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REPLICATION

Workplace heterogeneity and wage inequality in Denmark

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Summary

Wage inequality is on the rise in most developed economies, and this phenomenon has fostered a growing body of research on its potential drivers. Using German data over the period 1985–2009, Card et al. (*The Quarterly Journal of Economics* 2013, 128(3), 967-1015) argue that rising workplace heterogeneity has contributed substantially to the rise in wage inequality. I revisit their findings in two ways. First, because the generalization of their findings remains an open question, I apply their methodological approach to Danish register data and test whether rising workplace heterogeneity explains a significant share of the rise in wage inequality in Denmark. I find that, contrary to Germany, workplace heterogeneity remained practically stable over time, and this pattern contributed slightly negatively to the rise in wage inequality. Second, I complement Card et al.'s (2013) methods with the variance decomposition exercise proposed by Song et al. (2019) to identify more precisely the sources of the rise in wage inequality in Denmark. Although the rise in wage inequality is partly a between-establishment phenomenon, I show that the strengthening of assortative matching patterns and the rising heterogeneity of workers within establishments are the main drivers of growing inequality.

KEYWORDS

assortative matching, firm and worker heterogeneity, fixed-effect wage models, wage inequality

1 | INTRODUCTION

Rising wage inequality is a well-documented trend observed in most industrialized countries over the last decades. Several factors have been identified as contributing to the widening of the cross-sectional wage distribution over time, such as institutional factors (Goldschmidt & Schmieder, 2017; Lemieux, 2006), non-market factors (Card & DiNardo, 2002), and market factors linked to changes in production technology (Autor et al., 2008; Krusell et al., 2000). Providing a novel approach to understanding the sources of wage inequality, Card et al. (2013) tackle the question of whether rising workplace heterogeneity contributed to the rise in wage inequality in Germany over the period 1985–2009.[1] They find that the increasing dispersion in wage premia offered in different establishments accounted for about 25% of the rising wage inequality, for both male and female workers. The increase in the heterogeneity of workers and in assortative matching contributed to the remainder.

[1] As of July 2020, Card et al. (2013) has been cited 1022 times in Google Scholar, 426 times in EconPapers, and 324 times on RePEc.

The rise in workplace heterogeneity is therefore an economically important trend in Germany. As Card et al. (2013, p. 1011) note, "a key question is whether similar trends have occurred in other developed economies." Therefore, in this paper, I first apply the methodological approach of Card et al. (2013) to the Danish register data to test whether their findings can be generalized to the case of Denmark. I show that, in sharp contrast with Germany, the heterogeneity in establishment-specific pay premia remained nearly stable over the period 1982–2007, and this stability curbed the rise in wage inequality observed in Denmark, although mildly so. The stability of workplace heterogeneity over time is a finding that is robust to the implementation of the limited mobility bias correction proposed by Kline et al. (2020).

Moreover, Card et al.'s (2013) study on the rise in workplace heterogeneity fostered further research on the potential drivers of this phenomenon. Song et al. (2019) confirm that the increased dispersion in earnings observed in the United States from 1978 to today is primarily a between-firm phenomenon. However, they show that the rising between-firm dispersion is not explained by the firms per se becoming more heterogeneous over time. Rather, increased between-firm dispersion was generated by the widening gap between firms in the composition of their workers, resulting from increased assortative matching and worker segregation.[2] In this paper, I complement Card et al.'s (2013) modeling approach by applying the within/between-workplace wage decomposition exercise proposed by Song et al. (2019). I first show that, in Denmark, the rise in wage inequality occurred roughly equally within and between establishments. Second, although the contribution of the increased between-workplace dispersion is substantial, workplace heterogeneity did not rise in Denmark after controlling for worker composition, a result that is in line with Song et al.'s (2019) findings.

In the context of public policy often structured to combat inequality, the Danish labor market appears to be a relevant test case. Indeed, wage inequality only increased moderately in Denmark compared to other industrialized countries such as Germany or the United States,[3] and the stability of workplace heterogeneity contributed to this trend. This conclusion calls for a better understanding of the dissimilar dynamics of workplace heterogeneity across countries, since they partly explain the international variation in inequality patterns. Moreover, by stressing the major role of sorting in enhancing wage inequality, this paper directs attention to the importance of testing models of worker mobility that focus on the assortative matching process between workers and firms.[4]

2 | DATA

This study exploits the linked worker-firm data from Statistics Denmark for the period 1982–2007. The data contain the employment history, the labor market status, and the estimated hourly wage for the job held in November of every working-age citizen residing in Denmark.[5] Hourly wages are deflated using the 2000 Consumer Price Index. I merge in person-level administrative registers to obtain workers' age, gender, and education.[6] Note that, to insure consistency over time, establishments rather than firms are the unit of analysis.[7] The raw sample contains 85,663,762 observations. I follow the data cleaning procedure of Card et al. (2013) as closely as possible. I delete all public sector observations (18,970,500 observations deleted) as well as observations pertaining to self-employment or secondary employment (23,716,240 observations deleted). I discard observations with hourly wage estimates deemed to be low quality by Statistics Denmark (6,129,205 observations deleted).[8] I restrict the sample to all workers between 20 and 60 years old (6,805,309 observations

[2] Barth et al. (2016) also find that, in the Unites States, most of the rise in inequality results from increased between-firm dispersion. However, their variance decomposition exercise does not allow for a further decomposition into dispersion in firm effects, assortative matching, and segregation.

