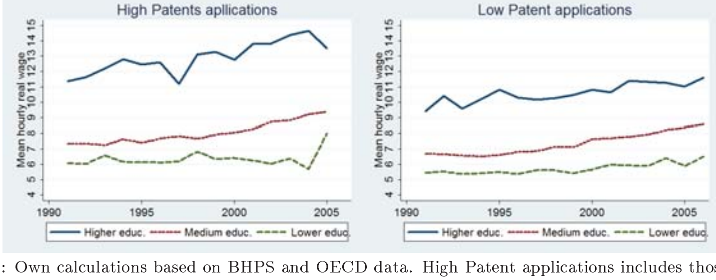
Source: Own calculations based on BHPS and OECD data.

Figure 5: Wages by Education and R&D Expenditure over Time



Source: Own calculations based on BHPS and OECD data. High R&D expenditure includes those industries which spend more than average on R&D and low R&D expenditure includes those industries which spend less than average on R&D.

Figure 6: Wages by Education and Patent Applications over Time



Source: Own calculations based on BHPS and OECD data. High Patent applications includes those industries which apply more than average for patents and low Patent applications includes those industries which apply less than average for patents.

Table A1: Descriptive statistics

	1991-1994	1995-1998	1999-2002	2003-2005
Industry characteristics				
R&D expenditure	0.17	0.18	0.22	0.25
	(0.18)	(0.18)	(0.23)	(0.26)
Patents	0.08	0.09	0.12	0.11
	(0.10)	(0.12)	(0.17)	(0.17)
Production	7.89	8.83	9.15	10.68
	(2.52)	(2.33)	(2.25)	(2.66)
Job characteristics				
Hourly wage	6.96	7.29	7.86	8.60
	(3.35)	(3.57)	(3.58)	(3.76)
Tenure	10.06	9.24	9.80	10.63
	(11.27)	(11.12)	(11.57)	(11.86)
1-24 employees	0.16	0.18	0.19	0.20
	(0.37)	(0.38)	(0.39)	(0.40)
25-99 employees	0.22	0.23	0.24	0.22
	(0.41)	(0.42)	(0.43)	(0.42)
99- employees	0.62	0.59	0.57	0.58
	(0.49)	(0.49)	(0.49)	(0.49)
Union member	0.15	0.27	0.28	0.26
	(0.36)	(0.44)	(0.45)	(0.44)
Personal characteristics				
High education	0.09	0.10	0.09	0.11
	(0.29)	(0.30)	(0.28)	(0.32)
Medium Education	0.71	0.75	0.78	0.79
	(0.45)	(0.43)	(0.42)	(0.41)
Low Education	0.20	0.15	0.13	0.10
	(0.40)	(0.36)	(0.34)	(0.30)
Age 20-29	0.27	0.28	0.24	0.21
	(0.45)	(0.45)	(0.43)	(0.41)
Age 30-39	0.28	0.29	0.30	0.26
	(0.45)	(0.45)	(0.46)	(0.44)
Age 30-49	0.27	0.24	0.26	0.30
	(0.44)	(0.43)	(0.44)	(0.46)
Age 50-64	0.18	0.18	0.19	0.23
	(0.39)	(0.39)	(0.40)	(0.42)
Married	0.65	0.58	0.60	0.60
	(0.48)	(0.49)	(0.49)	(0.49)
Children	0.38	0.36	0.40	0.37
	(0.48)	(0.48)	(0.49)	(0.48)
Health status	1.96	2.00	2.10	2.03
	(0.81)	(0.82)	(0.86)	(0.80)
N	3471	3435	4412	2246
$\sum$N		13564		

Note: Authour's calculations based on BHPS and OECD data. The sum of all observations including the year 2006 (excluding patent information is 14247).

Table A2: Correlation Between Indicators

	R&D exp.	Patents	Production
R&D exp.	1.000		
Patents	0.189***	1.000	
	(0.000)		
Production	0.647***	-0.081***	1.000
	(0.000)	(0.000)	

Note: Significance in parentheses. *** denote significance level of 1%.

