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The Importance of Worker, Firm and Match Fixed Effects in the Formation of Wages

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Abstract

This paper estimates a Mincerian wage equation with worker, firm, and match specific fixed effects and thereby complements the growing empirical literature started by the seminal paper of Abowd, Kramarz and Margolis (1999). The analysis takes advantage of the extensive Danish IDA data, which provides wage information on the whole working population for a 24-year period. We find that the major part of wage dispersion in the Danish labor market can be explained by differences in worker characteristics. However, the relative contribution of the three components varies across subgroups of workers. The match effect contributes a non-neglible part to the overall wage dispersion and, furthermore, corrects the estimated returns to experience. An analysis of inter-industry wage differentials shows that firm characteristics are more important at the industry level than at the worker level. Likewise, we find evidence of high wage workers sorting into high wage industries but not into high wage firms within industries. The mobility pattern of workers is related to the quality of the firm and the match, and we find that the wage gain from job mobility depends on worker characteristics.

Keywords: MEE data, fixed effects, wage dispersion

JEL codes: J21, J31

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1 Introduction

Wage dispersion is an intrinsic feature of the labor market, and the extent of economic research devoted to describing and understanding the sources of wage dispersion is immense. Since the work of Mincer (1974) innumerable studies have documented a relationship between labor market earnings and worker characteristics such as education, race, gender and labor market experience. A still ongoing research agenda aims at understanding the causal nature behind these empirical realationships. However, worker characteristics are not sufficient to explain all of the observed wage dispersion, not even when highly detailed information on worker characteristics is available. Therefore attention is drawn towards differences on the employer side of the labor market as an important determinant in wage formation. The theoretical foundation for such differences is solid (e.g. efficiency wages, compensating differentials and rent-sharing) and, for instance, the existence and persistency of inter-industry wage differentials (i.e. significant differences in the industry average wage after controlling for vast sets of observable worker characteristics) has been interpreted as supportive evidence. However, a competing candidate explanation for the inter-industry wage differentials is unobserved abilities of the workers. High ability workers earn higher wages and, hence, industries that employ proportionally more high ability workers will pay observable equivalent workers more compared to industries employing workers with low unobserved abilities. The work of Murphy and Topel (1987), Katz (1987) and Gibbons and Katz (1992) lends support to this view. However, Krueger and Summers (1988) cast doubt on this by showing that the wage changes of workers switching industries compare very well to the cross-sectional estimates of inter-industry differentials. These are just a few of the studies that have tried to disentangle the relative importance of worker and firm heterogeneity in wage formation. However, common to these studies is the lack of appropiate data relating the characteristics of workers to the characteristics of firms. The recent, and growing, availability of matched employer-employee data sets with a considerable longitudinal dimension allows the simultanoues identification of worker and firm heterogeneity (including unobservable differences). The development of suitable econometric methods to take advantage of these new data structures was initiated by the seminal paper of Abowd, Kramarz and Margolis (1999) who introduced conditional methods to estimate wage equations featuring both worker and firm fixed effects. Later, Abowd, Creezy and Kramarz (2002) provided an algorithm allowing the exact least squares solution. The person and firm effects model of Abowd, Kramarz and Margolis (1999) (henceforth AKM) has contributed significantly to the analyses of wage determination and, in particular, the relative importance of worker and firm characteristics.

In this paper we make a decomposition of the wage dispersion in the Danish labor market. We adopt a slight extension of AKM's person and firm effects model as analysed by Woodcock (2008) in which a wage component specific to the firm-worker match is allowed. The theoretical labor market models featuring match specific components are many and diverse (see e.g. Jovanovic (1979), Mortensen and Pissarides (1994), Bowlus (1995) and Nagypal (2007)) but the empirical evidence on the existence and magnitude is limited. The match effects extension of the AKM model allows such an assesment. Furthermore, if match effects are indeed present, an analysis of wage determination that excludes a match specific component is likely to suffer from omitted variables bias. For instance, if workers move around the labor market searching for better matches, then on average more experienced workers will be employed in higher paying matches. Without explicitly modelling the match effect, a measure of labor market experience would capture both the wage growth due to human capital accumulation and the wage increases due to the sorting of workers into better matches. The match effects model allow us to disentangle these two components, and we do find that controlling for match effects moderates the estimated returns to experience. Although our reduced form model can be derived from a structural representation of productivity and wage setting, we mainly consider our analysis as providing some interesting descriptive features of the Danish labor market which can subsequently guide the designing of structural labor market models. If the match component comprises an important part in the wage equation, then structural models should be able to replicate this feature of the data.

Estimation of the match effects model allows us to decompose the observed wage dispersion into components pertaining to worker, firm and match heterogeneity. We find worker characteristics to be the main driving force of wage dispersion accounting for around 60% of observed wage differences, whereas the firm and match components explain 14% and 11%, respectively. However, these numbers mask considerable differences across the work force. Dividing the sample according to gender and educational level, we find the worker component to be relatively more important for men and for high educated workers, whereas firm differences play a more pronounced role in shaping the wages of women and workers with lower levels of educational attainment. Experimenting with non-constant firm effects, we find that the distinction between the firm and the match component in wages is sensitive to the flexibility of firms' wage policies.

The correlation structure of the worker and firm effects is unrestricted in the model and has, therefore, been of individual interest in the analyses applying the AKM framework. Based on the positive assortative matching theory in Becker (1973) intuition suggests that good workers would tend to work at good firms, which is also supported by theory in case of complementarity of worker and firm input in the production function. Therefore, it has been considered a puzzle that most papers applying the AKM framework find a non-positive correlation between estimated person and firm effects, e.g. AKM (1999), Abowd, Finer and Kramarz (1999), Goux and Maurin (1999) and Woodcock (2008). Two non-competing explanations for this "counter-intuitive" result have emerged. The first explanation emphasises that the estimated correlation is biased due to either limited mobility, e.g. Andrews et al. (2008) and Abowd et al. (2003), or omitted variables, e.g. Le Maire and Scheuer (2008) and Woodcock (2008). Andrews et al. (2006) propose a correction method to adjust the estimated correlation according to the extent of mobility in the data analysed. However, Abowd et al. (2003), Abowd and Kramarz(2004) and Woodcock (2008) make limited mobility corrections and find it to have little impact on the estimated correlation. Le Maire and Scheuer (2008) are in some aspects very much in line with this paper. They also use the Danish IDA data, and they allow a match effect in the AKM framework as well. They compare the estimated correlation between the worker effect and the firm effect (0.12) to the estimate found by applying the person and firm effects model of AKM (in the range 0.03-0.06). They ascribe the difference to omitted variables bias in the AKM model from neglecting the potential match effects. In contrast, we find little difference between the correlation of estimated worker and firm effects in the match effects model and the AKM model. In fact we find an almost zero correlation in both models. An important difference between our analysis and the one in Le Maire and Scheuer (2008) is that we make fixed effect assumptions whereas they perform a mixed effects analysis.

The second explanation for the non-positive correlation between the worker and the firm effects is more fundamental. It argues that the fixed effects in the wage equation do not necessarily correlate very well with the underlying productivity of the firm and worker, respectively. When motivating the AKM specification as a structural representation of the wage equation, it is generally assumed that the outside options of workers and firms are independent of the prevailing match. Recently several studies have illustrated the implications of relaxing this assumption. Eeckhout and Kircher (2008) and Melo (2008) both generate a non-monotonicity in the wage equation due to high productivity firms facing better outside options than their counterparts when they match with a low productivity worker. A low productivity worker has to compensate a high productivity firm for giving up the opportunity to match with a more productive worker. Eeckhout and Kircher (2008) illustrate the insufficiency of wage data alone to identify sorting in the labour market: for every production function that induces positive sorting they can find a production function inducing negative sorting whilst generating identical wages. In Postel-Vinay and

Robin (2002) the dynamic nature of the wage bargaining process implies that although workers always move up in the productivity distribution upon a job-to-job transition, a move may be associated with a drop in the wage. Bagger and Lentz (2008) adopt this wage setting in an on-the-job search model and show that positive sorting can be consistent with a negative correlation between the fixed effects in the wage equation. Shimer (2005) makes the same point within an assignment model. This recent strand of the literature shows that one should be very careful when interpreting AKM type wage decompositions and, hence, we do not push our results in the direction of revealing the underlying productivity structure of the labour market.

Upon estimation of the match effects model we take the estimated parameters as input in further analyses. In turn we consider the implications of job mobility on wage dynamics and we address the inter-industry wage differentials. Several studies have discussed the impact of job mobility on wage growth. For example, Topel and Ward (1992) show that workers changing jobs experience above-average wage growth. Altonji and Williams (1992) report considerable wage loss upon layoffs, whereas voluntary quits are associated with substantial gains. With firm and match specific effects of wages identified by the match effects model, a natural application of the estimated parameters is to consider the wage growth of job movers and divide this into parts arising from changes in firm and match effects, respectively. We find job mobility to be associated with small but significant improvements in both components. Taking worker characteristics into account, we find these small effects to mask substantial differences.

One of the main applications of the AKM model has been to reassess the determinants of the inter-industry wage differentials documented and discussed intensively in the late eighties and early nineties. AKM (1999) and Goux and Maurin (1999) analyse French data and find unobserved worker heterogeneity to explain the bulk part of the inter-industry differentials. Abowd, Finer and Kramarz (1999) find unobserved differences on both sides of the labor market to be almost equally important using data on the State of Washington. In contrast, Gruetter and Lalive (2004) find firm differences to account for around three quarters of the inter-industry wage differentials in Austria. Likewise, using data from the US Census Bureau's Longitudinal Employer-Household Dynamics Database, Woodcock (2007) finds firm heterogeneity to be most important and, furthermore, he shows how the inclusion of match effects can affect the industry level decomposition even though the direct contribution of match effects in explaining inter-industry wage differentials is neglible. We supplement our inter-industry decomposition with worker group specific decompositions and by analysing high and low wage industries separately. The latter shows that the sorting of workers and firms into industries is substantially stronger among low wage industries.