[3] In Denmark over the period 1982–2007, the variance of log wages increased by 0.016 (+21.3%) for men and 0.078 (+39.3%) for women (see Section 2 for the data). In comparison, it increased by 0.112 (+81.8%) for men and 0.095 (+54.5%) for women in Germany over the period 1985–2009 (Card et al., 2013), and by 0.141 (+30.5%) for men in the United States over the period 1980–2013 (Song et al., 2019). Note that methodological differences might partly explain this disparity, since inequality is presently measured by the variance of hourly wages while Card et al. (2013) and Song et al. (2019) study the variance of daily and yearly wages, respectively.

[4] For studies on assortative matching in Denmark, see Bagger and Lentz (2018), Lentz et al. (2018), He et al. (2018), and Bagger et al. (2013). Despite their restricted access, the Danish register data have been widely used to investigate a large range of labor market topics, such as worker and firm heterogeneity (Jinkins & Morin, 2018; Sørensen & Vejlin, 2013; 2011), the gender wage gap (Gallen et al., 2019), the wage distribution (Christensen et al., 2005), or wage growth (Bagger et al., 2014).

[5] Statistics Denmark divides yearly earnings by an estimate of the number of hours worked during the year. Because on the focus on full-time workers, this analysis based on hourly wages can be compared to the results of Card et al. (2013) who use the daily wage of full-timers.

[6] Education levels are categorized into four groups: secondary and high school education, vocational and short tertiary education, medium-length tertiary education, and long-length tertiary education.

[7] Establishments are also the unit of analysis in Card et al. (2013), while the analysis is performed at the firm level in Song et al. (2019). Note that, in Denmark, only around 4% of all firms have more than one establishment, and these multi-establishment firms gather around half of the workforce.

[8] Almost 98% of these discarded observations are part-timers whom number of hours worked is poorly estimated. These observations would in any case be dropped further in the cleaning process when I discard part-timers.

deleted). I drop all observations with zero or missing hourly wages (86,925 observations deleted) and undisclosed establishment identification numbers (1,879,836 observations deleted). I drop all observations that belong to the bottom or top percentile of the yearly wage distributions (554,805 observations deleted).[9] Finally, I keep full-time workers (8,463,234 observations deleted). The full sample, containing 19,057,708 observations, brings together 2,274,333 workers and 352,372 establishments.

Over the period 1982–2007, male and female real hourly wages increased steadily by 4.4% and 6.7%, respectively (Table A1). When measured by the standard deviation of log wages, male wage inequality increased by roughly 10% between 1982 and 1998 and plateaued thereafter, while female wage inequality increased continuously over the entire period, by almost 20% (Figure A1).

3 | WORKPLACE HETEROGENEITY OVER TIME

To assess the relative contribution of worker-specific and workplace-specific heterogeneity to the rise in wage inequality, I follow Card et al. (2013) and decompose log wage w_{it} of worker i in time t into additively separable worker and establishment components (Abowd et al., 1999, hereafter AKM):

$$w_{i,t} = \alpha_i + \psi_{J(i,t)} + x'_{i,t}\beta + \epsilon_{i,t} \tag{1}$$

where $x_{i,t}$ captures the time-varying effect of observed characteristics,[10] α_i and $\psi_{J(i,t)}$ represent the time-invariant determinants of wages that are specific to the worker and the establishment, respectively, and $\epsilon_{i,t}$ is the error term.

I split the sample into four overlapping intervals: 1982–1988, 1988–1994, 1994–2000, and 2000–2007.[11] Inter-firm mobility being critical to the estimation,[12] I keep observations that belong to the largest connected set in the matching graph (95% of the full sample, Table A2) and fit the two-way fixed-effect wage model into these four intervals.[13] The wage estimation results are presented in Section B1.

Next, I use Equation (1) to decompose the variance of wages as follows:

$$\begin{aligned} \text{var}(w_{i,t}) &= \text{var}(\alpha_i) + \text{var}(\psi_{J(i,t)}) + \text{var}(x'_{i,t}\beta) + \text{var}(\epsilon_{i,t}) \\ &\quad + 2\text{cov}(\alpha_i, \psi_{J(i,t)}) + 2\text{cov}(\alpha_i, x'_{i,t}\beta) + 2\text{cov}(\psi_{J(i,t)}, x'_{i,t}\beta) \end{aligned} \tag{2}$$

As shown in Table 1, male and female workers became increasingly heterogeneous over time. This rising dispersion in worker effects accounts for 54% of the rise in male wage inequality and for 36% of the rise in female wage inequality. However, the main explanation for the rising wage inequality observed in Denmark lies in the rising covariance between the worker and establishment effects. This increase in assortative matching contributes 56% and 55% of the rise in wage inequality, for male and female workers respectively.[14] Conversely, establishment effects featured slightly lower dispersion over time, therefore contributing negatively to the increasing wage inequality (−15% for male workers, −9% for female workers). This result stands in sharp contrast to the rising heterogeneity between workplaces observed in Germany, which contributed 25% of the rise in both male and female wage variance. These findings are robust to using the untrimmed hourly wage distributions, with the bottom and top percentiles being capped at the yearly 1st and 99th percentile values (see Table C1).[15]

[9]Dropping the top and bottom percentiles is made to avoid possible outliers produced by the imperfect estimation of hours worked used in the computation of hourly wages.

