Economics Working Papers

2012-17

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Jesper Bagger, Rune Vejlin and Kenneth L. Sørensen

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AARHUS UNIVERSITY
BUSINESS AND SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS AND BUSINESS

Wage Sorting Trends*

Jesper Bagger[†]
Royal Holloway College

Rune Vejlin[‡]
Aarhus University

Kenneth L. Sørensen[§]
Aarhus University

August 9, 2012

Abstract

Using a population-wide Danish Matched Employer-Employee panel from 1980-2006, we document a strong trend towards more positive assortative wage sorting. The correlation between worker and firm fixed effects estimated from a log wage regression increases from $-.07$ in 1981 to .14 in 2001. The nonstationary wage sorting pattern is not due to compositional changes in the labor market, primarily occurs among high wage workers, and comprises 41 percent of the increase in the standard deviation of log real wages between 1980 and 2006. We show that the wage sorting trend is associated with worker reallocation via voluntary quits.

Keywords: Matched Employer-Employee Data, Firm fixed effects, Worker fixed effects, Wage sorting, Wage inequality, Voluntary quits.

JEL codes: J30, J31, J62

*We would like to thank Juan Pablo Rud, Dan Hamermesh, Michael Svarer, and Francis Kramarz for helpful comments and suggestions, and The Cycles, Adjustment, and Policy research unit, CAP, Department of Economics and Business, Aarhus University, for support and for making the data available. Vejlin greatly acknowledges financial support from the Danish Social Sciences Research Council (grant no. FSE 09-066745).

†Department of Economics, Royal Holloway College, University of London, Egham, Surrey TW20 0EX, United Kingdom; E-mail: jesper.bagger@rhul.ac.uk

‡Department of Economics and Business, Aarhus University, Fuglesangs Allé 4, DK-8210 Aarhus V, Denmark; E-mail: rvejlin@econ.au.dk.

§Department of Economics and Business, Aarhus University, Fuglesangs Allé 4, DK-8210 Aarhus V, Denmark; E-mail: ksoerensen@econ.au.dk.

1 Introduction

The seminal paper of Abowd et al. (1999), refined and extended in Abowd et al. (2002), investigates whether "high wage firms" employ "high wage workers". The empirical analysis builds on a log wage regression with fixed worker and firm effects. In this context, a high wage worker is a worker with a relatively high worker fixed effect. A high wage firm is defined analogously. Subsequent to estimation on French and US Matched Employer-Employee (MEE) panels, the authors compute the empirical correlation between worker and firm fixed effects, pooling annual cross sections, and find that it is negative in France (correlation $-.28$ using data from 1976-1987) and in the US (correlation $-.03$ using data from 1984-1993).[1] Similar studies have since been conducted on a number of different datasets.[2] We refer to the correlation between worker and firm fixed effects, as estimated from a log linear wage regression, as wage sorting.[3]

The purpose of this paper is to document and examine trends in wage sorting. We use a Danish full population MEE panel for 1980-2006. Pooling across annual cross sections, the correlation between worker and firm fixed effects is .05. We show that this estimate masks a systematic nonstationarity. By computing cross section specific correlations we find that the correlation between worker and firm effects increases from a low $-.07$ in 1981 to a high .14 in 2001. The trend towards positive assortative wage sorting occurs almost exclusively in the top quartile of the distribution of workers effects, i.e. among high wage workers, and is economically important: it comprises 41 percent of the increase in the standard deviation of log wages between 1980 and 2006.

We ascertain that the nonstationary wage sorting pattern is due to nonstationarity in the covariance between firm and worker effects, and that it is not driven by compositional changes in the labor force in terms of education, age, and gender. Further evidence suggests that the trend towards more positive assortative wage sorting is driven in part by entry and exit of workers, although this channel is likely to be weak, and in part by voluntary quits.[4] The increasing wage sorting trend in the top quartile of worker effects could be related to high wage workers employed in high wage firms being increasingly likely to transit to another high wage firm, or to high wage workers employed in low wage firms being increasingly likely to transit to a high wage firm. Our analysis supports the former relation.

[1]These results are reported in Abowd et al. (2002).

[2]See e.g. Gruetter and Lalive (2004) (1990-1997, correlation $-.22$, Austria), Andrews et al. (2008) (1993-1997, correlation $-.21$ to $-.15$, Germany), Sørensen and Vejlin (2012) (1980-2006, correlation $-.06$ to .11, Denmark).

[3]This notion of wage sorting is not linked to economic theory, and is distinct from that of productivity sorting, i.e. sorting on worker and firm productivity. A number of recent studies of productivity sorting (see e.g. Eeckhout and Kircher (2011), Bagger and Lentz (2012), and Bartolucci and Devicienti (2012)) find that it is difficult to identify productivity sorting from wage data alone.

[4]In our terminology, a worker who is employed in different firms at date $t-1$ and t has made a voluntary quit between $t-1$ and t.

2 Data

Our empirical analysis is based on IDA, a Danish register-based annual MEE panel covering 1980-2006. This data set is unique in an international comparison since it covers 27 years full labor force population and is perfectly suited for this study. The unit of observation is a given individual in a given year with measurements generally referring to the last week of November. Measures of actual labor market experience are available from 1964. For workers entering the labor market prior to 1964 (born before 1948) we add the potential pre-1964 experience net of education.[5]

The raw data consists of 60,847,593 observations. We inflate wages to 2006 levels. We discard (i) public sector jobs and individuals under education (19,191,599 observations), (ii) observations with missing data (6,103,607 observations), (iii) observations preceding observed labor market entry or if the individual enters later than age 35 (13,804,815 observations). We trim the within-experience-education group wage distribution (top and bottom 1 percent deleted, 503,454 observations) and select the maximal set of connected workers and firms (99,953 observations deleted).[6] The analysis data contains 21,144,165 observations.