The paper is organised as follows: Section 2 presents our empirical model, discusses identification and summarises the implementation procedure. We describe the Danish IDA data in Section 3 and, in particular, the realised mobility patterns that are of high importance for both identification and precision of the parameters. In Section 4 we present the results of the wage decomposition and the analyses taking the estimated parameters as input. Section 5 concludes.

2 The Match Effects Model

Our empirical specification of the wage equation is identical to the one in Woodcock (2008). We assume that worker i's t'th log-wage when employed at firm j, w_{ijt}, arises from the linear model:

$$w_{ijt} = x'_{it}\beta + \phi_i + \psi_j + \theta_{ij} + \varepsilon_{ijt}, \tag{1}$$

where x_{it} is a $1 \times K$ vector of observed time-varying covariates, β is a conformable vector of slope parameters, ϕ_i, ψ_j and θ_{ij} are the determinants of log wages that are specific to the worker, the firm and the match, respectively. ε_{it} is the residual wage. Woodcock (2008) shows that (1) is structurally identical to the wage equation derived from a simple model of productivity and wage formation. Hence, $x'_{it}\beta + \phi_i$ can be interpreted as the market value of the workers' productive characteristics that are portable in the labor market. The productive characteristics may vary over time due to e.g. human capital accumulation. ψ_j reflects the productivity of the firm, the market conditions that it operates in and the compensation policy. Without information on productivity or product market conditions the three cannot be separated and we will henceforth refer to ψ_j as the wage policy of the firm. θ_{ij} is interpreted as the market value of the complementarity between worker i's and firm j's productive attributes. The worker, firm and match effects capture persistent differences in compensation between individuals, firms and matches, respectively. Each of the fixed effects may be decomposed into an observable and an unobservable component when observable characteristics are available. However, we choose not to do so, since the distinction between observable and unobservable components is not important for our analysis. Equation (1) nests the person and firm effects model by Abowd et al (1999), which restricts the match effects to zero, $\theta_{ij} = 0$ for all i, j. These restrictions are immediately testable within the match effects specification.

2.1 Identification and Estimation

We identify the parameters of the model in (1), (2) and (3) using fixed effect techniques; that is, rather than imposing functional forms on the joint distribution of the wage components we treat ψ_j, ϕ_i and θ_{ij} as parameters to be estimated. This allows us to estimate the model using least squares techniques at the cost of a loss of degrees of freedom.[1]

We shall treat the residual ε_{ijt} in (1) as a genuine statistical residual. That means we impose the (identifying) assumptions:

$$\mathrm{E}[\varepsilon_{ijt}|x_{ijt}, i, j, t] = 0, \quad \forall n \in \mathcal{N}_i \text{ and } \forall i \in \mathcal{I} \tag{2}$$

$$\begin{aligned} \mathrm{Cov}[\varepsilon_{ijt}\varepsilon_{nms}|x_{ijt}, x_{nms}, i, n, j, m, t, s] &= \sigma^2 < \infty, \quad \forall i = n, j = m, t = s \\ \mathrm{Cov}[\varepsilon_{ijt}\varepsilon_{nms}|x_{ijt}, x_{nms}, i, n, j, m, t, s] &= 0, \text{ otherwise} \end{aligned} \tag{3}$$

Assumption (3) should be considered a regularity condition, but assumption (2) carries economic content in the sense that it rules out endogenous mobility. Since we are conditioning on both worker, firm, and match effects, assumption (2) is consistent with both the "mover-stayer" theory of job mobility, stressing worker effects in the wage-mobility pattern (e.g. Munasinghe and Sigman, 2003), the job search theory which points to firm effects as a joint determinant of wages and mobility (e.g. Mortensen, 2003), and models that feature match effects in earnings (e.g. Jovanovic, 1979). In contrast to the canonical person and firm effects model proposed by AKM, the match effects model allows labor market mobility to depend on a constant match component.

It is useful to restate the wage equation (1) in matrix notation. Let $i \in \mathcal{I} = \{1, ..., I\}$ index workers. Worker i is represented by N_i observations, indexed by $n \in \mathcal{N}_i = \{1, ..., N_i\}$, so the total number of observations in the data is $N = \sum_{i \in \mathcal{I}} N_i$. The notation thus allows for unbalanced and incomplete panels. The set of firms is $\mathcal{J} = \{1, ..., J\}$ with index j. Let there be M distinct matches between workers

[1] Given the size of our dataset (see Section 3) the loss of degrees of freedom is not critical. However, there is another critique of the fixed effect approach taken here: When the subjects under study are generated and evolve according to stochastic processes—as is arguably the case of the subjects considered in this study—the fixed effect approach is usually deemed inappropriate (Baltagi, 2001, ch. 2). The fixed effect approach is subject to the incidental parameter problem (Lancaster, 2000): Consistent estimates of the fixed effects cannot be obtained except when applying the somewhat awkward asymptotics of keeping I, M and J fixed while $N_i \to \infty$. However, the aim of this paper is to achieve economic insight through descriptive accuracy and not to impose and test a specific theory of matching in the labor market. In this case, a random effect approach would amount to imposing a set of theoretically unfounded functional forms resulting in a likely loss of descriptive accuracy and potential economic insights.

and firms. Let w be the $N \times 1$ vector of log-wages and X the $N \times K$ matrix of observed time-varying covariates. Furthermore, if d^i is an $N \times 1$ vector indicating observations on worker $i \in \mathcal{I}$ and f^j is the $N \times 1$ vector indicating employment in firm $j \in \mathcal{J}$ we can design matrices of worker indicators $D = [d^1 \ d^2 \ ... \ d^I]$ and firm indicators $F = [f^1 \ f^2 \ ... \ f^J]$.[2] Likewise, H is $N \times M$ design matrix of match effects indicators. Letting $e = [\varepsilon_{11}, ..., \varepsilon_{in}, ..., \varepsilon_{IN_i}]'$ be the $N \times 1$ vector of stacked residuals, we can write

$$w = X\beta + D\phi + F\psi + H\theta + e \tag{4}$$

where β, as before, is a $K \times 1$ vector of slope parameters, ϕ is the $I \times 1$ vector of stacked worker effects, ψ is the $J \times 1$ vector of stacked firm effects, and θ is the $M \times 1$ vector of match effects.The least square estimator of the parameters in (4) solves the system of normal equations:

$$\begin{bmatrix} X'X & X'D & X'F & X'H \\ D'X & D'D & D'F & D'H \\ F'X & F'D & F'F & F'H \\ H'X & H'D & H'F & H'H \end{bmatrix} \begin{bmatrix} \widehat{\beta} \\ \widehat{\phi} \\ \widehat{\psi} \\ \widehat{\theta} \end{bmatrix} = \begin{bmatrix} X'w \\ D'w \\ F'w \\ H'w \end{bmatrix}. \tag{5}$$

Partioning this system of equations, the least squares estimator of β is given by:

$$\widehat{\beta} = \left(X' P_{[D \ F \ H]} X\right)^{-1} X P_{[D \ F \ H]} w \tag{6}$$

where $P_{[\mathbf{A}]} \equiv I - A'(A'A)^{-1}A$. In the presence of match effects $P_{[D \ F \ H]}$ takes deviations from match-specific means; see Woodcock (2008). This implies that the least squares estimator, $\widehat{\beta}$, is readily available from the regression:

$$w_{ijt} - \overline{w}_{ij.} = \widehat{\beta}\left(x_{ijt} - \overline{x}_{ij}\right) + u_{ijt} \tag{7}$$

where $\overline{w}_{ij.}$ and $\overline{x}_{ij.}$ are the sample means within the match between worker i and firm j and u_{ijt} is a statistical error.

With $\widehat{\beta}$ determined by the regression in (7) we are still left with the task of identifying the remaining parameters, $\widehat{\phi}$, $\widehat{\psi}$ and $\widehat{\theta}$. However, the fixed effects specification is over-parameterized since there are $I + J + M$ person effects, firm effects and match effects but only M distinct cells from which to estimate

[2] More precisely, if $f^j_{in} = \mathbf{1}_{\{J(i,n)=j\}}$, then $f^j = [f^j_{11}, ..., f^j_{in}, ..., f^j_{IN_i}]'$. Similarly for d^i.

them; namely the within-match sample means:

$$\overline{\mu}_{ij.} = \frac{1}{N_{ij}} \sum_{t=n_{ij}^1}^{N_{ij}} \left(w_{ijt} - x_{ijt}\widehat{\beta} \right) = \widehat{\phi}_i + \widehat{\psi}_j + \widehat{\theta}_{ij} \tag{8}$$

where $n_{ij}^1, n_{ij}^2, ..., N_{ij}$ are the periods in which worker i is employed in firm j. There is no unique solution to decomposing these M elements into I worker effects, J firm effects and M match effects. For instance, we cannot tell apart a worker who has a large person effect from a worker who has a small person effect, but tends to be employed in better matches. Similarly, we cannot disentangle a high firm effect from a tendency to employ workers in good matches. Therefore, to proceed we need further assumptions. We impose that the match specific effect is orthogonal to the worker and firm effects:

$$\mathbf{E}[\theta_{ij}|i, j] = 0 \tag{9}$$

This is a strong assumption and restricts the mobility pattern allowed by the model. However, it leaves us with only the problem of separating the worker and firm effects. Hence, the orthogonal match effects model is identified whenever the person and firm effects model is identified. A thorough discussion on identification in that model is presented in Abowd et al. (2002). Below we just briefly summarise.