Table A3: Pooled OLS and Panel Regressions for Indicator: R&D Expenditure

	OLS		Random Effects		Mundlak		Hausman-Taylor	
Higher Education	0.205***	0.132***	0.321***	0.274***	0.313***	0.291***	0.634***	0.572***
	(0.011)	(0.017)	(0.021)	(0.027)	(0.021)	(0.032)	(0.113)	(0.114)
R&D exp.	0.199***	0.172***	0.144***	0.127***	0.102***	0.085***	0.104***	0.086***
	(0.017)	(0.017)	(0.026)	(0.026)	(0.030)	(0.030)	(0.018)	(0.019)
HE×R&D exp.	–	0.269***	–	0.180***	–	0.202**	–	0.208***
		(0.041)		(0.062)		(0.084)		(0.050)
Production	-0.000	-0.001	-0.002	-0.002	-0.001	-0.002	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Female	-0.254***	-0.254***	-0.268***	-0.269***	-0.266***	-0.266***	-0.263***	-0.263***
	(0.007)	(0.007)	(0.013)	(0.013)	(0.013)	(0.013)	(0.020)	(0.020)
Tenure	0.002***	0.002**	0.003***	0.003***	0.003***	0.003***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
25-99 employees	0.062***	0.062***	0.044***	0.043***	0.043***	0.043***	0.039***	0.039***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)
99- employees	0.177***	0.176***	0.107***	0.106***	0.105***	0.105***	0.086***	0.086***
	(0.009)	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)
Union member	0.104***	0.105***	0.044***	0.044***	0.044***	0.044***	0.024***	0.024***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
Married	0.086***	0.085***	0.070***	0.070***	0.071***	0.071***	0.061***	0.061***
	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)
Children	0.014**	0.014**	0.011	0.011	0.012	0.012	0.017***	0.017***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)
Health status	-0.029***	-0.029***	-0.013***	-0.013***	-0.013***	-0.013***	-0.010***	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age 30-39	0.116***	0.116***	0.114***	0.114***	0.115***	0.114***	0.104***	0.103***
	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)
Age 40-49	0.141***	0.141***	0.144***	0.144***	0.146***	0.145***	0.127***	0.127***
	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)
Age 50-64	0.098***	0.099***	0.111***	0.112***	0.115***	0.114***	0.088***	0.088***
	(0.010)	(0.010)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Constant	2.135***	2.156***	1.913***	1.926***	1.898***	1.905***	1.676***	1.685***
	(0.031)	(0.031)	(0.044)	(0.045)	(0.044)	(0.045)	(0.053)	(0.053)
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14247	14247	14247	14247	14247	14247	14247	14247
F	246	248	–	–	–	–	76	75
p	0.000	0.000	0.000	0.000	0.000	0.000	–	–
R^2	0.455	0.457	0.408	0.410	0.410	0.411	–	–
Chi^2	–	–	3300	3370	3431	3482	4155	4179

Note: Standard errors in parentheses. *,** and *** denote significance level of 1%, 5% and 10% respectively. 18 regional dummies, 9 occupational and 15 year dummies included.