Table 1 documents that average (real) log wages and their dispersion are increasing over our data period. Moreover, average education increases by around 1.5 years over the data period, the labor force ages due to the general demographic development, average experience is stable, and female (private sector) labor force participation is increasing.[7]

Table 1: Summary Statistics

Year	Obs.	Avg. $\ln w$	S.d. $\ln w$	Share women	Avg. age	Avg. years of education	Avg. experience
1980	767,088	5.069	.304	.24	36.43	10.45	21.50
1985	787,526	5.103	.293	.24	36.47	10.81	20.14
1990	777,097	5.246	.296	.26	37.09	11.19	19.59
1995	778,641	5.257	.303	.28	38.82	11.49	19.91
2000	816,112	5.291	.326	.31	41.44	11.67	21.11
2005	799,643	5.299	.335	.32	43.06	11.78	21.86

[5] In this specification older workers are assigned too much experience. We have experimented with different forms of pre-1964 experience, including specifications that assign too little experience to older workers. Our results are very robust to these changes.

[6] See Abowd et al. (2002) for an explanation of the necessity of conditioning on workers and firms being connected.

[7] Potential experience is trending upwards while our actual experience measure is stationary. We ascribe this to older cohorts being assigned too much experience, and an increased prevalence of sabbaticals from education during 1980-2006.

3 Econometric Framework

Let i index individuals, j index employers, and let t index annual cross sections. The function $\mathrm{J}(i,t)$ maps individual observations into employer IDs. Consider a log-linear two-way error component wage equation:

$$\ln w_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + \theta_i + \psi_{\mathrm{J}(i,t)} + \varepsilon_{it}, \tag{1}$$

where $\ln w_{it}$ is the log-wage, $\mathbf{x}_{it}'$ contains time-varying regressors: experience, experience squared and a set of year dummies, θ_i is a time-invariant worker effect, $\psi_{\mathrm{J}(i,t)}$ is a time-invariant firm effect, and ε_{it} is the residual log-wage. Throughout we maintain the assumption that $\mathrm{E}[\varepsilon_{it}|\mathbf{x}_{it}', \mathrm{J}(\cdot,\cdot), i, t] = 0$.[8] Conditioning on workers and firms being connected ensures that the matrix of regressors in (1) has full column rank.

Abowd and Kramarz (1999) argue that many existing models of wage determination under two-sided heterogeneity fail to deliver a log-linear wage equation with worker and firm effects. Estimated worker and firm effects from an OLS regression are therefore complicated functions of the underlying true (i.e. economically well-defined) worker and firm effects, and in general do not admit a structural interpretation.[9] Nonetheless, for descriptive purposes, (1) is a useful and widely used representation of log wages.

Wage sorting is measured by Pearson's correlation coefficient between the estimated worker and firm effects. As is usual, the correlation is computed by pooling all available cross sections, and it is here denoted $\widehat{\rho}$. We are interested in the evolution of wage sorting over time and report cross section specific estimates of Pearson's correlation coefficient, a time-varying measure of wage sorting, which we denote $\widehat{\rho}_t$. Formally, let $\widetilde{\theta}_{it} = (\widehat{\theta}_i - \widehat{\mu}_{\theta,t})/\widehat{\sigma}_{\theta,t}$ and $\widetilde{\psi}_{\mathrm{J}(i,t)t} = (\widehat{\psi}_{\mathrm{J}(i,t)} - \widehat{\mu}_{\psi,t})/\widehat{\sigma}_{\psi,t}$ be worker and firm effects standardized with respect to cross section t averages and standard errors, denoted $\widehat{\mu}_{\theta,t}$ and $\widehat{\sigma}_{\theta,t}$, and $\widehat{\mu}_{\psi,t}$ and $\widehat{\sigma}_{\psi,t}$ for worker and firm effects, respectively. Let N be the total number of observations and let $\mathbb{I}_t$ be the index set of workers present in cross section t. Then,

$$\widehat{\rho}_t = \frac{1}{|\mathbb{I}_t|}\sum_{i=1}^{N} \mathbf{1}(i \in \mathbb{I}_t)\widetilde{\theta}_{it}\widetilde{\psi}_{\mathrm{J}(i,t)t}, \tag{2}$$

where $\mathbf{1}(\cdot)$ is an indicator function.

Part of our analysis involves partitioning each cross section into K groups to investigate possible sources of trends in $\widehat{\rho}_t$. In these cases it will be useful to employ the

[8]See Abowd et al. (1999) and Postel-Vinay and Robin (2006) for discussions of the economic content of this assumption.