Separately identifying worker and firm effects requires (at least) one normalisation. This is readily seen from (4) by adding λI_I to ϕ and substracting λI_J from ψ, which will leave $\mathbf{w}$ unaffected. That is, we cannot distinguish the mean of worker effects from the mean of firm effects. Without loss of generality we choose to normalise one firm effect to zero. Identifying the remaining worker and firm effects requires that we can relate these to the normalised firm. Therefore, workers and firms have to be in the same connected group as the normalized firm:

> "*When a group of persons and firms is connected, the group contains all the workers who ever worked for any of the firms in the group and all the firms at which any of the workers were ever employed. In contrast, when a group of persons and firms is not connected to a second group, no firm in the first group has ever employed a person from the second group, nor has any person in the first group ever been employed by a firm in the second group.*" Abowd et al. (2002).

A normalisation is needed within each connected group, leaving $I + J - G$ identifiable worker and firm effects where G is the number of connected groups in the labor market. The requirement of a normalization in each group highligths the importance of having a considerable longitudinal dimension and sufficient job mobility, not only for precision but also for identification. We will describe these features of the data in section 3.

Implementation

With a real size data set a systematic way of identifying connected groups of workers and firms is needed. Abowd et al. (2002) show that the graph theoretical concept of *strong Hall components* proves very useful in this respect. We apply their algorithm to identify connected groups of firms and workers. Hence, our estimation procedure for the model in (1), (2) and (3) proceeds in the following steps:

1. Identify connected groups of workers and firms. We keep only the largest group.[3]

2. Estimate $\widehat{\beta}$ from the partioned regression specified in (7).

3. Let $\overline{\mu}$ be a $N \times 1$ vector of the sample cell means defined in (8). The least squares estimates of the person and firm effects solve

$$\begin{bmatrix} D'D & D'F \\ F'D & F'F \end{bmatrix} \begin{bmatrix} \widehat{\phi} \\ \widehat{\psi} \end{bmatrix} = \begin{bmatrix} D'\overline{\mu} \\ F'\overline{\mu} \end{bmatrix} \tag{10}$$

   subject to the normalisation of an arbitrary firm effect. We use the Abowd et al. (2002) version of the conjugate gradient algorithm to solve (10), which takes advantage of the sparse structure of the data matrices.

4. The vector of orthogonal match effects is given by $\widehat{\theta} = \overline{\mu} - D\widehat{\phi} - F\widehat{\psi}$.

3 The Data

Our estimation sample is extracted from the Danish register-based matched employer-employee dataset, IDA, covering the period 1980 to 2003.[4] IDA contains socio-economic information on workers and background information on employers on an annual basis, and covers the entire Danish population. Although not all information pertains to November each year (some information is registered ultimo each year,

[3]The analysis could exploit all of the connected groups by making a normalization within each group. However, as the person and firm effects are measured relatively to G different normalisations the comparison of person and worker effects across the connected groups in the labor market is impossible. It turns out that the largest identified group contains the vast majority of observations, so the loss of ignoring the remaining groups is arguably neglible.

[4]IDA: *Integreret Database for Arbejdsmarkedsforskning* (Integrated Database for Labor Market Research) is constructed and maintained by Statistics Denmark.

i.e. by the 31st of December), we shall treat the data as providing repeated cross-sections taken ultimo November each year. Besides the worker and firm identifiers, the most important piece of information for the present study is the wage records, which consist of the annual average hourly wage in the job occupied in the last week of November.[5]

For the purpose of relating wage dynamics to the employment history of the workers in section 4.4, we utilize an accompanying spell data set. The raw spell data consists of worker and employer id, start date and end date of the spell and a variable describing the labor market state of the worker. To make the data more suited for this study, we manipulate it in the following way: The sixteen states that the worker can occupy in the raw data are aggregated into five states; employment (E), unemployment (U), nonparticipation (N), self-employment (S), and retirement (O). Temporary unemployment and nonparticipation spells (shorter than 12 weeks) where the previous and next employer is the same is treated as a single employment spell. Likewise, if the duration of an unemployment spell or a nonparticipation spell between two employment spells at different employers is shorter than 4 weeks, we include the nonemployment spell in the second employment spell and register two consecutive employment spells. We disregard workers with invalid information, such as gaps in spell history, missing variables, double observations etc. The spell data is only available for 1985 and onwards. Thus, this part of the analysis excludes observations pertaining to the first five years of the IDA data.

3.1 Sample Selection

In the raw data we have 53,947,823 worker-year observations for which we observe the identity of the worker, the identity of the firm and the socio-economic information of the worker. The estimation sample is obtained through the following selection process. First, only observations on private sector jobs are included, i.e. we delete worker-years where the worker is employed in the public sector (32,390,838 observations left). Second, we delete worker-years where the worker is classified as self-employed.[6] Third, we delete worker-years where the wage information is missing (32,216,168 observations left). Forth, we define labor market entry as the year where the highest attained education is completed and delete any pre-entry labor market history.[7] If the worker is above the age of 35 at this time, we discard the worker

[5] Basically, the hourly wage is calculated as the total wage bill divided by the number of hours worked, where number of hours worked is imputed from pension payments. The pension payments have four levels depending on the hours worked.

[6] A worker is classified as being self-employed if the primary labor market state in the past year has been self-employed.

[7] For the part of the sample who enters the labor market within our sample period, we could define potential experience as age minus age at entry. However, this would either require that we restrict attention to this group of workers or treat those who enter in the sample period differently from those who entered prior to the sample period. Hence, this option was abandoned. Our definition of potential experience thus entails the assumption that pre-entry experience enters in the same way as post-entry experience when wages are determined.

entirely (27,718,604 observations left). We delete workers observed in school after the completion of the highest obtained education (25,116,574 observations left).[8] Fifth, we delete workers who have negative potential experience (see below). Sixth, we delete workers whose real experience is higher than age - 16, whose real experience falls from one year to the next, and whose real experience rises by more than two years in a single year (23,313,575 observations left). Finally, we trim the wage distribution from above at the 97.5 percentile and from below at the 2.5 percentile to rid the data of abnormal wage observations. The trimming is done year by year. Our final sample then contains 21,968,633 observations.

3.2 Observable Characteristics

The IDA data contains actual labor market experience but only measured from 1964 and onwards. Hence, for workers entering the labor market prior to 1964 this experience measure is left-censored. Therefore, we construct our own measure of experience as potential experience (age-16-length of education) at the first observation for a given worker and then add actual increments in experience. Woodcock (2008) uses a similar measure except that he only knows whether or not a worker was employed sometime during a quarter, whereas we have more precise information on the actual experience accumulated during the year. Table 1 presents summary statistics of our measure of experience. In our sample men are relatively more experienced than women and low educated are more experienced than high educated. The latter partly reflects that high educated enter the labor market later.

The time varying observables, x'_{it}, consist of calendar time and labor market experience. In the implementation we include a full set of year dummies and parameterise the experience profile by a piecewise-linear function. Time-invariant characteristics are gender and length of education. We construct an education measure which divides the sample into three mutually exclusive groups: less than 12 years of education, 12-14 years and more than 14 years. The first group contains high-school drop-outs, the second contains high-school graduates and individuals with a short cycle tertiary education, and the third contains those with medium and long cycle tertiary educations. We will denote these educational groups as low, medium and high educated workers, respectively. The IDA data does contain considerable further information on the workers. However, the paper focuses on disentangling worker, firm and match effects and not on which particular characteristics on either the worker or the firm side that drive wage differentials. Hence, the time-invariant worker characteristics included in the analysis are chosen such

[8] This mainly captures workers still in school in the final year of our sample (2003). In Denmark the delay of entry into tertiary educations is substantial. Hence, our sample contains a nonneglible amount of observations pertaining to the period between high school graduation and college entry. We want to discard these.

that well-defined subsamples can be formed on which separate analyses can be performed.

3.3 Labor Market Mobility and Connectedness

As discussed in section 2.1 the labor market mobility is important for the separate identification of worker and firm effects in (1). Table 2 provides evidence that considerable labor mobility is indeed present in our data. We observe roughly two-thirds of the workers at at least two different employers, and 14 percent of the workers are employed at more than five different employers in our sample. The average number of employers per worker is 2.61. The average number of employers per worker differs across gender and educational group with women and high educated on average being observed at fewer employers. However, for these groups the average number of observations per worker is also smaller as presented in Table 3. Hence, one should be careful not to draw conclusions about the relative mobility of the different subgroups from these figures. In the full sample we have more than nine observations on average per worker and more than 12% of the workers are observed for at least 21 years. Table 4 shows that the firm size distribution is highly skewed. The mean number of workers per firm in our sample is 59 whereas the median is only 8. The few worker-year observations of these firms may make the analysis subject to the limited mobility bias discussed by e.g. Andrews et al. (2008).[9] Le Maire and Scheuer (2008) exclude small firms in the estimation sample to circumvent this potential bias. However, in doing so one has to bear in mind that the sample excluding small firms is not likely to be representative of the full labor market. Woodcock (2008) and Abowd et al. (2004) argue that the limited mobility bias might be limited in size. Therefore, we keep all firms in our sample.

Table 5 provides descriptive statistics on the connected groups found by applying the grouping algorithm provided by Abowd et al. (2002). In the full sample we identify more than 25,000 connected groups of workers and firms. Note, however, that the largest group contains 99.5 percent of the observations, 98.7 percent of the workers and 92.6 percent of the firms. Although we could exploit all groups, we retain only the largest identified group for estimating the empirical model in (1), (2) and (3). As the numbers in Table 5 suggest, this entails little loss of generality of our results. Moreover, using only a single group of workers and firms implies that all the identified firm and worker effects are measured relatively to the same normalised firm effect.