[10]Observable characteristics include year dummies and a quadratic and cubic term in age interacted with education dummies.

[11]Because, from 2008 onwards, a change in both the data source (E-Income) and methodology used by statistics Denmark to compile the number of hours worked creates a break in the time series and artificially raises the variance of hourly wages, the intervals I consider are shifted forward by 2 to 3 years compared to Card et al. (2013).

[12]Low mobility rates are known to generate biases in the quadratic forms of the parameters (Abowd et al., 2004; Andrews et al., 2008). See the robustness exercise carried out at the end of this section. See also Bonhomme et al. (2019), Hagedorn et al. (2017), and Borovičková and Shimer (2017) for alternative methods to retrieve worker and firm unobserved heterogeneity.

[13]Note that the sample size allows me to estimate the results for both men and women together.

[14]This strong trend toward more positive assortative matching has also been documented by Bagger et al. (2013), who use the same Danish register data over the period 1980–2006 and assume time-invariant fixed effects over this period. While they do not examine the relative contribution of worker and firm heterogeneities, they argue that wage sorting comprises 41% of the increase in wage inequality.

[15]Using the untrimmed and uncapped hourly wage distributions has also little effect on the results (presented upon request).

TABLE 1 Variance decomposition, interval 1 to 4

	Interval 1 1982–1988		Interval 4 2000–2007		Change from interval 1 to 4	
	(1) Value	(2) %	(3) Value	(4) %	(5) Change	(6) %
Men						
Variance of log wages	0.080	100.0	0.097	100.0	0.016	100.0
Variance of worker effect	0.058	70.7	0.066	68.1	0.008	54.1
Variance of establ. effect	0.016	20.1	0.014	14.6	−0.002	−14.8
Variance of Xb	0.010	11.8	0.008	8.6	−0.001	−8.0
Variance of residual	0.007	8.3	0.010	9.9	0.003	18.7
2cov(worker, establ.)	−0.010	−11.8	−0.001	−1.1	0.009	55.7
2cov(worker, Xb)	−0.001	−0.7	−0.001	−1.0	−0.000	−2.8
2cov(establ., Xb)	0.001	1.2	0.001	0.6	−0.000	−2.5
Women						
Variance of log wages	0.056	100.0	0.078	100.0	0.021	100.0
Variance of worker effect	0.047	83.0	0.055	70.1	0.008	36.0
Variance of establ. effect	0.016	29.1	0.015	18.7	−0.002	−8.9
Variance of Xb	0.009	16.4	0.009	11.2	−0.001	−2.4
Variance of residual	0.005	9.6	0.007	9.4	0.002	9.0
2cov(worker, establ.)	−0.017	−30.3	−0.005	−6.8	0.012	55.3
2cov(worker, Xb)	−0.004	−7.5	−0.002	−2.5	0.002	10.8
2cov(establ., Xb)	0.000	0.5	−0.000	0.2	−0.000	−2.2

Note: The variances and covariances are calculated across worker-year observations. The time-varying observables X include year dummies and a quadratic and cubic term in age, all interacted with education dummies.

The above variance component estimators hinge on the assumption that the error terms in Equation (1) are independently drawn from a normal distribution, an assumption that is increasingly questioned in the literature. In particular, limited worker mobility tends to invalidate it and generates substantial biases in the estimates of the contribution of firm effects and assortative matching to wage inequality (Abowd et al., 2004; Andrews et al., 2008; Bonhomme et al., 2020; Kline et al., 2020). Therefore, I implement the fixed-effect method for bias correction proposed by Kline et al. (2020) and estimate Equation (1) on the “leave-one-out” subsample, that is, the set that would remain connected if any observation were to be removed. The resulting estimators of worker and establishment effects are robust to the presence of heteroscedasticity.

