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What drives the convergence in male and female wage distributions in Israel? A Shapley decomposition approach

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What drives the convergence in male and female wage distributions in Israel? A Shapley decomposition approach

Ayal Kimhi[1] and Nirit Hanuka-Taflia[2]

Abstract

We examine the drivers of the convergence of the hourly wage distributions of males and females in Israel between 1995 and 2008. Israel is an interesting case study in this respect, since it experienced declining wage inequality in recent decades, as opposed to most developed countries. We found convergence of both average wages and wage inequality. In particular, average wages increased faster for females than for males, while wage inequality declined faster for males than for females. We decomposed these distributional changes into the contributions of worker and job attributes, the returns on these attributes and residuals using a Shapley approach applied to counterfactual simulated wage distributions. We found that most of the increase in male wages was due to the increased wage gaps in favor of specific occupations and industries, while female wages increased mostly due to the increase in the returns to experience. The decline in wage inequality was driven mostly by changes in attributes, the decline in the returns to education, and the catching-up of immigrant workers, and each of these components was stronger for males than for females. We conclude that the convergence of the male and female wage distributions was due to both changes in the supply of labor, especially among females, and changes in the demand for labor leading to changes in the returns to various skills.

Introduction

Income inequality has been on the rise in most developed countries in recent decades. Israel is no exception in this regard, and Israeli income inequality is currently one of the highest among Western countries (Ben David, 2015, p. 10; OECD, 2013, p. 54). The labor market is often blamed for the high and rising income inequality, despite the fact that the labor share is on a downward trend in recent years (International Labor Organization, 2015). In fact, in many developed countries, including the US (Autor, Katz and Kearney, 2008), UK (Machin, 2011), Canada (Fortin et al., 2012), Australia (Chatterjee, Singh and Stone, 2016), Germany (Ehrl, 2017), Italy

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(Devicienti, 2010) and Israel (Deutsch and Silber, 2008), wage inequality has increased over time. It makes sense to put a high weight on wage inequality when one tries to explain the rise in overall income inequality, because in developed countries, wage income is the major income source for most households. However, the results of Deutsch and Silber (2008) for Israel pertain to the 1990s, and there is more recent evidence that the upward trend of wage inequality has been reversed during the early 2000s (Kimhi and Shraberman, 2014).

One possible explanation for the recent decline in wage inequality in Israel is the expansion of higher education. However, wage gaps between more and less educated workers have increased quite significantly in the last decade (Ben-David and Kimhi, 2017). A more plausible explanation is the decreasing gender wage gap. The gender wage gap has declined in many countries due to multiple supply and demand factors, including increases in women's educational attainments (Goldin, 2014), decreases in the gender gap in cumulative work experience due to more continuous careers of women (Blau and Kahn, 2017), a more equal sharing of household tasks (Bertrand, 2018), increased demand for female-oriented social skills in high-wage occupations (Cortes, Jaimovich and Siu, 2018), and decreases in statistical discrimination against women (Gayle and Golan, 2012).

Ponthieux and Meurs (2015) suggested a link from overall wage inequality to the gender wage gap. They showed that the gender wage gap in Israel is one of the highest in the OECD. Fuchs (2016) reported that the gender gap in hourly wage has decreased in the majority of OECD countries during 2000-2014, but the decline in Israel was relatively modest compared to the OECD average. However, changes in the gap between average or median wage of males and females may not be sufficient to explain overall changes in wage inequality (Dolton and Makepeace, 1985; Jenkins, 1994; del Río, Gradín and Cantó, 2011). Rather, one has to consider higher moments of the wage distributions. Hence, a complementary research question is what happened to within-gender wage inequality. This question did not receive sufficient attention in the economic literature, as far as we can tell. Among the few researchers that raised this question and dealt with it empirically, Papps (2010) found that during a period in which wage inequality in New Zealand increased and then decreased, within-gender wage inequality followed similar trends, while the male and female wage distributions converged to each other. Selezneva and Van Kerm (2016) showed that accounting for gender-specific wage inequality makes a considerable difference when comparing gender wage gaps in Eastern and Western Germany.