[9] For the educational/gender subgroups the firms are even smaller.

4 Results

As the match effects model in equation (1) is a generalization of the more familiar person and firm effects model of Abowd et al (1999), a natural first step is to see how these two models compare. Hence, we present our results in the following order. First, we present the results of the match effects model and the AKM-model both estimated on the full sample. Secondly, we exploit observable characteristics on the worker side (gender and education) to allow for heterogeneity in the firm effects. Thirdly, we take the estimated parameters as input in further analyses of the Danish labor market. In particular, we address the relationship between mobility and wages and the inter-industry wage differentials.

4.1 The Match Effects Model vs the AKM Model

The main purpose of the wage decomposition is to determine the relative importance of the respective wage components. In contrast to the AKM model, the match effects model can explain the part of wage dispersion due to systematic differences across worker-firm matches conditional on worker and firm effects. However, the contribution of the match effects model is not only to provide insight on the existence and magnitude of a match specific component in wages. If match effects are present, then omitting them in the wage decomposition will give rise to standard omitted variables bias in the other parameters of the model, see Woodcock (2008) for a more formal discussion. For instance, the expected value of $\widehat{\beta}$ equals the true return to time-varying characteristics, β, plus a duration weighted average of the omitted match effects, conditional on the design matrices D and F. Note, however, that the orthogonality assumption in (9) implies that the match effects do not correct any bias in the firm and worker effects: if match effects are indeed orthogonal, then there is no bias to adjust. The match effects model corrects the omitted variables bias in the estimate of β that is present whenever $\theta \neq 0$.[10]

We present results for the match effects model in (4) and the AKM model (i.e. imposing $\theta = 0$). The returns to labor market experience is specified as a piecewise-linear function with nodes at 5, 10, 15, 20 and 30 years of experience. The experience function is fully interacted with gender and education. Calender time effects are estimated non-parametrically by including year dummies; interacted with gender and education as well. Our wage data is not deflated, hence, the time effects represent both nominal and real wage growth. The estimated experience profiles are presented in Figures 2 and 3 for men and women, respectively. The discrepancy between the match effects model and the AKM model is considerable.

[10] If the true data generating process is given by (4) then $E(\beta_{AKM}) = \beta + (X'P_{[D\ F]}X)^{-1}X'P_{[D\ F]}H\theta$, Hence, the estimate based on the AKM model is biased whenever $\theta \neq 0$ since H is never orthogonal to D and F. This is intuitive as D provides information on "who you are", F provides information on "where you work" and H provides information on both.

Except for medium educated men, the estimated experience profiles are steeper in the AKM model than in the match effects model. For instance, for high educated men the return to 20 years of experience is 1.17 log points (222 percent) in the AKM model but only 1.09 log points (198 percent) in the match effects model, whereas for low educated women the estimated returns are 0.40 log points (49 percent) and 0.29 log points (34 percent), respectively. This suggests that a part of individual wage growth is explained by a tendency for workers to sort into better matches as their labor market career progresses. Thus the estimates of the returns to experience are upward biased in the AKM model. The two sets of estimates show that both human capital accumulation and mobility seem to be important determinants of observed wage growth over the working life of workers. Note that for medium educated men, the AKM model estimates a slightly flatter experience profile than the match effects model suggesting that this group of workers tend to be employed in the better matches early in their career. The discrepancy between the match effects model and the AKM model is not the only interesting insight provided by Figures 2 and 3. We see that the estimated returns to experience vary considerably between the six groups of workers defined by gender and educational attainment. Related studies based on the AKM model typically allow the returns to time varying characteristics to vary with gender (e.g. Abowd et al. (1999), Abowd, Kramarz and Roux (2006) and Woodcock (2008)) but our analysis shows that returns to experience may differ substantially across educational levels as well. The estimated returns to experience are higher for men than women and increasing in the educational level. The degree of heterogeneity allowed in the returns to time-varying characteristics have implications for the relative importance of worker and firm characteristics in explaining wage dispersion.

Panel A in Table 6 presents the variance of the estimated log wage components. A more easily interpretable measure of the relatively importance of the log wage components is presented in Panel B which makes a proportional decomposition along the lines of Gruetter and Lalive (2004). Notice that the variance of log wages can be decomposed into the pairwise covariances between the log wage and the respective wage components:

$$Var(w_{ijt}) = Cov(w_{ijt}, x_{it}\widehat{\beta}) + Cov(w_{ijt}, \widehat{\phi}_i) + Cov(w_{ijt}, \widehat{\psi}_j) + Cov(w_{ijt}, \widehat{\theta}_{ij}) + Cov(w_{ijt}, \widehat{\varepsilon_{ijt}}) \qquad (11)$$

Due to the long sample period and the fact that our wage measure is in nominal terms, a considerable fraction of the raw wage dispersion is due to aggregate wage growth (the year dummies). To get a cleaner decomposition into worker, firm and match components, we exclude the contribution of the year dummies. Therefore, if $x_{it} = \left[x_{it}^1 \; x_{it}^2\right]$, where x_{it}^1 contains the year dummies and x_{it}^2 the experience variables, we make the following decomposition:

$$Var(\widetilde{w}_{ijt}) = Cov(w_{ijt}, x_{it}^2\widehat{\beta}) + Cov(w_{ijt}, \widehat{\phi}_i) + Cov(w_{ijt}, \widehat{\psi}_j) + Cov(w_{ijt}, \widehat{\theta}_{ij}) + Cov(w_{ijt}, \widehat{\varepsilon_{ijt}}) \qquad (12)$$

where $\widetilde{w}_{ijt} = w_{ijt} - x_{it}^1\widehat{\beta}$ is the detrended log wage. Whenever we refer to the log wage in the following analyses we refer to $\widetilde{w}_{ijt}$. Because the returns to experience are interacted with worker characteristics (gender/education group) one should be careful when interpreting the worker fixed effect, $\widehat{\phi}$. When comparing workers of different gender or with different levels of education, the difference in worker fixed effects does not represent a persistent difference in wages since the workers earn different returns to experience. In fact, the worker fixed effect is primarily identified by the start wages of workers (wages of labor market entrants). Panel A of Table 6 shows a high variability of both the experience component, $x_{it}^2\widehat{\beta}$, and the fixed worker component, $\widehat{\phi}$. In fact, the variance of each of the components exceeds the total variance of log wages. This is compensated by a considerable negative correlation between the two components (-0.78). This indicates that the starting wages of high educated are lower than those of lower educated workers, since the former earn considerably larger returns to experience, see Figures 2 and 3. The combination of fixed worker effects and the interaction of returns to experience with observable worker characteristics basically amount to estimating group specific experience functions where $\widehat{\beta}_j$ is the vector of slope parameters of worker group j and $\overline{\phi}_j = \sum\limits_{i \in j} \widehat{\phi}_i$ is the group specific intercept.[11] Hence, when distinguishing between high and low wage workers, it makes little sense to consider either the slope parameters or the intercepts independently of the other. Instead we focus on the total worker effect, $x_{it}^2\widehat{\beta} + \widehat{\phi}_i$, as the worker specific component of log wages. Comparing the variances of the wage components in the match effects model and the AKM model we find that the variances of the worker specific component, $x_{it}^2\widehat{\beta} + \widehat{\phi}_i$, and the firm component, $\widehat{\psi}_j$, are quite similar in the two models. The variance of the match component is almost as high as the variance of the firm component. Accordingly, the residual wage dispersion is lower in the match effects model. The proportional decompositions in Panel B show that worker characteristics account for 60 percent of wage dispersion whereas the firm fixed effect explains roughly 15 percent. Match specific effects account for 11 percent of the wage dispersion

[11] This would be the case if instead of worker specific fixed effects we included only group specific effects. In our case the slope parameters are specific to the worker group, but the intercept is specific to the individual worker.

and thus play a non-neglible role in the wage formation. This is more than twice as much as in the fixed effects analysis of Woodcock (2008) and may be attributed to the longer time dimension of the IDA data that, ceteris paribus, allows more matches to be observed for each worker.[12] Notice that orthogonality of the match effects implies that for workers observed in only one firm, the estimated match effect is zero. More than 40% of the wage variability that is left unexplained by the AKM model can be accounted for when allowing a match specific component. Therefore, it is no surprise that a test of the joint significance of the match effects strongly rejects the null hypothesis of $\widehat{\theta} = 0$. The relative contributions of worker and firm heterogeneity ($x_{it}^2\widehat{\beta} + \widehat{\phi}_i$ and $\widehat{\psi}_j$) are very similar in the match effects model and the AKM model. However, as illustrated in Figures 2 and 3, allowing for match effects reduces the estimated returns to experience. This is also apparent from the proportional decomposition where the experience component, $x_{it}^2\widehat{\beta}$, explains a relatively higher share in the AKM model compared to the match effects model (30.2% versus 23.1%). Thus, besides the direct explanatory power of the match component, the match effects model corrects the omitted variables bias in the estimated returns to experience. The correlation between the worker component, $x_{it}^2\widehat{\beta} + \widehat{\phi}_i$, and the firm component, $\widehat{\psi}_j$, is basically zero in both models indicating no tendency for high wage workers to sort into specific firms. This is in line with the existing literature.