Table C3 reports the results of the corresponding variance decomposition exercise. While the variance of worker effects is essentially unaffected by limited mobility bias correction, the contribution of establishment heterogeneity to the variance of wages is substantially lower and the contribution of assortative matching is larger. These findings are in line with Andrews et al. (2008), Kline et al. (2020), and Bonhomme et al. (2020). Moreover, when analyzing the rise in wage inequality over time, the robustness exercise confirms that workplace heterogeneity remained practically stable from the first to the fourth period. Despite turning positive, its contribution to the growth in wage inequality remains modest (7.2% for male workers, 0.3% for female workers). Note that, after bias correction, the strengthening over time of assortative matching patterns is reduced and its contribution to the increasing wage inequality decreases to 16% for both male and female workers.[16]

4 | BETWEEN- AND WITHIN-ESTABLISHMENT DISPERSION

To identify more precisely the causes of rising wage inequality in Denmark, I apply the between/within-establishment variance decomposition proposed by Song et al. (2019). Specifically, I further decompose the variance of wages using the AKM (Abowd et al., 1999) wage decomposition, Equation (1), and gather each element into a between- or

[16]Because the limited mobility bias is more salient in smaller samples, the upward bias in the variance of establishment effects is larger in interval 1 than in interval 4. The bias correction therefore flattens the decrease in workplace heterogeneity obtained in the baseline estimation. The same argument applies to the downward-biased assortative matching estimate.

TABLE 2 Within and between-establishment variance decomposition, interval 1 to 4

	Interval 1 1982–1988		Interval 4 2000–2007		Change from interval 1 to 4	
	(1) Value	(2) %	(3) Value	(4) %	(5) Change	(6) %
Men						
Variance of log wages	0.080	100.0	0.097	100.0	0.016	100.0
Between-establishment variance	0.031	38.2	0.041	41.9	0.009	61.5
$\text{var}(\bar{\alpha})$	0.020	24.3	0.021	22.0	0.001	9.8
$\text{var}(\Psi)$	0.016	20.1	0.014	14.6	−0.002	−14.8
$\text{var}(\bar{X}b)$	0.002	2.3	0.002	1.7	−0.000	−1.2
$2\text{cov}(\bar{\alpha}, \Psi)$	−0.010	−11.8	−0.001	−1.1	0.009	55.7
$2\text{cov}(\bar{\alpha}, \bar{X}b)$	0.002	1.9	0.004	3.7	0.002	13.7
$2\text{cov}(\Psi, \bar{X}b)$	0.001	1.2	0.001	0.6	−0.000	−2.5
Within-establishment variance	0.050	61.8	0.056	58.1	0.006	38.4
$\text{var}(\alpha - \bar{\alpha})$	0.038	46.4	0.045	46.1	0.007	44.3
$\text{var}(Xb - \bar{X}b)$	0.008	9.5	0.007	6.9	−0.001	−6.8
$\text{var}(\epsilon)$	0.007	8.3	0.010	9.9	0.003	18.7
$2\text{cov}(\alpha - \bar{\alpha}, Xb - \bar{X}b)$	−0.002	−2.6	−0.005	−4.8	−0.003	−16.5
$2\text{cov}(\alpha - \bar{\alpha}, \epsilon)$	−0.000	−0.0	−0.000	−0.0	−0.000	−0.2
$2\text{cov}(Xb - \bar{X}b, \epsilon)$	0.000	0.2	0.000	0.0	−0.000	−0.9
Women						
Variance of log wages	0.056	100.0	0.078	100.0	0.021	100.0
Between-establishment variance	0.023	40.7	0.033	41.8	0.010	44.8
$\text{var}(\bar{\alpha})$	0.021	37.8	0.019	24.2	−0.003	−11.8
$\text{var}(\Psi)$	0.016	29.1	0.015	18.7	−0.002	−8.9
$\text{var}(\bar{X}b)$	0.002	3.5	0.002	2.4	−0.000	−0.5
$2\text{cov}(\bar{\alpha}, \Psi)$	−0.017	−30.3	−0.005	−6.8	0.012	55.3
$2\text{cov}(\bar{\alpha}, \bar{X}b)$	−0.000	−0.4	0.002	2.9	0.002	11.4
$2\text{cov}(\Psi, \bar{X}b)$	0.000	0.5	0.000	0.2	−0.000	−0.7
Within-establishment variance	0.033	59.3	0.045	58.2	0.012	55.2
$\text{var}(\alpha - \bar{\alpha})$	0.026	45.2	0.036	45.9	0.010	47.7
$\text{var}(Xb - \bar{X}b)$	0.007	12.8	0.007	8.8	−0.000	−1.9
$\text{var}(\epsilon)$	0.005	9.6	0.007	9.4	0.002	9.0
$2\text{cov}(\alpha - \bar{\alpha}, Xb - \bar{X}b)$	−0.004	−7.2	−0.004	−5.4	−0.000	−0.6
$2\text{cov}(\alpha - \bar{\alpha}, \epsilon)$	−0.000	−0.3	−0.000	−0.2	−0.000	−0.0
$2\text{cov}(Xb - \bar{X}b, \epsilon)$	−0.000	−0.5	−0.000	−0.1	0.000	1.0

Note: The variances and covariances are calculated across worker-year observations. The time-varying observables X include year dummies and a quadratic and cubic term in age, all interacted with education dummies. $\bar{X}b$ denotes the within-establishment average of the effect of time-varying observables.