It makes sense to expect that male and female wage inequality will not behave similarly during a period in which female education and employment change compared to those of males. In particular, the increase in female education allow more women to advance in the wage ladder, while the increase in female labor force participation, especially of those with lower education, is likely to increase female wage inequality. Hence, a decrease in the gender wage gap coupled with a relative increase in female wage inequality may affect overall wage inequality in opposite directions.

In this paper, we analyze the changes in the male and female hourly wage distributions in Israel between 1995 and 2008, and the determinants of these changes, using population census data for these years.[3] In addition to the mean wage, we look at several inequality indices including the Gini index, the coefficient of variation, and Theil's entropy index. We decompose the changes in each of these indices into various components by applying the Shapley approach to counterfactual wage distributions. We start by decomposing the changes into the contributions of changes in attributes, changes in coefficients, and changes in unobserved factors, and then further decompose the changes in coefficients into more detailed components related to subgroups of coefficients.

The period under investigation has been affected by notable changes in the Israeli economy in general and in the labor market in particular. The mass migration of mostly mature and highly educated people from the Former Soviet Union during the 1990s has been a challenge but also an opportunity (Paserman, 2013). The recession of the early 2000s due to the Palestinian uprising and the dot-com crisis ended with significant changes in government policy towards privatization of public services and weaker social safety nets, and the subsequent deterioration of worker protection made labor markets much more flexible, for better and for worse. The expansion of higher-education institutions since the early 1990s has led to an inflow of educated young workers into the labor market. At the same time, the labor market shifted towards service industries and white-collar occupations, mostly due to demand factors (Kimhi and Shraberman, 2014). Altogether, the increases in female educational attainment and employment were faster than in many other developed countries (Kimhi, 2012). All these have obvious implications for wage distributions.

In 1995, the hourly wage of full-time male employees was 24% higher than that of females. By 2008, male wages increased by 13% in real terms while female wages increased by 21%, and the male-female wage gap declined to 17%. The fastest wage growth has been observed at relatively younger ages, 25-34 for males and 35-44 for females, indicating that the new cohorts entering the labor market are responsible for much of the changes in the wage distributions. For both males and females, all inequality indices (squared CV, Gini and Theil) have declined, but male wage inequality decreased faster than female wage inequality. Altogether, these trends indicate a convergence of the male and female wage distributions.

Our methodology is composed of the following steps. First, we estimate separate Mincerian log-wage regressions for males and females in each of the periods. Then, we compute counterfactual wage distributions for several combinations of changes in attributes, changes in coefficients and changes in residuals, using the reweighting

[3] The advantage of using population censuses is the large sample sizes that allow a better coverage of the population, compared to the income surveys that are based on relatively small samples.

kernel density approach proposed by DiNardo, Fortin and Lemieux (1996) and also used by Lemieux (2002), by Daly and Valletta (2006) and by Autor, Katz and Kearney (2008).[4] Finally, we decompose changes in the mean wage and several inequality indicators into components related to changes in personal attributes, changes in the prices of these attributes (the regression coefficients) and changes in residual inequality, using the Shapley approach proposed by Shorrocks (2013) and used subsequently by Devicienti (2010) and Ehrl (2017).

To the best of our knowledge, this is the first application of the Shapley approach in the analysis of changes in gender-specific wage distributions. The application to Israeli data can highlight distinct aspects of the convergence of the male and female wage distributions, because Israel is one of the only developed countries in which wage inequality declined in recent decades.

The following section describes the empirical methodology. After that we present the data we use in this research. In the next section we present the results of the regression analysis and the estimated counterfactual distributions. Then we describe the Shapley decomposition results. The final section concludes with a discussion of the findings and their implications.

Methodology

Regressions have been used for decades in order to decompose differences or changes in outcomes into differences or changes in observable and unobservable factors. In the context of wages, Oaxaca (1973) and Blinder (1973) decomposed differences in average wages between two population groups into differences in average attributes and differences in regression coefficients, the latter considered as “prices” of the attributes. A slightly modified version was used by Neuman and Oaxaca (2005), who found that gender wage differential are larger than ethnic wage differentials in Israel, and that gender wage differentials still exist after holding observable attributes equal.