4.2 Group Specific Analyses

The analysis above was flexible in the sense that the returns to time-varying characteristics were allowed to vary across the six gender/education groups. However, we restricted the firm effects to be constant for all workers. However, it is not obvious that firms apply the same wage policy to all their employees. For instance, one might suspect that different occupational groups face different wage policies. To address the issue of potential heterogeneity in a firm's wage policy, we form six subsamples based on gender and educational attainment as explained in section 3 and estimate (4) on each of the subsamples.[13] Dividing the data into subsamples and still maintaining reasonable precision of the estimates are feasible for us due to high dimensions of the Danish IDA data.

The analysis in this section consists of two parts. First, we address the extent to which firm effects differ across the six worker groups defined by gender and educational level. Second, we make separate wage decompositions for each of the worker groups and address the implications of allowing firm effects to be non-constant.

[12] We refer to the fixed effects analysis of Woodcock (2008) as the benchmarch for our analysis. However, in his hybrid mixed model match effects explain almost 16 percent of the variation in earnings.

[13] Alternatively, we could estimate (4) on the full sample but interacting firm effects with gender and education. However, this would require an appropriate extension of the grouping algorithm.

A full comparison of the firm effects across the six subsamples is not feasible due to large number of firms; hence, we need measures, simple to compute, that summarise the extent to which firm effects differ across the six subgroups. Basically, we would like to know whether a firm with a high firm effect in one subgroup also tends to have a high firm effect in the other subgroups. Several issues arise when trying to answer this question. First, some firms might not be hiring workers from a particular subgroup, which makes the comparison infeasible. Second, it is not obvious how to weight the firms when calculating such a measure. A given firm might have a precisely estimated firm effect in one subgroup, but an imprecise effect in another, where only few observations on the firm is available. To judge the extent to which firm effects are consistent across subgroups we calculate the pairwise correlation between the estimated firm effects of any two subgroups. We apply three different weighting schemes. Let n_{js} denote the number of observations on firm j in subsample s. Then we construct three sets of weights for calculating the correlation of firm effects between subsample s and subsample r:

$$W^1_{j,sr} = \min(n_{js}, n_{jr}) \tag{13}$$

$$W^2_{j,sr} = n_{js} + n_{jr} \tag{14}$$

$$W^3_{j,sr} = n_{js} n_{jr} \tag{15}$$

For all three weighting schemes we only include firms for which $W^1_{j,sr} \geq 5$, i.e. there has to be at least five observations on the firm in each subsample. The first weight, $W^1_{j,sr}$, downweights a firm if there are few observations pertaining to it in either of the two subsamples. The second, $W^2_{j,sr}$, gives high weight to firms with a high number of total observations, whereas the third weight, $W^3_{j,sr}$, gives extra weight to firms with similar numbers of observations in the two subsamples. Selected pairwise correlations are presented in Table 7. Column 4 shows the number of firms with at least 5 observations in each of the subsamples. $W^1_{j,sr}$ and $W^2_{j,sr}$ produce very similar correlations, whereas the correlations using $W^3_{j,sr}$ are consistently higher. However, the ranking of the correlations are similar across all three weighting schemes. For both men and women, the correlation between the low and medium educated subsamples is high, indicating that firms' wage policies towards these two educational categories are relatively similar. The high educated subsample correlates to a lesser extent with the two other subsamples. This suggests that there might be some discrepancy between the wage policy that firms apply to high educated employees compared to those with medium or low education. The bottom four rows indicate that firms' wage policies vary with gender as well. This is not necessarily due to discrimination, since it can easily be explained by a systematic difference in occupation between men and women within the same firm. Separating the two explanations is, however, not within the objectives of this analysis. Arguably, the applied measures in Table 7 are not perfect indicators of similarity of wage policy across the subsamples but, nevertheless, we think the exercise does question the assumption of constant firm effects. The wage policy of a firm seems to differ both across gender and educational groups.[14]

Allowing a firm to have a separate firm effect for each group of workers is statistically equivalent to treating the firm as six individual firms. This implies that workers in one subgroup is not connected through the labor market with workers in another subgroup. Since we cannot separately identify the mean of worker effects from the mean of firm effects, we can calculate within-group variances of the fixed effect but not between-group variances or the total variances for the full population. Hence, to address the implications of non-constant firm effects, we compare within-group decompositions based on separate regressions with corresponding within-group decompositions based on the full sample. Panel A of Table 8 presents the proportional decompositions based on parameters estimated on the full sample. That is, we take the parameter estimates of the previous subsection and make separate decompositions for each of the worker groups. The first row shows that the variance of (detrended) log wages is higher for men than women and is increasing in the educational level. The total contribution of worker heterogeneity replicates this pattern. That is, worker characteristics are more important in wage determination for high educated relative to low educated and for men relative to women. For low educated women, worker heterogeneity explains less than 47 percent whereas the relative contribution of worker characteristics in explaining wage dispersion of high educated men is more than 72 percent. In contrast, the explanatory power of both firm and match effects is decreasing in educational level.

In Panel B the decompositions are based on estimates from separate regressions for each worker group. In general, the decompositions resemble those in Panel A, except when comparing the relative contribution of firm and match effects. Firm effects are more important in Panel B, whereas match effects are more important in Panel A, but the total contribution of the match and the firm effects is very similar in the two panels. Thus allowing for non-constant firm effects mainly affects the distinction between firm and match effects.

[14] When allowing firm effects to be non-constant, the distinction between firm and match effects may be subtle. A match effect can be interpreted as a worker specific firm effect. Hence, the worker group specific firm effects are just aggregations of the individual match effects. However, if we think of the firm effect to be observable to agents in the labor market whereas the match effect to a larger extent is not realized before engaging in a match, the distinction can be important. In our case it seems reasonable that workers do observe the differences in a firm's wage policies towards the widely defined worker groups.

4.3 Mobility and Wages

Both the theoretical and the empirical literature point at the effect of mobility on wage dynamics. For instance, Topel & Ward (1992) show that workers changing jobs experience above-average wage growth. In our framework this would arise from improvements in either the firm or the match component of wages. Several models within the search literature generate a job-ladder structure of mobility consistent with this empirical finding, e.g. Burdett-Mortensen (1998). These models typically imply that an unemployment spell is associated with a subsequent wage drop compared to the pre-unemployment job. This is consistent with Altonji and Williams (1992) who estimate layoffs to be associated with considerable wage losses. Our match effects model allows us to take a closer look at wage changes upon different types of job moves and, in particular, disentangle the change into parts pertaining to the firm and match components, respectively.

We take the estimates of wage components in (4) as input in an analysis of mobility and wage growth. To be able to distinguish job-to-job (JTJ) and job-unemployment-job transistions (JUJ) we make use of complementary spell data.[15] We categorise a job move as JUJ if we observe an intermediate period of unemployment lasting at least 4 weeks. The remaining job moves are classified as JTJ. However, it is likely that some observations classified as JTJ transitions actually involve workers who have been laid off. For the majority of the workers in the sample, a layoff has to be preceded by a notification at least three months in advance. If the laid off worker finds a new employer during the notification period, we count the move as a JTJ transition, although the worker's outside option in fact was unemployment.

The change in log wage for worker i between period t and period s can be decomposed as follows

$$\widetilde{w}_{ims} - \widetilde{w}_{ijs} = (x'_{is} - x'_{it})\beta + \psi_m - \psi_j + \theta_{im} - \theta_{ij} + \varepsilon_{ims} - \varepsilon_{ijt}, \tag{16}$$

when the worker is employed at employer j in period t and at employer m in period s. If the worker stays at the same employer (and, hence, in the same match) then $\psi_m = \psi_j$ and $\theta_{im} = \theta_{ij}$ in which case wage growth only comes from changes in labor market experience and changes in the idiosyncratic shock. In Table 9, we present a decomposition of the change in (detrended) log wages based on (16). We make a first difference of the data, but since some workers are not observed every year, this difference does not necessarily correspond to a yearly difference. We take this into account by adjusting the change in the returns to experience component for the number of years between two successive observations in the

[15] Spell information is only avaible from 1985 and onwards. Hence, we disregard observations pertaining to 1980-1984.

data. The first two columns in Panel A present the mean change in wage components for stayers and movers, respectively. The mean change in log wage is mainly due to increased labor market experience. Job transitions are on average associated with small, although statistically significant, increases in firm and match effects. Columns 3 and 4 divide the job transitions into job-to-job and job-unemployment-job transitions. JTJ transitions are associated with improvements in both firm and match components whereas a JUJ transition on average leads to a drop in both. Wage growth due to the change in firm effect is on average 0.009 log points higher for JTJ movers than JUJ movers, whereas the corresponding difference in terms of the match effect is 0.013 log points. Combining the two we find that on average JTJ transitions are associated with more than 2 percent higher wage growth than JUJ transitions.

In Panel B we report the mean change in the firm component (Columns 3 and 4) and the match component (Columns 5 and 6) for different subsets of the data. The discrepancy between JTJ transitions and JUJ transitions increases in the educational level. In particular, a JUJ transition is associated with a considerable drop in match quality for high educated (-0.028 and -0.026 log points for men and women, respectively). Hence, high educated workers suffer from unemployment in terms of future wage outcomes. The last two sets of results in Panel B divide the mean change in the wage components according to quartiles in the distributions of the total worker component, $x_{it}^{2}\widehat{\beta} + \widehat{\phi}_i$, and the quartiles in the distribution of labor market experience, respectively. As for educational attainment a high worker component is associated with a large drop in match quality upon a JUJ transition. This pattern is also present in terms of the firm component. Hence, high wage workers experience a drop in both the firm and match when making a JUJ transition. The drop in subsequent wage from getting unemployed when combining the firm and match effect is on average 0.039 log points for workers in the top quartile of the worker component distribution. In contrast, workers in the bottom quartile are not affected adversely by a spell of unemployment. Whereas high wage workers suffer more from a JUJ transition they also gain more from a JTJ transition; at least in terms of the match component. Hence, for a high wage worker the difference in wage growth following a JTJ and a JUJ transition, respectively, is on average 0.055 log points. The positive returns to experience induce a positive correlation between the total worker component, $x_{it}'\widehat{\beta} + \phi_i$, and years of labor market experience. Hence, it is no surprise that we also find the severity of a JUJ transition to be increasing in labor market experience. For the most experienced workers a JUJ transition is associated with a combined drop in firm and match component of 0.043 log points, whereas the least experienced workers actually gain 0.011 log points. It is interesting to note that there is a negative relationship between labor market experience and the gain from a JTJ transition.