within-establishment component:[17]

$$\begin{aligned}\text{var}(w_{i,t}) = & \underbrace{\text{var}(\bar{\alpha}_i^{J(i,t)}) + \text{var}(\psi_{J(i,t)}) + 2\text{cov}(\bar{\alpha}_i^{J(i,t)}, \psi_{J(i,t)})}_{\text{Between-establishment dispersion}} \\ & + \underbrace{\text{var}(\alpha_i - \bar{\alpha}_i^{J(i,t)}) + \text{var}(\epsilon_{i,t}) + 2\text{cov}(\alpha_i - \bar{\alpha}_i^{J(i,t)}, \epsilon_{i,t})}_{\text{Within-establishment dispersion}}\end{aligned} \quad (3)$$

where $\bar{\alpha}_i^{J(i,t)}$ is the average worker fixed effect in establishment J that employs worker i. The between-establishment component is therefore the sum of the variance of the within-establishment average worker effects, the variance of the establishment effects, and the covariance of worker and establishment effects.

Shown in Table 2, two main conclusions can be drawn from this additional variance decomposition exercise. First, the small rise in wage inequality observed in Denmark has been triggered by both an increase in within- and

[17] For the sake of presentation, this decomposition abstracts from the observable characteristics Xb. The full decomposition, that is, including Xb, is shown in Table 2.

between-establishment dispersion. Contributing 62% of the rise in male wage inequality and 45% of the rise in female wage inequality (column (6)), the increase in the between-establishment component is indeed substantial, although not predominant for women. Second, the rise in between-establishment wage dispersion can not be explained by an increasing heterogeneity in the workplaces themselves. Indeed, as argued in the previous section, the variance of the establishment effects slightly decreased over time. Rather, the rise in between-establishment wage dispersion is almost entirely accounted for by an increase in assortative matching, as captured by the covariance of worker and establishment effects, $\text{cov}(\bar{\alpha}, \psi)$. Last, contrary to Song et al.'s (Song et al., 2019) findings on the United States, worker segregation, as captured by the variance of the within-establishment average worker effects, $\text{var}(\bar{\alpha})$, seems to play a minor role, contributing slightly positively to the overall increase in male wage inequality (10%) and slightly negatively to the overall increase in female wage inequality (−12%). Shown in Table C2, the within-/between-establishment variance decomposition results obtained with untrimmed hourly wage distributions, where the bottom and top percentiles are capped at the yearly 1st and 99th percentile values, are qualitatively similar.[18]

5 | DISCUSSION AND CONCLUSION

Card et al. (2013) show that rising workplace heterogeneity contributed markedly to the rise in wage inequality in Germany. Following their methodological approach, I provide evidence that this result can not be generalized to the case of Denmark. Specifically, I find that around half of the moderate rise in Danish wage inequality is accounted for by an increase in the dispersion of average wages between establishments. However, this rise in between-establishment wage dispersion is not explained by increased heterogeneity in the workplaces themselves, nor by stronger segregation of workers within firms, but rather by the rise in assortative matching between workers and workplaces.

The implications are twofold. First, this finding suggests that, in Denmark, the distribution of firm characteristics, be it productivity, management practices, age, or collective bargaining status, might not have widened over time, therein tempering the overall rise in wage inequality. Second, the trend toward more positive assortative matching and the rising heterogeneity of workers within workplaces strike as being the two main drivers of wage inequality, a result that highlights the importance of better understanding how worker mobility and the related sorting patterns shape the wage distribution.

Last, Card et al. (2013) emphasize the role of changing labor market institutions, such as the fall in collective bargaining coverage and the decentralization process that took place in the 1990s and 2000s. They provide suggestive evidence that these changes played a proximate role in the rise in establishment-level heterogeneity. Although the context and implementation differed, Denmark experienced a similar decentralization process over the same period, which led to an increase in wage inequality (Dahl et al., 2013). However, the present results suggest that this labor market change did not trigger any rise in workplace heterogeneity. Instead, the decentralization process coincided with the rise in both worker heterogeneity and wage sorting. Whether decentralization prompted an increase in worker heterogeneity—because it brought wages into accordance with individual productivity—as hinted by Dahl et al. (2013), or it contributed to the rise in wage sorting, as speculated by Bagger et al. (2013), remains to be shown.

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OPEN RESEARCH BADGES

This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results.

DATA AVAILABILITY STATEMENT

The data used in the paper have been provided by Statistics Denmark: https://www.dst.dk/da/Statistik/dokumentation/Times. The data are confidential.

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[18]The results are also robust to using the untrimmed and uncapped hourly wage distributions. Results presented upon request.