[9]Abowd et al. (2012) show how a version of the model developed in Shimer (2005) conditions the structure of worker and firm effects as estimated from a log linear wage equation, and use this structure to test for assortative matching in the labor market.

following decomposition of $\widehat{\rho}_t$:

$$\widehat{\rho}_t = \sum_{k=1}^{K} \widehat{\pi}_{kt}\widehat{\rho}_{kt}, \tag{3}$$

where $\widehat{\pi}_{kt} = |\mathbb{I}_{kt}|/|\mathbb{I}_t|$ is the empirical share of cross section t workers belonging to group k ($\mathbb{I}_{kt}$ is the index set of workers in group k in cross-section t), and $\widehat{\rho}_{kt} = \sum_{i=1}^{N} \mathbf{1}(i \in \mathbb{I}_{kt})\widetilde{\theta}_{it}\widetilde{\psi}_{\mathrm{J}(i,t)t}/|\mathbb{I}_{kt}|$ measures the strength of the statistical dependence between $\widetilde{\theta}_{it}$ and $\widetilde{\psi}_{\mathrm{J}(i,t)t}$ in group k in cross section t. Note that $\widehat{\rho}_t$ is not a within-group Pearson's correlation coefficient as the worker and firm effects are standardized using cross section specific means and standard deviations.[10] Expression (3) is useful in that it allows us to assert the extent to which changes to $\widehat{\rho}_t$ stem from compositional changes, i.e. changes to $\widehat{\pi}_{kt}$, and from group changes in wage sorting, i.e. changes to $\widehat{\rho}_{kt}$.

4 Results

The correlation over pooled cross-sections between the estimated worker and firm fixed effects is found to be $\widehat{\rho} = .05$. Figure 1 plots the $\widehat{\rho}_t$-profile (solid line) which exhibits a strong upward trend. This phenomenon has not been documented in previous studies. Overall, the correlation increases from a low $-.07$ in 1981 to a high .14 in 2001 at which point the correlation declines slightly. Conducting the analysis separately for two subperiods, 1980-1993 and 1994-2006, we obtain estimates of the pooled correlation of $-.03$ in 1980-1993 and .07 in 1994-2006.

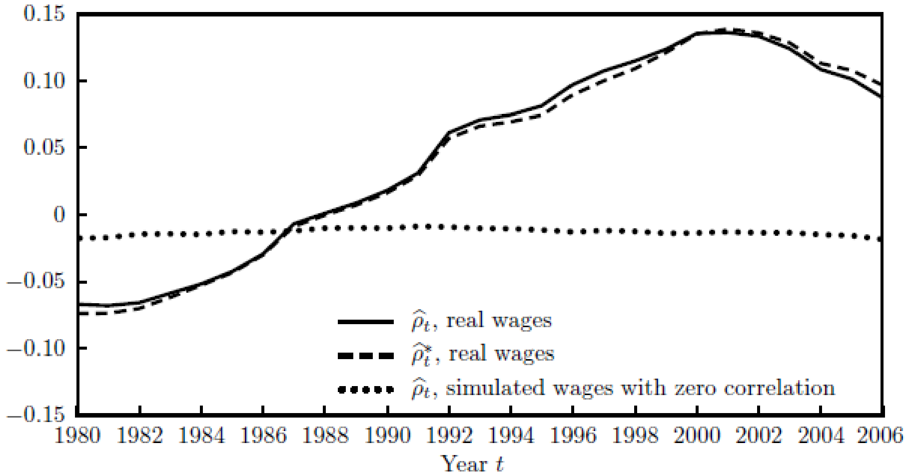
A correlation between two variables may change because the covariance changes or because of changes to the marginal distributions. The dashed line in Figure 1 plots the time profile of $\widehat{\rho}_t^*$, which is computed similarly to $\widehat{\rho}_t$ (cf. (2)), except that worker and firm effects are standardized using the means and standard errors in the pooled cross-sections. If the marginal distributions of worker and firm effects are constant over time we have $\widehat{\rho}_t^* = \widehat{\rho}_t$. Comparing the solid and dashed lines in Figure 1, we note they are almost coinciding; the rising $\widehat{\rho}_t$-profile is driven exclusively by changes in the covariance between worker and firm effects.

It is well-known that the empirical covariance between estimated worker and firm effects underestimates the true covariance (cf. Andrews et al. (2008)). The intuition is simple: if a firm effect is under-estimated, workers at that firm will have over-estimated worker effects, and vice versa. This could drive the rising ρ_t-profile if the bias is more pronounced in earlier years. This could happen if, for example, the number of job movers, firms, worker observations, or firm size distribution are not stable over the time period considered. To ascertain that this is not the case we retain the allocation of workers to

[10] Using Pearson's correlation coefficient within groups in each cross section has the severe drawback that, if the marginal distributions of worker and firm effects differ across groups, the notions of high wage workers and high wage firms differ across groups, invalidating inter-group comparisons of wage sorting.

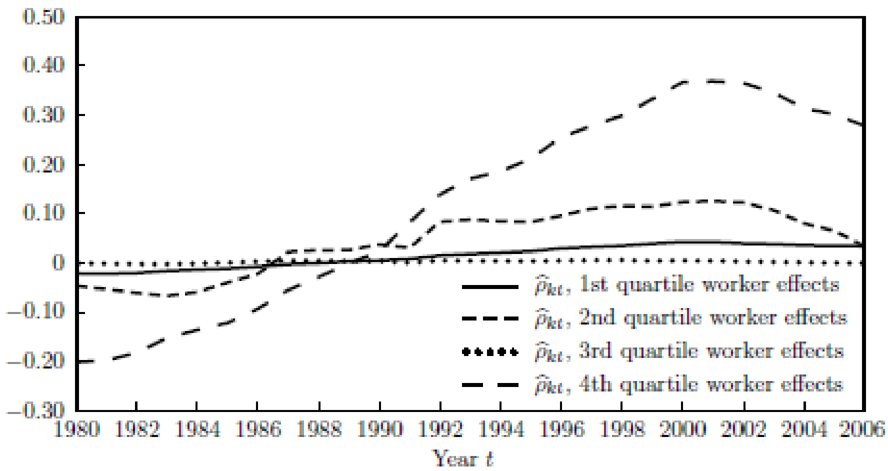
firms as found in the data, but simulate counterfactual individual wages by independently and randomly sampling the empirical marginal distributions of firm and worker effects, and residual wages. This generates a "true" zero correlation between worker and firm effects, with a flat ρ_t-profile. The dotted line in Figure 1 shows the $\widehat{\rho}_t$-profile from re-estimating (1) on this simulated data. There is a small negative bias in the estimated covariance, but the counterfactual $\widehat{\rho}_t$-profile is flat.