Whereas the least experienced workers gain in terms of both firm and match component (0.011 and 0.017 log points, respectively), the most experienced workers actually loose in terms of both components. This partly reflects that high experience workers have had more time to already sort into high wage firms and high wage matches and, therefore, the return to on-the-job search is, on average, higher in the beginning of a worker's labor market career. Another interpretation is that low and high experience workers differ with respect to their preferences over job attributes. The firm and match components in this analysis represent differences in wages. However, other aspects of a job influence mobility decisions of workers (e.g. working conditions, hours, job security etc.). If older workers put more weight on non-pecuniary attributes, they would be more likely to accept wage cuts.

4.4 Decomposing Inter-Industry Wage Differentials

The inter-industry wage differential is one of the wage differentials in the labor market that has received the most attention. Although the existence and the consistency across time and countries is well-documented, Krueger and Summers (1987, 1988), the sources of inter-industry wage differentials are not well established. In general, the fundamental question has been whether these differentials are driven mainly by differences in the composition of workers across industries or by systematic differences in firms' compensation policies between industries. The starting point for the earlier studies on this topic has been the presence of inter-industry wage differentials conditional on more or less detailed observable worker characteristics. Whereas Krueger and Summers (1987, 1988) pointed at industry differences on the firm side as the explanation, studies such as Murphy and Topel (1987) and Gibbons and Katz (1992) stress the importance of unobserved worker heterogeneity. Common to all of the studies is the lack of appropiate data to fully disentangle worker and firm heterogeneity (including unobserved heterogeneity). However, with the availability of matched employer-employee data, this has become feasible and, in fact, reassessing the inter-industry wage differential has been one of the most common applications of the person and firm effects model; see Abowd, Kramarz and Margolis (1999), Abowed, Finer and Kramarz (1999), Goux and Maurin (1999) and Gruetter and Lalive (2004). These studies take the residual inter-industry wage differential upon controlling for observable worker characteristics as input for their analysis. They then judge the extent to which this conditional wage differential can be explained by unobserved person and firm components, respectively. Doing this enables them to relate to the earlier literature, but the distinction between the worker and the firm component is bound to depend on the conditioning variables. A rich set of observable worker characteristics is thus likely to make unobserved firm heterogeneity more important in explaining the conditional inter-industry wage differential. We do no attempt to make our analysis directly comparable to the previous studies. Instead we make a decompostion of the inter-industry wage differential in line with the decomposition of individual wages in section 2.1 and utilize our observable worker characteristics to make group specific decompositions.

In Table 10 we present results for an industry classification dividing firms into 8 mutually exclusive industries.[16] Column 2 in Panel A gives the raw inter-industry wage differentials, defined as the difference between the within-industry average log wage and the overall average of log wages. The average wage is 0.097 log points lower within Agriculture, Fishing and Quarrying (AFQ) compared to the overall average log wage, 0.107 higher within Finance and Business Activities (FBA) and the weighted variance (WV) of the industry average wages is 0.0034.[17] Columns 3-5 report the inter-industry differences in the average worker, firm and match component, respectively. Like the raw wage these are also measured relatively to the overall mean. Note that the low average wage within AFQ is due to the combination of low wage workers and low wage firms (-0.047 and -0.051, respectively) and the relative high average wage within FBA is mainly attributable to the presence of high wage workers within the industry (0.084 and 0.023, respectively). In general, high wage industries seem to be characterized mainly by high wage workers, whereas low wage industries are characterized by both low wage workers and low wage firms. We discuss this further below. In the decomposition of industry average wages, worker heterogeneity explains roughly 60 percent of the raw inter-industry variance, and firm heterogeneity explains almost the remaining 40 percent. Match effects do not contribute to the inter-industry wage differentials. This is not surprising given the orthogonality assumption discussed in Section 2.1. Compared to the decomposition of individual wages, firm heterogeneity is relatively more important in explaining the inter-industry wage differentials. Column 6 shows that the correlation between worker and firm effects within industries are either zero or negative. However, we find a strong positive correlation across industries of 0.54. Hence, high wage workers tend to sort into high wage industries but not into high wage firms within industries.

Two of the more recent papers decomposing inter-industry wage differentials, Gruetter and Lalive (2004) and Woodcock (2007), both find that firm differences, i.e. the pure industry effect, explain the bulk part of the variation in industry average wages (75 percent and 72 percent, respectively). Although we, like these two studies, find firm differences to be more important at the industry level than at the

[16] The classification is based on the Danish industry coding, DB03, which is structured along the lines of the NACE coding by the European Commission.

[17] The weighted variance of the raw inter-industry wage differentials is WV=$\sum \pi_k(\overline{w}_k - \overline{w})^2$, where $\overline{w}_k$ is the average log wage in industry k, $\overline{w}$ is the overall average wage and π_k is the relative number of observations pertaining to industry k.

individual level, worker differences are still the single most important component in our application. In this respect our results are more in line with the earlier work of AKM (1999) and Abowd, Finer and Kramarz (1999). Note, however, that the worker component in our analysis includes both time-varying and time-invariant characteristics, whereas the former studies only include the time-invariant component. This, of course, is likely to make worker characteristics more important in our analysis.

Panel B presents the proportional decomposition of inter-industry wage differentials separately for each of the six worker groups defined by gender and education. Consistent with the decompositions of individual wages in Table 6, we find that the worker characteristics are more important for high educated workers in explaining inter-industry wage differentials. For low educated workers the contribution of the average firm component is actually larger than the contribution of worker heterogeneity. Hence, for low wage workers it matters more "where you work" (in terms of industry) than "who you are". The correlations in Column 5 indicate that after controlling for gender and education, high wage workers in general tend to sort into high wage industries with the exception of low educated men, where there are no systematic relationship between the average worker and average firm components.

In Table 11 we present decompositions of inter-industry wage differentials for more disaggregated industry classifications and find the decomposition to be robust against the level of industry aggregation.[18] However, considering low and high wage industries, separately, we see some important differences. We divide the sample of industry differentials into two groups: One containing industries with average wage below the overall mean wage and another with industries having above mean average wages. Within high wage industries, average worker characteristics are considerably more important in explaining industry differences, whereas primarily firm characteristics drive wage differences between low wage industries. In Column 5 we report the correlation of average worker and average firm characteristics. The industry aggregation level per se does not affect the correlation. However, we find the correlation to be strongly positive for low wage industries but to be considerably lower, for some levels of aggregation even negative, for high wage industries. This suggests that high wage industries are primarily characterised by high wage workers, whereas low wage industries include both low wage workers and low wage firms.

[18] Aggregation bias due to differences in wage policies between sub-industries is not an issue in this analysis since we identify wage component at the firm level.

5 Conclusion

We have shown that the match effects model provides some insights not attainable by the AKM-model. First, orthogonal match effects can explain 11 percent of the observed wage dispersion and thereby help reduce the share of wage dispersion left unexplained by the AKM-model considerably. Second, the inclusion of match effects allows us to separate the positive relationship between labor market experience and wages into a part capturing general human capital accumulation and a part representing workers tendency to sort into better matches during their labor market career. The results based on the full sample show that worker heterogeneity (in terms of both time-invariant characteristics and labor market experience) explains the major part of wage dispersion (60 percent), whereas the firm and match components explain 14 percent and 11 percent, respectively. Separately analysing selected groups of workers, we find that these numbers mask considerable differences. For high educated men, worker and firm heterogeneity account for 74 percent and 10 percent of the wage dispersion, respectively, whereas the corresponding shares for low educated women are 42 percent and 26 percent.

The correlation between the estimated worker component and the firm component is essentially zero or even slightly negative when we consider the worker groups separately. In line with the previous literature we thus find no evidence that high wage workers sort into high wage firms. However, at the level of industries we do, which means that high wage workers are proportionally overrepresented in industries with high paying firms. Whereas the contribution of worker differences in explaining inter-industry wage differentials is similar to the corresponding contribution in explaining differences in individual wages (around 60 percent), we find the firm component to be considerably more important at the industry level, explaining nearly 40 percent of the differences in within industry average wages. Similar to the analysis of individual wages, we find the decomposition of inter-industry wage differentials to differ across worker groups. Analysing high wage and low wage industries separately, we find wage differences among the former to be driven primarily by variation in worker characteristics, whereas wage differences within the latter are due to differences in both worker and firm characteristics and a strong, positive correlation between the two.

Considering the changes in firm and match components of workers switching employers, we find some interesting patterns. Job-to-job transitions are on average associated with gains in terms of both the firm and the match components. In contrast, workers who experience an intermediate period of unemployment between two job spells tend to be reemployed in worse firms and in worse matches. These findings support theories implying a job-ladder structure of mobility. The adverse consequences of an unemployment spell on subsequent firm and match quality are found to be more pronounced among high educated workers and workers with high labor market experience. On the other hand, we find that the gains associated with job-to-job transitions are higher for workers with low experience and even negative for high experience workers. This suggests that the gains from on-the-job search is higher early in the worker's career and that non-pecuniary job attributes are valued more by older workers.