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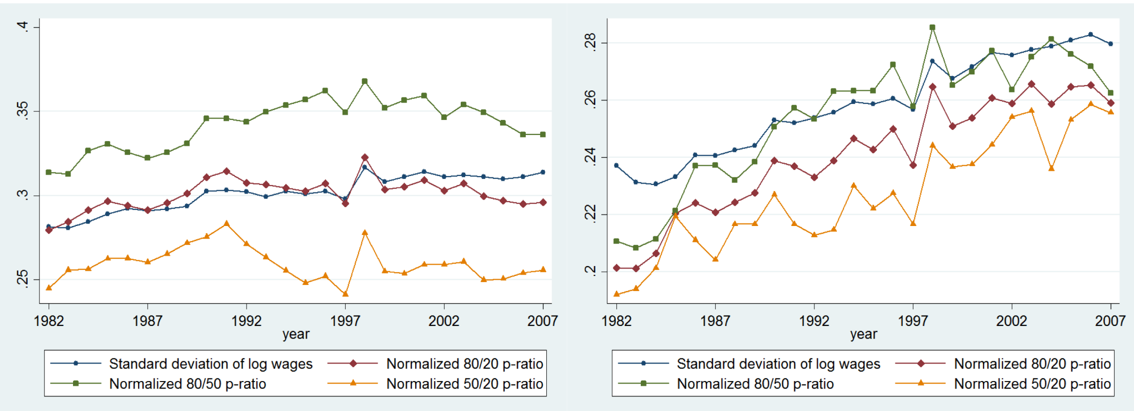
APPENDIX A: SUMMARY STATISTICS

Summary statistics for both male and female workers are presented in Table A1. Over the period 1982–2007, male and female real hourly wages increased steadily by 4.4% and 6.7%, respectively. Figure A1 compares the trends in wage inequality for both male and female workers. When measured by the standard deviation of log wages, male wage inequality increased by roughly 10% between 1982 and 1998 and plateaued thereafter. The time trends of the three percentile ratios reveal that this pattern mainly stems from the evolution of the upper part of the hourly wage distribution. In contrast, female wage inequality increased continuously over the entire period, by almost 20%, a trend that is explained by the constant widening of both the lower and upper halves of the wage distribution. Note that the bump in the trends observed in 1997–1998 seems to be related to the sudden and unexplained jump in the number of workers with undisclosed establishment identification numbers. Summary statistics for workers employed in the largest connected set are presented in Table A2.

TABLE A1 Summary statistics for samples of full-time men and women

	Men			Women		
		Log real hourly wage			Log real hourly wage	
	N	Mean	Std. dev.	*N*	Mean	Std. dev.
1982	280,726	5.061	0.281	96,797	4.790	0.237
1987	375,400	5.158	0.291	156,470	4.899	0.241
1992	396,348	5.220	0.302	202,424	4.995	0.254
1997	570,757	5.180	0.298	290,138	4.982	0.257
2002	615,612	5.236	0.311	343,485	5.051	0.276
2007	646,726	5.285	0.314	419,875	5.110	0.280



(a) Men (b) Women

FIGURE A1 Trends in wage inequality for (a) male and (b) female workers. Note: Normalized i/j p-ratio is the ith/jth percentile log wage differential. Normalization is obtained by dividing the log wage differential by the corresponding percentile differential of a standard normal random variable

TABLE A2 Summary statistics for full sample and individuals in largest connected set, all workers

	All full-time workers, age 20–60				Workers in largest connected set			
Interval	*N*	# Workers	Mean	Std. dev.	*N*	# Workers	Mean	Std. dev.
1982–1988	3,300,606	849,423	5.037	0.301	3,030,139	768,861	5.052	0.297
1988–1994	4,265,193	1,129,808	5.126	0.305	3,935,002	1,028,879	5.140	0.303
1994–2000	5,946,272	1,429,205	5.136	0.307	5,680,897	1,354,730	5.143	0.306
2000–2007	7,779,545	1,703,403	5.177	0.313	7,566,239	1,644,511	5.181	0.312

TABLE B1 Wage estimation results, fit by interval

	(1) Interval 1 1982–1988		(2) Interval 2 1988–1994		(3) Interval 3 1994–2000		(4) Interval 4 2000–2007	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
Workers and establishments								
Number of workers	545,159	223,702	690,197	338,682	871,824	482,906	998,546	645,965
Number of establishments	87,769	54,068	94,470	66,393	110,512	80,804	142,438	107,634
Summary of parameter estimates								
Std. dev. worker effects	0.240	0.217	0.255	0.225	0.251	0.222	0.257	0.234
Std. dev. establ. effects	0.128	0.128	0.131	0.131	0.121	0.123	0.119	0.121
Std. dev. Xb	0.098	0.096	0.070	0.070	0.087	0.086	0.092	0.093
Corr. worker/establ. effects	−0.156	−0.308	−0.130	−0.251	−0.047	−0.136	−0.017	−0.094
Corr. worker effects/Xb	−0.012	−0.102	0.091	0.024	−0.052	−0.005	−0.021	−0.045
Corr. establ. effects/Xb	0.040	0.012	0.003	−0.019	0.032	0.002	0.029	0.007
RMSE of AKM residual	0.082	0.073	0.082	0.071	0.088	0.077	0.098	0.086
Adjusted R^2	0.900	0.900	0.907	0.907	0.898	0.898	0.882	0.882
Comparison match model								
RMSE of match model	0.067	0.061	0.066	0.058	0.070	0.062	0.076	0.066
Adjusted R^2	0.920	0.920	0.927	0.927	0.924	0.924	0.916	0.916
Std. dev. match effects	0.047	0.040	0.049	0.041	0.053	0.046	0.062	0.055
Addendum								
Std. dev. log wages	0.284	0.234	0.297	0.252	0.305	0.264	0.312	0.280
Sample size	2,201,764	828,375	2,677,653	1,257,349	3,777,319	1,903,578	4,843,787	2,722,452

Note: The standard deviations and correlations are calculated across worker-year observations. The time-varying observables X include year dummies and a quadratic and cubic term in age, all interacted with education dummies. The match model includes the time-varying observables X and a dummy for each worker-establishment match. The standard deviation of the match effects is calculated as the square root of the difference in mean squared errors between the AKM (Abowd et al., 1999) model and the match effect model.