Figure 1: Wage Sorting Trends



Partitioning each annual cross section into quartiles of the distribution of worker effects, we can compute quartile-specific $\widehat{\rho}_{kt}$-profiles according to (3). These are plotted in Figure 2. Wage sorting in the first and third quartile of the worker effect distribution is stationary, whereas it is weakly increasing in the second and strongly trending among the highest worker effects, increasing from a low −.20 to a high .37. Hence, the economic forces that generated the nonstationary wage sorting pattern appear to have impacted almost exclusively on high wage workers.

Figure 2: Wage Sorting Trends in Worker Quartiles



As many other countries, Denmark has experienced an increase in wage inequality (cf. Krueger et al. (2010) and Table 1). Ceteris paribus, a rising $\widehat{\rho}_t$-profile contributes to this increase. To relate the documented wage sorting trend to wage inequality trends, we compute the standard deviation of log wages and a counterfactual standard deviation under stationary wage sorting. Using (1), the (cross section t) counterfactual standard deviation is constructed as $\sqrt{[\text{Var}(\ln w_{it}) + 2\text{Cov}(\widehat{\theta}_i, \widehat{\psi}_{\text{J}(i,t)}|t = 1980) - 2\text{Cov}(\widehat{\theta}_i, \widehat{\psi}_{\text{J}(i,t)})]}$. The adjustment to $\text{Var}(\ln w_{it})$ ensures that wage sorting, $\text{Cov}(\widehat{\theta}_i, \widehat{\psi}_{\text{J}(i,t)})$, is fixed at the 1980 level for all t, and thus stationary. The standard deviation of log wages increases from .30 to .34 between 1980 and 2006. Nonstationary wage sorting comprises 41 percent of this increase. We make no attempt at identifying the direction of causality, but conclude that nonstationary wage sorting is an economically important phenomenon.

4.1 Compositional Changes in Education, Age, and Gender

Table 1 documented three compositional shifts in the (private sector) labor market: rising education, aging, and rising female labor force participation. These offer potential explanations for the wage sorting trend. If, for example, the market for highly educated workers exhibits higher wage sorting than that of workers with low education, a shift towards a more educated labor force will induce an increase in overall wage sorting, even if wage sorting is stationary in each education group. We assess these explanations by partitioning the data according to workers' education, age, and gender, and decompose the $\widehat{\rho}_t$ according to (3). The decomposition in (3) also allows us to construct two alternative ρ_t-profiles, by holding in turn labor market composition (the π_{kt}s) and group wage sorting (the ρ_{kt}s) constant at their 1980 level.[11]

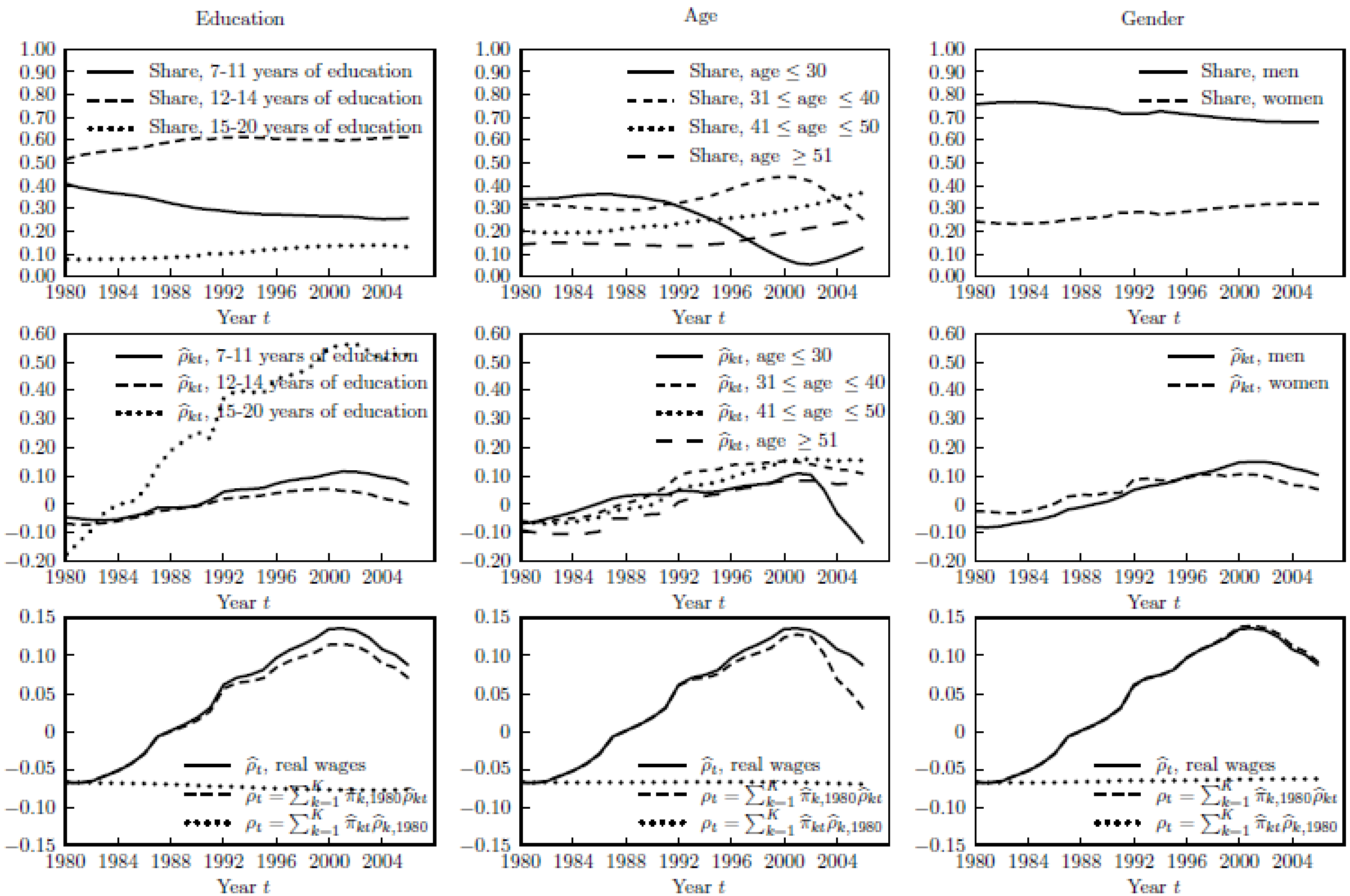
We define three education groups (7-11, 12-14 and 15-20 years of education),[12] and four age groups ($\leq$ 30, 31-40, 41-50, $\geq$ 51 years). We also split the data according to gender. The top panel of Figure 3 traces the time profiles of the shares of each of the groups in our data (i.e. the $\widehat{\pi}_{kt}$'s in (3)) related to education (top-left), age (top-middle) and gender (top-right), respectively. The middle panel of Figure 3 plots the corresponding $\widehat{\rho}_{kt}$-profiles. And finally, the bottom panel depicts the alternative ρ_t-profiles.