DiNardo, Fortin and Lemieux (1996) went beyond the decomposition of changes in mean wages, and introduced a method to decompose shifts in the entire wage distribution using counterfactual simulations. Consider each observation to be composed of the logarithm of hourly wage (y), a vector of observable wage determinants (x) and calendar time (t). Each observation belongs to a joint distribution $F(y,x,t)$. The density function of y at a given time t can be computed as:

$$(1) \quad f(y \mid t_y = t, t_x = t) = \int_{x \in \Omega_x} f(y \mid x, t_y = t)\, dF(x \mid t_x = t)$$

Where Ω_x is the domain of definition of x. Our decomposition analysis is based on a comparison of a simulated counterfactual distribution to an estimate of the original

[4] Picchio, M., Mussida, C. (2011) offered an extension to the DiNardo, Fortin and Lemieux (1996) that includes correcting for selectivity into employment.

distribution. The density function in (1) can be estimated nonparametrically using a kernel density estimation technique. For the counterfactual distributions, consider two time periods, 1995 and 2008, corresponding to our census years, and define the counterfactual density of y in 2008 holding x at its 1995 values as:

$$(2)\quad f(y \mid t_y = 08,\ t_x = 95) = \int f(y \mid x, t_y = 08)\ dF(x \mid t_x = 95)$$
$$= \int f(y \mid x, t_y = 08) \psi_x dF(x \mid t_x = 08)$$

where:

$$(3)\qquad \psi_x(x) = dF(x \mid t_x = 95) / dF(x \mid t_x = 08)$$

In (2), ψ_x is a reweighting function, giving each value of x in 2008 its corresponding weight in the 1995 distribution. In other words, (2) can be estimated nonparametrically just as the actual 2008 wage distribution is estimated, but using ψ_x as sampling weights.

To estimate ψ_x, one can write, using Bayes' rule:

$$dF(x \mid t_x = t) = \Pr(x \mid t_x = t) = \Pr(t_x = t \mid x)\Pr(x) / \Pr(t_x = t)$$

and hence (3) can be written as

$$(4)\qquad \psi_x = \frac{\dfrac{\Pr(t_x = 95 \mid x)}{\Pr(t_x = 95)}}{\dfrac{\Pr(t_x = 08 \mid x)}{\Pr(t_x = 08)}} = \frac{\Pr(t_x = 95 \mid x)}{\Pr(t_x = 08 \mid x)} \cdot \frac{\Pr(t_x = 08)}{\Pr(t_x = 95)}$$

Estimating (4) is quite simple. $\Pr(t_x = 95 \mid x)$ can be estimated by a binary choice model (such as logit or probit) applied to the pooled 1995 and 2008 data set, where the dependent variable is a dummy which assumes the value of one for 1995 observations and zero otherwise, and the explanatory variables include x but could include other covariates and interactions in order to obtain a better fit. $\Pr(t_x = 08 \mid x)$ is simply computed by 1- $\Pr(t_x = 95 \mid x)$. Finally, $\Pr(t_x = 08)$ is the fraction of 2008 observations in the pooled data set, and $\Pr(t_x = 95) = 1 - \Pr(t_x = 08)$.

The next step is to consider changes in the distribution of wages. For this, a Mincerian log-wage equation of the form $y_{it} = x_{it}\beta_t + u_{it}$ is estimated separately for t=1995 and t=2008. Hence, the changes in the distribution of log-wages can be summarized by the changes in attributes x_{it}, the changes in the vector of coefficients β_t and the changes in the distribution of the residuals u_{it}. The counterfactual log-wage distribution $f(y \mid t_x = 08, t_b = 95, t_u = 08)$ can be computed as the sum of predicted log-wages in 2008 using the 1995 coefficients and 2008 residuals. To account for the changes in the distribution of the residuals, we follow Lemieux (2002) and divide each of the residual vectors into K intervals with equal number of observations. Then we compute the average residual for each interval k in, say, 1995 and assign it to each 2008 observation whose residual belongs to interval k. This way we can compute the counterfactual $f(y \mid t_x = 08, t_b = 08, t_u = 95)$. A combination of the last two procedures yields the counterfactual $f(y \mid t_x = 08, t_b = 95, t_u = 95)$. Finally, the weighting methodology used to derive the counterfactual in (2) can be applied together with the two previous derivations to obtain $f(y \mid t_x = 95, t_b = 08, t_u = 95)$ and $f(y \mid t_x = 95, t_b = 95, t_u = 95)$.