Based on the match effects model, this paper presents some central features of the Danish labor market which are of individual interest themselves but also serve as empirical regularities which structural models of the labor market should be able to replicate. Although the paper answers some central questions about the wage structure in Denmark, it also motivates further research into the issues touched upon. The significant longitudinal dimension of the IDA data makes it feasible to consider the dynamic evolution of the wage decomposition. This would give insight into the effect of the business cycle on the relative contribution of worker, firm and match components and could also detect long-run trends due to e.g. major labor market reforms or increased internationalisation in both the labor and the product markets. Our brief analysis of the wage effect of job changes calls upon a more thorough analysis of the mobility pattern and, in particular, the determinants of job mobility and labor turnover. An obvious complementary analysis to ours would be the estimation of a corresponding mobility equation. Of special interest would be the joint distribution of fixed effects in the wage equation and the fixed effects in the mobility equation.

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Table 1: Descriptive Statistics of Labor Market Experience

	Mean	St.Dev.	10th Percentile	90th Percentile
Full Sample	21.41	11.69	6.48	38.00
Men				
Low Educ.	26.78	12.46	9.00	43.28
Medium Educ.	19.91	10.88	6.00	35.79
High Educ.	17.96	10.10	6.00	33.00
Women				
Low Educ.	25.63	11.78	8.81	41.05
Medium Educ.	18.03	10.27	5.18	32.95
High Educ.	14.60	8.75	5.00	27.73

Table 2: Number of Employers Per Worker

	Number of Employers Per Worker						Average Number
	1	2	3	4	5-10	11+	of Employers
Full Sample	859,753	539,260	365,324	241,884	332,236	8,044	2.61
	36.6%	*23.0%*	*15.6%*	*10.3%*	*14.2%*	*0.3%*	
Men							
Low Educ.	144,040	90,145	62,294	43,571	73,241	2,611	2.83
	34.6%	*21.7%*	*15.0%*	*10.5%*	*17.6%*	*0.6%*	
Medium Educ.	235,960	177,307	136,206	97,327	151,814	4,721	2.97
	29.4%	*22.1%*	*17.0%*	*12.1%*	*18.9%*	*0.6%*	
High Educ.	61,406	39,385	26,382	16,171	17,973	164	2.43
	38.0%	*24.4%*	*16.3%*	*10.0%*	*11.1%*	*0.1%*	
Women							
Low Educ.	178,713	93,950	54,194	31,379	34,145	222	2.18
	45.5%	*23.9%*	*13.8%*	*8.0%*	*8.7%*	*0.1%*	
Medium Educ.	194,136	120,645	77,504	49,269	51,986	312	2.37
	39.3%	*24.4%*	*15.7%*	*10.0%*	*10.5%*	*0.1%*	
High Educ.	45,498	17,828	8,744	4,167	3,077	14	1.79
	57.4%	*22.5%*	*11.0%*	*5.3%*	*3.9%*	*0.0%*	

Table 3: Number of Observations Per Worker

	Number of Observations Per Worker						Average Number
	1	2	3-5	6-10	11-20	21+	of Observations
Full Sample	322,748	208,680	420,583	494,227	626,543	273,720	9.36
	13.8%	*8.9%*	*17.9%*	*21.1%*	*26.7%*	*11.7%*	
Men							
Low Educ.	47,203	36,157	70,550	87,518	115,177	59,297	10.07
	11.3%	*8.7%*	*17.0%*	*21.0%*	*27.7%*	*14.3%*	
Medium Educ.	76,670	55,093	125,726	168,799	249,674	127,373	10.87
	9.5%	*6.9%*	*15.7%*	*21.0%*	*31.1%*	*15.9%*	
High Educ.	19,681	14,091	32,040	40,208	42,729	12,732	8.77
	12.2%	*8.7%*	*19.8%*	*24.9%*	*26.5%*	*7.9%*	
Women							
Low Educ.	72,908	44,994	81,086	81,638	84,419	27,558	7.62
	18.6%	*11.5%*	*20.7%*	*20.8%*	*21.5%*	*7.0%*	
Medium Educ.	84,236	47,924	92,286	100,232	123,940	45,234	8.54
	17.1%	*9.7%*	*18.7%*	*20.3%*	*25.1%*	*9.2%*	
High Educ.	22,050	10,421	18,895	15,832	10,604	1,526	5.35
	27.8%	*13.1%*	*23.8%*	*20.0%*	*13.4%*	*1.9%*	

Table 4: Number of Workers per Firm

	Number of Firms	Mean Size	Median Size	St.Dev	Max Size
Full Sample	371,184	59.19	8.00	911.34	262,285
Men					
Low Educ.	169,423	24.72	4.00	245.68	28,381
Medium Educ.	238,063	36.68	6.00	409.19	84,108
High Educ.	169,423	24.72	4.00	245.68	28,381
Women					
Low Educ.	147,069	20.34	4.00	278.77	60,951
Medium Educ.	179,177	23.54	5.00	394.17	89,961
High Educ.	40,342	10.52	3.00	71.55	7,986

Table 5: Connected Groups

		Men			Women		
		Years of education			Years of education		
	Full sample	less than 12	12 to 14	more than 14	less than 12	12 to 14	more than 14
Observations							
Total	21,968,633	4,187,675	8,731,490	1,415,578	2,991,580	4,218,001	424,309
Largest group	21,857,528	4,113,709	8,652,256	1,351,038	2,861,188	4,107,927	355,865
Fraction	99.5%	98.2%	99.1%	95.4%	95.6%	97.4%	83.9%
Workers							
Total	2,346,501	415,902	803,335	161,481	392,603	493,852	79,328
Largest group	2,315,003	398,897	785,488	147,418	364,188	470,442	61,949
Fraction	98.7%	95.9%	97.8%	91.3%	92.8%	95.3%	78.1%
Firms							
Total	371,184	169,423	238,063	66,408	147,069	179,177	40,342
Largest group	343,600	150,929	219,827	51,403	116,906	154,410	23,240
Fraction	92.6%	89.1%	92.3%	77.4%	79.5%	86.2%	57.6%
Number of groups	25,476	15,136	15,615	11,251	23,961	19,999	12,944

Table 6: Variance of Estimated Wage Components

	(1) Match Effects Model	(2) AKM Model
Panel A		
Variance of Detrended Log Wages (w)	0.081	0.082
Variance of Total Worker Component ($x\beta + \phi$)	0.049	0.049
Variance of Returns to Experience ($x\beta$)	0.102	0.084
Variance of Worker Fixed Effect (ϕ)	0.118	0.088
Variance of Firm Fixed Effect (ψ)	0.011	0.012
Variance of Match Fixed Effect (θ)	0.009	
Residual Variance (ϵ)	0.011	0.020
Panel B		
Proportion of Variance Explained By		
Total Worker Component ($x\beta + \phi$)	0.608	0.604
Returns to Experience ($x\beta$)	0.231	0.302
Worker Fixed Effect (ϕ)	0.377	0.302
Firm Fixed Effect (ψ)	0.143	0.149
Match Fixed Effect (θ)	0.109	
Residual (ϵ)	0.140	0.247
Corr($x\beta + \phi$,ψ)	0.018	0.030
H_0: No Match Effects (p-value)	$<$0.00001	
Degress of Freedom	14,016,529	19,198,926

Table 7: Correlation of Firm Effects Across Subsamples

		(1)	(2)	(3)	(4)
		Corr(ψ_r, ψ_s)			Firms represented
Subsample r	Subsample s	$W^1_{j,rs}$	$W^2_{j,rs}$	$W^3_{j,rs}$	in both samples
Men, Low Educ.	Men, Medium Educ.	0.744	0.713	0.925	54,698
Men, Low Educ.	Men, High Educ.	0.327	0.319	0.513	13,470
Men, Medium Educ.	Men, High Educ.	0.372	0.358	0.587	18,333
Women, Low Educ.	Women, Medium Educ.	0.493	0.483	0.919	36,298
Women, Low Educ.	Women, High Educ.	0.181	0.227	0.509	6,622
Women, Medium Educ.	Women, High Educ.	0.247	0.272	0.695	8,750
Men, Low Educ.	Women, Low Educ.	0.494	0.426	0.640	23,504
Men, Medium Educ.	Women, Medium Educ.	0.429	0.382	0.715	50,309
Men, High Educ.	Women, High Educ.	0.274	0.284	0.813	6,694
Men, All Educ.	Women, All Educ.	0.698	0.410	0.698	73,870

Table 8: Decomposition of the variance of log hourly wage

	(1)	(2)	(3)	(4)	(5)	(6)
		Men			Women	
	Low Educ.	Med. Educ.	High Educ.	Low Educ.	Med. Educ.	High Educ.
A: Based on the Full Sample						
Variance of Log Wages (w)	0.065	0.087	0.096	0.053	0.065	0.094
Prop. of Variance Explained By						
Total Worker Component ($x\beta + \phi$)	0.490	0.629	0.723	0.466	0.537	0.664
Returns to Experience ($x\beta$)	0.104	0.239	0.257	0.027	0.142	0.036
Worker Fixed Effect (ϕ)	0.386	0.390	0.466	0.440	0.395	0.627
Firm Fixed Effect (ψ)	0.197	0.129	0.089	0.175	0.151	0.115
Match Fixed Effect (θ)	0.147	0.113	0.075	0.141	0.121	0.079
Residual (ϵ)	0.167	0.129	0.113	0.217	0.191	0.142
Corr($x\beta + \phi$,ψ)	0.030	0.003	-0.031	-0.072	-0.029	-0.134
B: Based on Subsamples						
Variance of Log Wages (w)	0.065	0.088	0.099	0.052	0.065	0.088
Prop. of Variance Explained By						
Total Worker Component ($x\beta + \phi$)	0.467	0.624	0.737	0.420	0.539	0.660
Returns to Experience ($x\beta$)	0.110	0.244	0.291	0.028	0.147	0.072
Worker Fixed Effect (ϕ)	0.357	0.380	0.445	0.393	0.392	0.588
Firm Fixed Effect (ψ)	0.253	0.150	0.102	0.263	0.170	0.156
Match Fixed Effect (θ)	0.115	0.099	0.058	0.104	0.103	0.051
Residual (ϵ)	0.165	0.127	0.103	0.213	0.188	0.133
Corr($x\beta + \phi$,ψ)	0.025	0.010	-0.003	-0.071	-0.013	-0.107