With respect to education, the share of workers with 7-11 years of education is in decline while those of workers with 12-14 and 15-20 years of education are on the rise. Turning to the $\widehat{\rho}_{kt}$-profiles, they are all nonstationary, with the $\widehat{\rho}_{kt}$-profile for high educated workers increasing more than the rest. This is reminiscent of the result obtained from Figure 2, since highly educated workers are more likely to have high worker effects. Putting these two results together, the alternative ρ_t-profiles in the bottom panel confirms that the increasing wage sorting profile is not associated with compositional changes in

[11]We deliberately refrain from denoting the alternative profiles counterfactual profiles. They are not counterfactual since one cannot, in general, manipulate $\widehat{\pi}_{kt}$ independent of $\widehat{\rho}_{kt}$, or vice versa.

[12]These groups correspond roughly to workers with primary school education, workers with high school or vocational education, and workers with some college education.

Figure 3: Wage Sorting and Compositional Trends in Education, Age, and Gender



educational attainment.

A similar pattern emerges when partitioning the data according to workers' age (middle panel) or gender (right panel). Thus, subgroup wage sorting exhibits nonstationarity similar to the overall trend: the rising $\widehat{\rho}_t$-profile does not appear to be associated with compositional changes in education, age and gender. Notice that for young workers, our group sorting measure $\widehat{\rho}_{kt}$ drops sharply from around year 2000. Workers who are young towards the end of the data period are only observed for a short period. This exacerbates the negative bias in the estimated covariance discussed earlier (cf. Andrews et al. (2008)). Hence, $\widehat{\rho}_{kt}$ is likely to be significantly underestimated for late t's among young workers. Results not reported also rule out shifts in industry-level employment as the main driver of the nonstationary wage sorting pattern.

4.2 Worker Reallocation, Entry, and Exit

Having documented a robust nonstationary wage sorting pattern we now consider how this pattern is related to worker entry and exit over the data period, as well as worker reallocation. Consider the following two partitions of workers in cross section t:

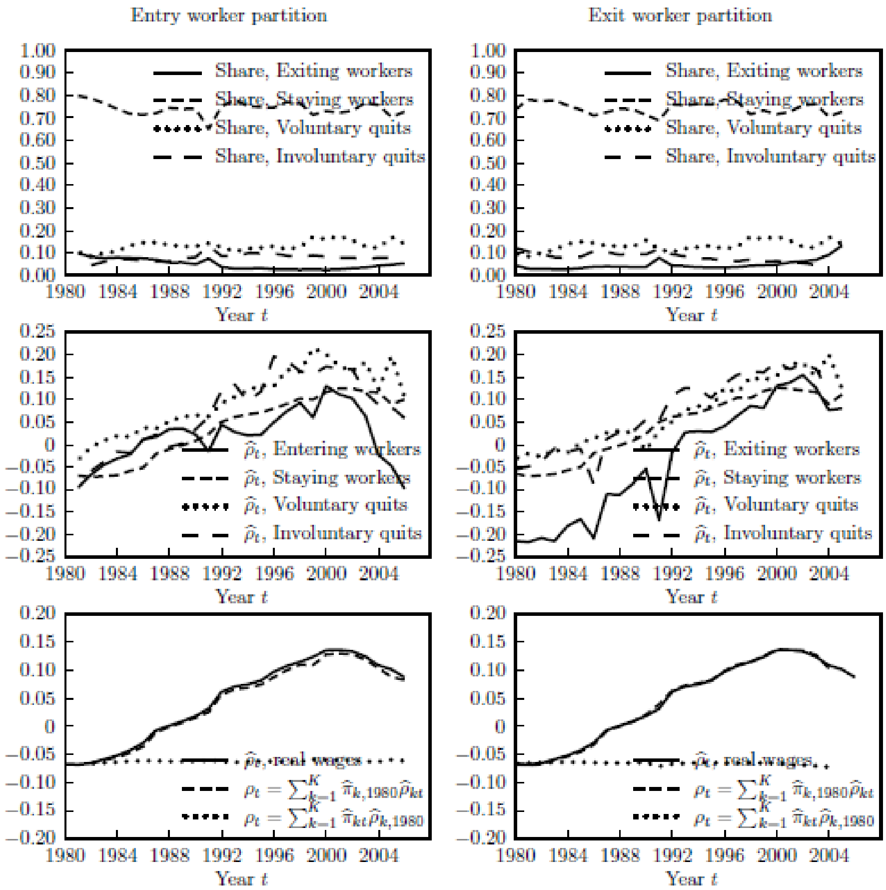
- **Entry worker partition:** An *entering worker* is not present in $t-k$ for $k \geq 1$, but present in t. A *staying worker* remains employed in the same employer in $t-1$ and t. A *voluntarily quitting worker* changes employer between t and $t-1$, while an *involuntarily quitting worker* is not present in $t-1$, but is present in the data at some date $t-k$, $k \geq 2$.

- **Exit worker partition:** An *exiting worker* is present in t, but not present at any date $t+k$ for $k \geq 1$. A *staying worker* remains employed by the same employer in t and $t+1$. A *voluntarily quitting worker* changes employer between t and $t+1$, while an *involuntarily quitting worker* is not present in $t+1$, but is present in the data at some date $t+k$, $k \geq 2$.

If a worker has a gap (e.g. is present at $t-2$, not at $t-1$, but again present at t) s/he most likely experienced a nonemployment or a public sector employment spell. However, with annual data, being present in two consecutive cross sections does not ensure that the worker did not undergo an unemployment period. Hence, the terms voluntary and involuntary quits are imprecise, but reflect the fact that workers who undergo an involuntary quit are more likely to have experienced an unemployment period in between jobs than workers who undergo a voluntary quit. Notice also that in the Entry worker partition, a voluntary (involuntary) quitting worker, is a worker who has just undergone a voluntary (involuntary) quit. In the Exit worker partition, a voluntary (involuntary) quitting worker, is a worker who is about to undergo a voluntary (involuntary) quit.

For each of the two partitions we plot, in Figure 4, the share of each group of workers (top panel), the subgroup wage sorting profile, $\widehat{\rho}_{kt}$ (middle panel), and the two alternative profiles (bottom panel). The shares of the groups are roughly constant over the period we consider in both partitions (cf. top panel in Figure 4). Hence, composition effects along the worker entry and exit dimensions are not likely drivers of the increasing $\widehat{\rho}_t$-profile. This is confirmed in the bottom panel. The middle panel in Figure 4 reveals nonstationary subgroup wage sorting patterns similar to the overall pattern in Figure 1.

Figure 4: Wage Sorting Trends and Worker Reallocation



Comparing the $\widehat{\rho}_{kt}$-profile of entering workers (middle-left) and exiting workers (middle-right) we see that the correlation is higher for entering workers in most years except from 2000 onwards where the correlation profile for entering workers is in decline (as is the overall $\widehat{\rho}_t$-profile in Figure 1). Similar to young workers in Figure 3, workers who enter late or exit early in the data period are only observed for short periods, and $\widehat{\rho}_{kt}$ is likely to be downward biased for late t's among entering workers and for early t's among exiting workers. Thus, the negative bias among the entering workers might be part of the explanation of the downward sloping $\widehat{\rho}_t$-profile in the early 2000s. Keeping this potential caveat in mind, entering workers exhibit stronger wage sorting than exiting workers over most of the data period. This selection process contributes to the increasing $\widehat{\rho}_t$-profile in Figure 1, although the share of workers entering and exiting every year is too low to generate the wage sorting trend in Figure 1.[13]

Next we focus on the role of worker reallocations in generating an increasing wage sorting trend. Considering the Entry worker partition, $\widehat{\rho}_{kt}$ is higher for workers who have just undergone a quit (voluntary or involuntary), than it is for staying (and entering) workers. It also seems that workers who have undergone a voluntary quit exhibit higher wage sorting than workers who quit involuntarily, except in a few years in the 1990s.[14] In the Exit worker partition, voluntarily quitting, involuntarily quitting, and staying workers appear similar in terms of $\widehat{\rho}_{kt}$-profiles. That is, job outflow seems to be a random sample in terms of wage sorting. Moreover, comparing the $\widehat{\rho}_{kt}$-profiles of voluntary quitting workers in the Entry and Exit partitions, we see that workers undergoing a voluntary quit move towards firms where the correlation between worker and firm effect is higher. In summary: (a) new matches initiated by a voluntary quit exhibit higher wage sorting than existing matches. In other words, wage sorting is more pronounced in the match inflow than in the stock. (b) Matches that break up are not different from matches that survive in terms of wage sorting. In other words, wage sorting in the match outflow and in the stock are similar. From (a) and (b), the correlation between worker and firm effects in the new match is higher than in the old match. These facts imply that wage sorting becomes increasingly positive assortative over time.