We are now in a position to decompose the change in the density function of log-wages into three components: (i) the contribution of the changes in wage determinants, (ii) the contribution of the changes in regression coefficients, and (iii) the contribution of the changes in the residual distribution:

$$
\begin{aligned}
(5)\quad & f_{08} - f_{95} \\
&= [f(y;t_x = 08, t_b = 08, t_u = 08) - f(y;t_x = 95, t_b = 08, t_u = 08)] \quad \text{i} \\
&+ [f(y;t_x = 95, t_b = 08, t_u = 08) - f(y;t_x = 95, t_b = 95, t_u = 08)] \quad \text{ii} \\
&+ [f(y;t_x = 95, t_b = 95, t_u = 08) - f(y;t_x = 95, t_b = 95, t_u = 95)] \quad \text{iii}
\end{aligned}
$$

Note that the order in which these changes are computed matters. For example, there is no good reason not to compute the contribution of the change in the residual distribution (iii) as $f(y \mid t_x = 95, t_b = 08, t_u = 08) - f(y \mid t_x = 95, t_b = 08, t_u = 95)$. Devicienti (2010) suggested using the Shapley approach to deal with this problem. The Shapley approach (Shorrocks, 2013) entails taking the average of all possible orderings. It our case, there are six different possibilities to order the three different changes: (x,b,u); (x,u,b); (b,x,u); (u,x,b); (b,u,x); (u,b,x).

Suppose that I is an index of interest (mean, inequality index, etc.) which is a function of the density $f(y)$. Let I_{95} and I_{08} be the values of the index in the two time periods, and let $\Delta I = I_{08} - I_{95}$. By analogy to (5), ΔI can be broken into the contribution of the changes in wage determinants, $C_{\Delta x}$, the contribution of the changes in regression coefficients, $C_{\Delta b}$, and the contribution of the changes in the residual distribution, $C_{\Delta u}$, so that $\Delta I = C_{\Delta x} + C_{\Delta b} + C_{\Delta u}$. Each of these components can be computed using the Shapley approach. For example, the Shapley computation of $C_{\Delta x}$ is:

$$
\begin{aligned}
(6)\qquad C_{\Delta x} &= \frac{2}{6}\{[I_{08}] - [\tilde{I}_{95}(x_{95}, b_{08}, u_{08})]\} \\
&+ \frac{1}{6}\{[\tilde{I}_{08}(x_{08}, b_{95}, u_{08})] - [\tilde{I}_{95}(x_{95}, b_{95}, u_{08})]\} \\
&+ \frac{1}{6}\{[\tilde{I}_{08}(x_{08}, b_{08}, u_{95})] - [\tilde{I}_{95}(x_{95}, b_{08}, u_{95})]\} \\
&+ \frac{2}{6}\{[\tilde{I}_{08}(x_{08}, b_{95}, u_{95})] - [I_{95}]\}
\end{aligned}
$$

where $\tilde{I}$ indicates that the index is computed using the counterfactual density. Note that the first line and the last line have a double weight because the order of b and u

does not matter in each of them, so that each of them represents two of the six possible orderings. The Shapley computation of $C_{\Delta b}$ and $C_{\Delta u}$ can be performed accordingly.[5]

Data

The data we use in this research are taken from the two recent population censuses in Israel, 1995 and 2008. In each of the census years, a random sample of the households (20% in 1995 and 14% in 2008) were asked to report in detail the work and income of all household members. We focus on full-time hired employees between the ages of 25 to 65. In order to enter the sample, employees had to (a) work at least 35 hours in the week preceding the survey; (b) work in each of the 12 months preceding the survey; and (c) report their wage and not report self-employment income.[6] We excluded employees whose hourly wages were outside the range of 15-400 NIS (roughly $4-105) in 2008 prices. Altogether, we ended up with 85,464 men and 44,501 women in 1995 (comprising 65.8% and 34.2%, respectively, of the civilian labor force), and 98,323 men and 71,897 women in 2008 (57.6% and 42.4%, respectively).