Table 9: Yearly Change in Log Wages

Panel A: Mean Change in Wage Components

	(1) Stayers	(2) Movers	(3) JTJ	(4) JUJ
Log Wage ($\overline{\Delta w_{it}}$)	0.021	0.030	0.037	0.015
Returns to Experience ($\overline{\Delta x_{it}\beta}$)	0.020	0.028	0.030	0.024
Firm Effect ($\overline{\Delta\psi_{J(i,t)}}$)		0.001	0.004	-0.005
Match Effect ($\overline{\Delta\theta_{it}}$)		0.002	0.006	-0.007
Residual ($\overline{\Delta\epsilon_{it}}$)	0.001	-0.001	-0.002	0.003
Years Between Observations	1.031	1.666	1.359	2.287
Yearly Change in Returns to Experience	0.020	0.021	0.024	0.014
Number of Observations	12,330,586	3,222,390	2,158,506	1,063,884

Panel B: Mean Change in Firm And Match Effects by Subgroups

	(1)	(2)	(3)	(4)
	Firm Effect		Match Effect	
	JTJ	JUJ	JTJ	JUJ
Men				
Low Educ.	0.001	-0.005	0.006	0.000
Medium Educ.	0.004	-0.005	0.009	-0.005
High Educ.	0.004	-0.008	0.002	-0.028
Women				
Low Educ.	0.001	-0.005	0.007	-0.008
Medium Educ.	0.008	-0.003	0.001	-0.018
High Educ.	0.009	0.000	0.003	-0.026
By $x\beta + \phi$				
1st quartile	0.005	-0.001	-0.001	0.000
2nd quartile	0.004	-0.005	0.003	-0.006
3rd quartile	0.004	-0.007	0.008	-0.009
4th quartile	0.004	-0.011	0.012	-0.028
By Labor Market Experience				
1st quartile	0.011	0.004	0.017	0.007
2nd quartile	0.004	-0.006	0.006	-0.010
3rd quartile	0.000	-0.012	0.000	-0.018
4th quartile	-0.004	-0.017	-0.005	-0.026

Table 10: Decomposition of Inter-Industry Wage Differentials

A: Within Industry Averages of Wage Componets

	(1)	(2)	(3)	(4)	(5)	(6)
		Within Industry Average				Within Industry
	Observations	$\overline{w}_k$	$\overline{x\beta+\phi}_k$	$\overline{\psi}_k$	$\overline{\theta}_k$	Corr($x\beta+\phi$,ψ)
AFQ	514,441	-0.097	-0.046	-0.051	0.001	-0.090
Manufacturing	7,996,472	0.006	-0.014	0.019	0.000	-0.001
EFWS	197,097	0.067	0.059	0.008	0.000	-0.039
Construction	2,215,641	-0.005	-0.013	0.008	0.000	-0.029
WRTHR	5,289,904	-0.074	-0.031	-0.042	-0.001	0.030
TPT	1,656,866	0.042	0.028	0.013	0.000	0.025
FBA	3,118,043	0.107	0.084	0.023	0.000	0.042
PPS	789,650	-0.015	0.010	-0.024	-0.001	-0.261
Weighted Variance (WV)		0.0034	0.0015	0.0008	0.0000	
Proportion of WV($\overline{w}_k$)			0.602	0.392	0.004	
Corr($\overline{x\beta+\phi}_k$,$\overline{\psi}_k$)	0.535					

B: Decomposition of Inter-Industry Wage Differentials by Worker Group

	(1)	(2)	(3)	(4)	(5)
		Proportion of WV($\overline{w}_k$)			
	WV($\overline{w}_k$)	$\overline{x\beta+\phi}_k$	$\overline{\psi}_k$	$\overline{\theta}_k$	Corr($\overline{x\beta+\phi}_k$,$\overline{\psi}_k$)
Men					
Low Education	0.0017	0.478	0.510	0.006	0.006
Medium Education	0.0021	0.563	0.430	0.004	0.225
High Education	0.0021	0.736	0.257	0.005	0.426
Women					
Low Education	0.0024	0.355	0.633	0.007	0.460
Medium Education	0.0042	0.587	0.409	0.002	0.433
High Education	0.0022	0.846	0.148	0.002	0.493

AFG: Agriculture, Fishing and Quarrying. EGWS: Electricity, Gas and Water Supply.

WRTHR: Wholesale and Retail Trade, Hotels and Restaurants. TPT: Transport, Post and Telecommunication.

FBA: Finance and Business Activities. PPS: Public and Personal Services

Table 11: Aggregation Level and Inter-Industry Wage Differentials

	(1)	(2)	(3)	(4)	(5)
	Number of	Proportion of WV($\overline{w}_k$)			
	Industries	$\overline{x\beta+\phi}_k$	$\overline{\psi}_k$	$\overline{\theta}_k$	Corr($\overline{x\beta+\phi}_k$,$\overline{\psi}_k$)
DB03-111	111	0.574	0.418	0.006	0.481
$\overline{w}_k < \overline{w}$	50	0.418	0.562	0.013	0.420
$\overline{w}_k > \overline{w}$	60	0.653	0.337	0.005	-0.130
DB03-52	52	0.584	0.408	0.006	0.523
$\overline{w}_k < \overline{w}$	22	0.420	0.568	0.010	0.625
$\overline{w}_k > \overline{w}$	30	0.679	0.316	0.003	0.059
DB03-26	26	0.584	0.408	0.006	0.525
$\overline{w}_k < \overline{w}$	12	0.412	0.577	0.008	0.871
$\overline{w}_k > \overline{w}$	14	0.802	0.196	0.001	-0.260
DB03-8	8	0.602	0.392	0.004	0.535
$\overline{w}_k < \overline{w}$	4	0.358	0.632	0.008	0.659
$\overline{w}_k > \overline{w}$	4	0.969	0.031	-0.001	0.340

Figure 1: Estimated Returns to Experience for Men

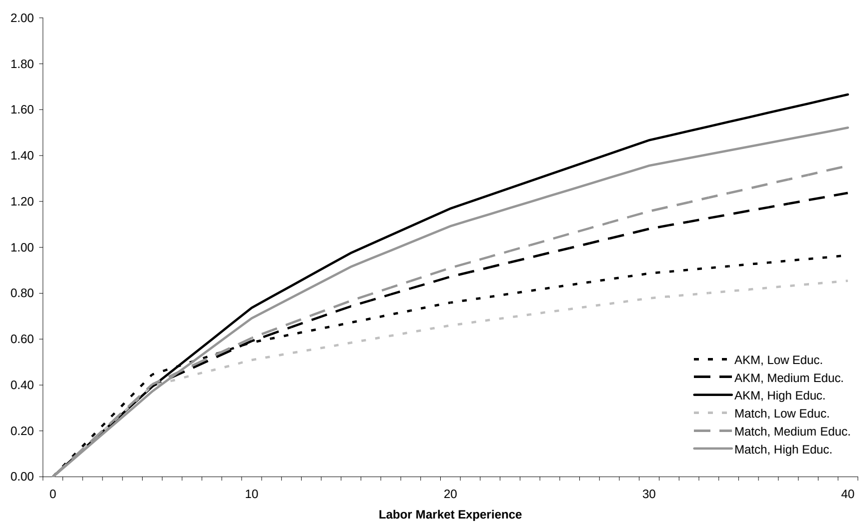
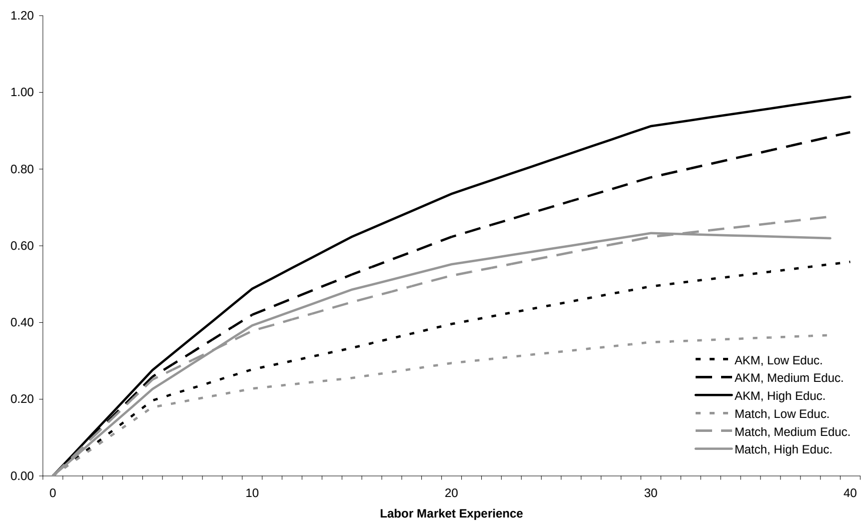


Figure 2:

Figure 3: Estimated Returns to Experience for Women



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