Table A4: Pooled OLS and Panel Regressions for Indicator: Patent Applications

	OLS		Random Effects		Mundlak		Hausman-Taylor	
Higher Education	0.213***	0.191***	0.326***	0.301***	0.325***	0.316***	0.692***	0.658***
	(0.012)	(0.015)	(0.022)	(0.024)	(0.022)	(0.028)	(0.125)	(0.125)
Patents	0.232***	0.214***	0.129***	0.109***	0.097***	0.075***	0.106***	0.084***
	(0.020)	(0.021)	(0.025)	(0.026)	(0.028)	(0.029)	(0.019)	(0.020)
HE×Patents	–	0.182***	–	0.224***	–	0.255***	–	0.262***
		(0.068)		(0.075)		(0.085)		(0.065)
Production	0.013***	0.013***	0.008***	0.008***	0.008***	0.008***	0.007***	0.007***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Female	-0.246***	-0.246***	-0.264***	-0.264***	-0.260***	-0.260***	-0.257***	-0.257***
	(0.007)	(0.007)	(0.013)	(0.013)	(0.013)	(0.013)	(0.020)	(0.020)
Tenure	0.002**	0.002**	0.003***	0.003***	0.003***	0.003***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
25-99 employees	0.065***	0.065***	0.045***	0.045***	0.045***	0.045***	0.040***	0.040***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)
99- employees	0.183***	0.183***	0.107***	0.107***	0.107***	0.107***	0.085***	0.085***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)
Union member	0.104***	0.104***	0.043***	0.043***	0.044***	0.044***	0.022***	0.023***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
Married	0.081***	0.081***	0.071***	0.071***	0.070***	0.070***	0.063***	0.063***
	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)
Children	0.018***	0.018***	0.015*	0.015*	0.015*	0.015*	0.022***	0.021***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)
Health status	-0.029***	-0.029***	-0.013***	-0.013***	-0.013***	-0.013***	-0.010***	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age 30-39	0.117***	0.117***	0.112***	0.111***	0.112***	0.112***	0.099***	0.098***
	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)
Age 40-49	0.143***	0.143***	0.141***	0.141***	0.142***	0.141***	0.121***	0.120***
	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Age 50-64	0.099***	0.100***	0.111***	0.110***	0.112***	0.111***	0.085***	0.084***
	(0.011)	(0.011)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
Constant	2.048***	2.054***	1.853***	1.860***	1.846***	1.849***	1.611***	1.616***
	(0.031)	(0.031)	(0.044)	(0.045)	(0.044)	(0.045)	(0.057)	(0.057)
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13564	13564	13564	13564	13564	13564	13564	13564
F	235	232	–	–	–	–	69	68
p	0.000	0.000	0.000	0.000	0.000	0.000	–	–
R^2	0.454	0.454	0.406	0.406	0.407	0.407	–	–
Chi^2	–	–	3102	3148	3135	3176	3732	3754

Note: Standard errors in parentheses. *,** and *** denote significance level of 1%, 5% and 10% respectively. 18 regional dummies, 9 occupational and 14 year dummies included.

Table A5: Fixed Effects Regressions

	Fixed Effects
HE×1995-1998	-0.001
	(0.020)
HE×1999-2002	0.109***
	(0.022)
HE×2003-2006	0.121***
	(0.024)
Constant	1.777***
	(0.058)
Characteristics	Yes
Regional dummies	Yes
Occup. dummies	Yes
Year dummies	Yes
N	14247
F	67
p	0.000
R^2	0.212

Note: Standard errors in parentheses. *,** and *** denote significance level of 1%, 5% and 10% respectively. 18 regional dummies, 9 occupational and 15 year dummies included.

Table A6: Fixed Effects Regressions Including Time Interactions

	Indicator			
	R&D expenditure		Patents	
Indicator				
1991-1994	-0.001	0.016	0.174***	0.168***
	(0.033)	(0.034)	(0.050)	(0.052)
1995-1998	0.091***	0.111***	0.181***	0.194***
	(0.031)	(0.032)	(0.037)	(0.039)
1999-2002	0.082***	0.071***	0.118***	0.097***
	(0.024)	(0.025)	(0.025)	(0.026)
2003-2006	0.093***	0.065***	0.057*	0.010
	(0.022)	(0.023)	(0.032)	(0.033)
Higher Education$\times$Indicator				
1991-1994		-0.102		0.100
		(0.086)		(0.137)
1995-1998		-0.118		-0.070
		(0.087)		(0.111)
1999-2002		0.140**		0.246***
		(0.065)		(0.076)
2003-2006		0.203***		0.423***
		(0.055)		(0.091)
Constant	Yes	Yes	Yes	Yes
Characteristics	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
Occupation dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
N	14247	14247	13564	13564
F	65	60	58	54
p	0.000	0.000	0.000	0.000
R^2	0.210	0.213	0.201	0.203

Note: Standard errors in parentheses. *,** and *** denote significance level of 1%, 5% and 10% respectively. 18 regional dummies, 9 occupational and 15 year dummies included. Charcatersitics inlcude prodiction output by industry, a female dummy, tenure tenure squared, two firmsize dummies, a dummy for union membership, a dummy for being married, having kids, self-rated healh and three age dummies. The patent data only covers 1991 to 2005, hence the last period is 2003-2005.