APPENDIX B: WAGE ESTIMATION RESULTS

As shown in Table B1, worker heterogeneity, measured by the standard deviation of the worker fixed effects, increased slightly but steadily over the four intervals, from 0.240 to 0.257 for male workers, and from 0.217 to 0.234 for female workers. Moreover, the correlation between worker and establishment effects increased considerably over time, and this rise also is observed among both male and female workers.[19] These two results are in line with the patterns documented by Card et al. (2013) for the case of Germany. In contrast, I find that the standard deviation of establishment effects is roughly stable over time. Hence, contrary to Card et al. (2013), establishment effects did not become more variable over time in Denmark.

Note that, as argued by Card et al. (2013), the two-way fixed-effect additive specification seems to approximate the wage structure relatively well. Indeed, a worker-establishment match model, which includes the time-varying observables and a dummy for each worker-establishment pair, features a smaller RMSE and a larger adjusted R^2 compared to the AKM (Abowd et al., 1999) wage model, but the increase in explanatory power is rather moderate. However, the standard deviation of the match effects, calculated as the square root of the difference in mean squared errors between the AKM (Abowd et al., 1999) and the match effect models, increased from 0.047 to 0.062 for male workers. This means that the relative fit of the AKM (Abowd et al., 1999) model deteriorated over time, while the standard deviation of the worker effects increased. The risk of model misspecification might therefore be a bigger concern in Denmark compared to Germany, since the simultaneous increase in the standard deviation of both the match effects and the worker effects might suggest that the orthogonality condition necessary to estimate the AKM (Abowd et al., 1999) wage model does not hold. See Abowd et al. (2019) for tests of this assumption and evaluation of the bias in fixed-effects estimates arising from endogenous job mobility. See Woodcock (2008) and Eeckhout and Kircher (2011) for discussions on the potential match effects in the formation of wages.

[19] Except for Abowd et al. (1999), all subsequent studies that did not implement any bias correction have documented either a negative correlation or a correlation close to zero (Bagger et al., 2013; Goux & Maurin, 1999; Gruetter & Lalive, 2009).

APPENDIX C: ROBUSTNESS CHECKS

C.1 | High and low wages

TABLE C1 Variance decomposition, interval 1 to 4

	Interval 1 1982–1988		Interval 4 2000–2007		Change from interval 1 to 4	
	(1) Value	(2) %	(3) Value	(4) %	(5) Change	(6) %
Men						
Variance of log wages	0.097	100.0	0.116	100.0	0.019	100.0
Variance of worker effect	0.070	72.3	0.079	68.1	0.009	49.7
Variance of establ. effect	0.018	19.0	0.016	14.0	−0.002	−11.0
Variance of Xb	0.011	11.3	0.010	8.6	−0.001	−5.6
Variance of residual	0.007	7.7	0.011	9.4	0.003	17.7
2cov(worker, establ.)	−0.010	−10.1	−0.001	−0.5	0.009	47.9
2cov(worker, Xb)	−0.002	−1.6	−0.001	−0.9	0.001	2.8
2cov(establ., Xb)	0.001	1.1	0.001	0.7	0.000	−1.3
Women						
Variance of log wages	0.064	100.0	0.085	100.0	0.021	100.0
Variance of worker effect	0.054	84.5	0.060	70.5	0.006	29.1
Variance of establ. effect	0.019	30.6	0.017	20.1	−0.002	−11.0
Variance of Xb	0.011	17.0	0.010	12.0	−0.001	−2.7
Variance of residual	0.006	9.3	0.008	9.6	0.002	10.4
2cov(worker, establ.)	−0.020	−31.4	−0.007	−8.6	0.013	59.0
2cov(worker, Xb)	−0.006	−9.9	−0.003	−3.5	0.003	15.5
2cov(establ., Xb)	0.000	0.8	−0.000	0.3	0.000	−1.0

Note: The variances and covariances are calculated across worker-year observations. The time-varying observables X include year dummies and a quadratic and cubic term in age, all interacted with education dummies. The bottom and top percentiles of the hourly wage distribution are capped at the 1st and 99th percentile values, respectively.