4.3 Voluntary Quits

We have shown that wage sorting is trending, that the trend appears mostly in the top quartile of the distribution of worker effects, and that the trend is associated with voluntary quits. We now further investigate the association between voluntary quits and the observed wage sorting pattern.

Let $D_{\theta,t}$ be the decile of the worker effect in an annual cross section t, let $D^{o}_{\psi,t}$ be the decile of the origin firm effect (the firm effect of the firm from which the worker made the transition), and let $D^{d}_{\psi,t}$ be the decile of the destination firm effect (the firm effect of the worker's current firm). Finally, let V_t be an indicator for a voluntary quit in cross section t as defined in the Entry worker partition above. We now consider the probability of making a voluntary quit that involves a given worker type moving to a similar firm

[13]Results not reported show that the increasing wage sorting trend is also weakly related to the entry and exit of firms.

[14]As mentioned earlier, our categorization of quits into voluntary and involuntary is imperfect. This leads to an underestimation of the difference between the two types of transitions in terms of wage sorting.

type.[15] That is, we consider

$$\Pr[D^d_\psi = D_\theta, V_t = 1 | D_\theta, D^o_\psi] = \Pr[D^d_\psi = D_\theta | D_\theta, D^o_\psi, V_t = 1] \times \Pr[V_t = 1 | D_\theta, D^o_\psi]. \quad (4)$$

Equation (4) decomposes the object of interest, $\Pr[D^d_\psi = D_\theta, V_t = 1|D_\theta, D^o_\psi]$, into the probability of $D^d_\psi = D_\theta$ conditional on D_θ, D^o_ψ and a voluntary quit, and the probability of a voluntary quit, conditional on D_θ and D^o_ψ. Without an explicit model of the labor market there is no formal relationship between wage sorting and $\Pr[D^d_\psi = D_\theta, V_t = 1|D_\theta, D^o_\psi]$, but it seems plausible that an increase in $\Pr[D^d_\psi = D_\theta, V_t = 1|D_\theta, D^o_\psi]$ is associated with an increase in wage sorting.[16]

We are interested in the evolution of $\Pr[D^d_\psi = D_\theta, V_t = 1|D_\theta, D^o_\psi]$ over time. As it turns out, $\Pr[V_t = 1|D_\theta, D^o_\psi]$, does not change systematically over our data period, and its contribution towards generating increased assortative wage sorting is therefore negligible, and we focus attention on $\Pr[D^d_\psi = D_\theta|D_\theta, D^o_\psi, V_t = 1]$.[17]

Unconditionally on ranking in the distributions of worker and origin firm effects, $\Pr[D^d_\psi = D_\theta|V_t = 1]$ is increasing over time from .09 in 1980 to .13 in 2002, a 44 percent increase. This pattern is consistent with an increasing wage sorting trend. Figure 5 shows contour plots of $\Pr[D^d_\psi = D_\theta|D_\theta, D^o_\psi, V_t = 1]$ for nine three-year subperiods. Darker areas indicate higher probabilities and are predominantly located in the south-west and north-east corners in each subperiod. Interestingly, the north-east areas (high worker effect, high origin firm effect) appear to darken further and expand from 1980 to 2000. Hence, during this period, voluntary quits among high wage workers employed in high wage firms are increasingly likely to involve a transition to another high wage firm. We cannot detect any other systematic changes over time in Figure 5. Considering involuntary quits, results not shown, but available upon request, document that $\Pr[D^d_\psi = D_\theta|D_\theta, D^o_\psi, I_t = 1]$,where I_t is an indicator for involuntary quits, does not exhibit systematic changes over the data period.