C.2 | Bias correction

TABLE C2 Within- and between-establishment variance decomposition, interval 1 to 4

	Interval 1 1982–1988		Interval 4 2000–2007		Change from interval 1 to 4	
	(1) Value	(2) %	(3) Value	(4) %	(5) Change	(6) %
Men						
Variance of log wages	0.097	100.0	0.116	100.0	0.019	100.0
Between-establishment variance	0.037	38.6	0.049	42.4	0.012	61.7
var($\bar{\alpha}$)	0.024	24.7	0.026	22.6	0.002	11.7
var(Ψ)	0.018	19.0	0.016	14.0	−0.002	−11.0
var($\bar{Xb}$)	0.002	2.2	0.002	1.7	0.000	−0.6
2cov($\bar{\alpha}, \Psi$)	−0.010	−10.1	−0.001	−0.5	0.009	48.0
2cov($\bar{\alpha}, \bar{Xb}$)	0.002	1.7	0.004	3.9	0.003	15.0
2cov($\Psi, \bar{Xb}$)	0.001	1.1	0.001	0.7	−0.000	−1.3
Within-establishment variance	0.059	61.3	0.066	57.5	0.007	37.8
var($\alpha - \bar{\alpha}$)	0.046	47.6	0.053	46.0	0.007	38.0
var($Xb - \bar{Xb}$)	0.009	9.2	0.008	6.8	−0.001	−5.0
var(ϵ)	0.007	7.7	0.011	9.4	0.003	17.7
2cov($\alpha - \bar{\alpha}, Xb - \bar{Xb}$)	−0.003	−3.3	−0.005	−4.8	0.000	−12.3
2cov($\alpha - \bar{\alpha}, \epsilon$)	−0.000	−0.0	0.000	0.0	−0.000	−0.1
2cov($Xb - \bar{Xb}, \epsilon$)	0.000	0.2	0.000	0.0	−0.000	−0.6

TABLE C2 Continued

	Interval 1 1982–1988		Interval 4 2000–2007		Change from interval 1 to 4	
	(1) Value	(2) %	(3) Value	(4) %	(5) Change	(6) %
Women						
Variance of log wages	0.064	100.0	0.085	100.0	0.021	100.0
Between-establishment variance	0.027	42.7	0.036	41.9	0.008	39.7
$\text{var}(\bar{\alpha})$	0.025	39.8	0.021	24.8	−0.004	−19.9
$\text{var}(\Psi)$	0.019	30.6	0.017	20.1	−0.002	−11.0
$\text{var}(\bar{Xb})$	0.002	3.8	0.002	2.6	−0.000	−0.9
$2\text{cov}(\bar{\alpha}, \Psi)$	−0.020	−31.4	−0.007	−8.6	0.016	59.0
$2\text{cov}(\bar{\alpha}, \bar{Xb})$	−0.001	−0.8	0.002	2.8	0.002	13.5
$2\text{cov}(\Psi, \bar{Xb})$	0.000	0.8	0.000	0.3	−0.000	−1.0
Within-establishment variance	0.036	57.3	0.049	58.1	0.013	60.5
$\text{var}(\alpha - \bar{\alpha})$	0.028	44.6	0.039	45.7	0.010	49.0
$\text{var}(Xb - \bar{Xb})$	0.008	13.2	0.008	9.4	−0.000	−1.8
$\text{var}(\epsilon)$	0.006	9.3	0.008	9.6	0.002	10.4
$2\text{cov}(\alpha - \bar{\alpha}, Xb - \bar{Xb})$	−0.006	−9.0	−0.005	−6.2	0.003	2.1
$2\text{cov}(\alpha - \bar{\alpha}, \epsilon)$	−0.000	−0.3	−0.000	−0.3	−0.000	−0.1
$2\text{cov}(Xb - \bar{Xb}, \epsilon)$	−0.000	−0.4	−0.000	−0.1	0.000	1.0

Note: The variances and covariances are calculated across worker-year observations. The time-varying observables X include year dummies and a quadratic and cubic term in age, all interacted with education dummies. $\bar{Xb}$ denotes the within-establishment average of the effect of time-varying observables. The bottom and top percentiles of the hourly wage distribution are capped at the 1st and 99th percentile values, respectively.

TABLE C3 Variance decomposition, interval 1 to 4

	Interval 1 1982–1988		Interval 4 2000–2007		Change from interval 1 to 4	
	(1) Value	(2) %	(3) Value	(4) %	(5) Change	(6) %
Men						
Variance of log wages	0.080	100.0	0.095	100.0	0.015	100.0
Variance of worker effect	0.053	66.7	0.064	67.8	0.011	73.2
Variance of establ. effect	0.011	13.9	0.012	12.8	0.001	7.2
2cov(worker, establ.)	0.002	1.9	0.004	4.3	0.003	16.2
Women						
Variance of log wages	0.059	100.0	0.077	100.0	0.018	100.0
Variance of worker effect	0.045	76.3	0.054	70.0	0.009	49.8
Variance of establ. effect	0.012	19.6	0.012	15.0	0.000	0.3
2cov(worker, establ.)	0.000	0.0	0.003	3.9	0.003	16.3

Note: The variances and covariances are calculated across worker-year observations. The time-varying observables X include year dummies and a quadratic and cubic term in age, all interacted with education dummies. The linear wage equation is estimated on the leave-one-out subsample.