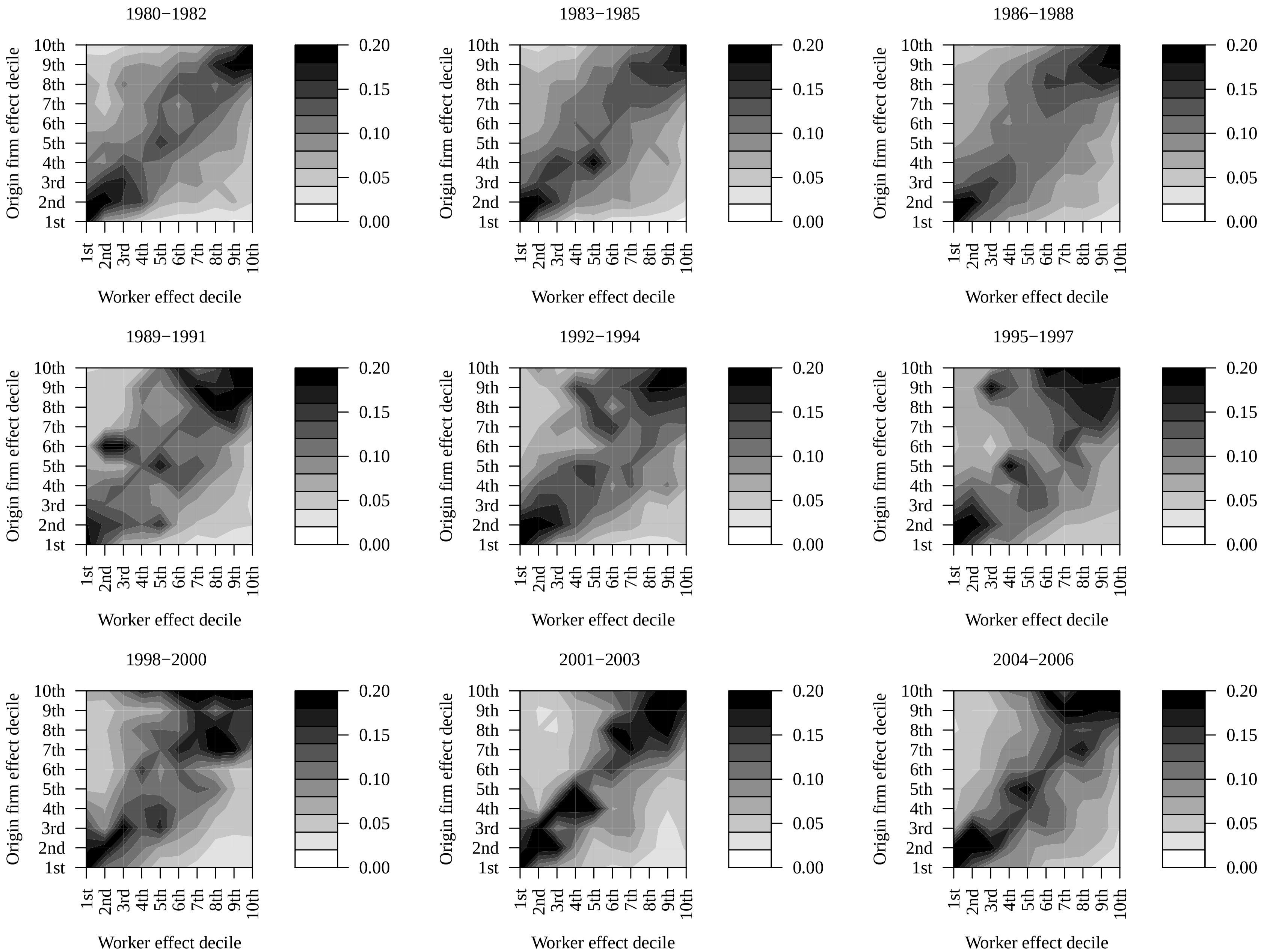
The increasing wage sorting trend in the top quartile of worker effects could be explained by two processes: (a) high wage workers employed in high wage firms are increasingly likely to transit to another high wage firm or (b) high wage workers employed in low wage firms are increasingly likely to transit to a high wage firm. The above analysis shows that the increased wage sorting arises (at least in part) because of (a). Ceteris paribus, both explanations result in increased wage sorting and cross section wage inequality. However, the two processes have different implications in terms of lifetime wage inequality. (a) is likely to lead to a higher increase in lifetime wage inequality than (b) as

[15] Using the definitions of voluntary and involuntary quits from the Exit worker partition leads to identical conclusions.

[16] It is of course possible to envisage situations where $\Pr[D^d_\psi = D_\theta, V_t = 1|D_\theta, D^o_\psi]$ and wage sorting move in opposite directions because changes in within-decile wage sorting, or because other decile transition probabilities also change.

[17] Contour plots of $\Pr[D^d_\psi = D_\theta, V_t = 1|D_\theta, D^o_\psi]$ for nine different subperiods are available upon request.

Figure 5: Wage Sorting Trends and Voluntary Quits



Note: The contours indicate $\Pr[D^d_\psi = D_\theta | D_\theta, D^o_\psi, V_t = 1]$, where D^d_ψ is the decile of the destination firm effect, D^o_ψ is the decile of the origin firm effect, D_θ is the decile of the worker effect, and a voluntary quit is defined as in the Entry worker partition. $\Pr[D^d_\psi = D_\theta | D_\theta, D^o_\psi, V_t = 1]$ is truncated at .20.

it stifles the transitions between deciles in the cross sectional wage distribution (simply because $\Pr[D_{\psi}^{d} = D_{\theta} | D_{\theta}, D_{\psi}^{o}, V_t = 1]$ increases).[18] Notice also that the increase in lifetime inequality generated by (a) is one in which the workers in the high deciles of the wage distribution benefits, whereas those in the bottom are not adversely affected.

5 Conclusion

Wage sorting is measured by the correlation between worker fixed effects and firm fixed effects, as estimated from a log-linear wage regression. Using a Danish MEE panel for 1980-2006, this paper documents a strong trend towards more positive assortative wage sorting. The correlation between worker and firm fixed effects computed from pooled annual cross sections is .05, but masks a systematic nonstationarity over the data period. Quantitatively, the correlation ranges from $-.07$ in 1981 to .14 in 2001. The nonstationarity is not explained by compositional shifts in the labor force in terms of education, age, and gender. We provide evidence that is consistent with the wage sorting trend being associated with entry and exit of workers, although this channel is likely to be weak, as well as worker reallocation. The latter is consistent with the observed wage sorting trend because, over the period we consider, wage sorting is more pronounced in the match inflow than in the stock, while wage sorting in the match outflow and in the stock are similar. The contribution to the wage sorting trend from the reallocation process is driven primarily by high wage workers employed in high wage firms. Finally, while it is beyond the scope of this paper to give a structural interpretation to the documented wage sorting trend, it is economically important in that it comprises 41 percent of the increase in the standard deviation of log wages between 1980 and 2006.

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[18]Flinn (2001) and Bowlus and Robin (2004) study lifetime wage inequality in Italy and the U.S. (Flinn) and in the U.S. (Bowlus and Robin), but do not use MEE data, and so, do not consider wage sorting.

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