Our main variable of interest is hourly wage, which is the monthly wage divided by monthly hours of work.[7] The average wage of males increased from 50.2 NIS ($13) in 1995 (in 2008 prices) to 56.9 NIS ($15) in 2008, an increase of 13.3%. The average wage of females increased from 40.4 NIS ($10.5) to 48.9 NIS ($12.9), an increase of 21%, during the same period. Hence, the gender wage differential has narrowed, from slightly over 24% in 1995 to slightly over 14% in 2008. Wage inequality has decreased for both males and females during the same period. For example, the coefficient of variation of hourly wages declined from 0.737 to 0.652 for males and from 0.642 to 0.611 for females.

The set of wage determinants include demographic, geographic and employment-related variables. The demographic variables include age and age-squared, years of schooling,[8] a set of ethnic origin dummies, and a dummy for recent immigrants. The ethnic origin dummies included a dummy for Arab Israelis, and additional dummies for Jewish Israelis depending on their country of origin. We differentiated between those born in an "Eastern" country (in Asia or Africa), those born in a "Western" country (in Europe, America or Oceania), and those born in Israel. The latter were further divided into those whose parents were born in an Eastern country, those whose parents were born in a Western country, those whose parents were born in Israel, and

[5] For other applications of the Shapley approach see for example Sastre and Trannoy (2002) and Deutsch and Silber (2006).
[6] The wages of those who have not worked in each of the 12 months preceding the census were significantly lower than the wages of those who did.
[7] Employees reported their weekly hours of work, and we multiplied them by 4.3.
[8] We experimented with a set of educational degree dummies instead of years of schooling, but the results were not very different.

those whose parents are of mixed origin. Ethnic origin still plays a role in labor market achievements in Israel, although less than in the past (Yitzhaki and Schechtman, 2009). Recent immigrants are those who immigrated since 1990 and acquired their education abroad. The year 1990 marks the beginning of the mass immigration from the FSU and to a lower extent from Ethiopia. We hypothesize that new immigrants take time to catch up with the native workers in terms of wages (Eckstein and Weiss, 2004). Although many of those immigrants were highly educated, their education was not always relevant to the Israeli labor market, and they also lacked language skills and social capital.[9]

The geographic variables include a set of regional dummies and a set of dummies reflecting the size of the municipality of residence in terms of population. These variables should capture differences between local labor markets. The employment-related variables include a set of occupational dummies and a set of industry dummies.

Table 1 provides descriptive statistics of the explanatory variables, as well as the mean wage in each category of each variable (except for the continuous variables of age and schooling). Figure 1 shows kernel density estimates of the log-wage distribution for both years, by gender. It is easy to see that both wage distributions shifted to the right, perhaps more so for females than for males.

Estimation results

The log-wage regression results are reported in table 2. The age coefficients imply an inverted-U age profiles of wages. The returns to schooling are higher for females, and have declined over time for both males and females. The decline could be due to the rise in the average schooling over time (table 1). Kimhi and Shraberman (2014) have found that the returns to schooling have risen over time because the increase in educational attainment was not sufficient to overcome the increased demand for human capital, but their analysis did not control for the full set of covariates. Wages are related to ethnic origin in various ways. Second-generation immigrants from western countries have higher wages compared to natives, while second-generation immigrants from eastern countries have lower wages compared to natives. These differences are smaller in 2008 than in 1995 and are smaller for females than for males. First-generation immigrants have lower wages in 1995 compared to natives, but these wage differences declined by 2008 and even reversed for females. Arabs earn lower wages, and between 1995 and 2008 the Jewish-Arab wage gap increased for males and decreased for females. New immigrants earn less than others who were

[9] Immigrants who arrived at young age and acquired their education in Israel had labor market achievements similar to native Israelis.

born in the same countries (mostly FSU and Ethiopia), but their wage penalty declined between 1995 and 2008.[10]

Regional differences in wages are observed for both males and females, with the central region leading the wage gradient for males while the Tel-Aviv region leading the wage gradient for females. Regional wage disparities seemed to have intensified between 1995 and 2008. Wages are also related to locality size in various ways. Residents of the smallest localities seem to have the highest wages, then come localities with 20-100 thousand residents, and then the largest localities. Wages are higher in managerial and academic occupations, technical occupations and clerical occupations, in this order. Occupational wage gaps are higher for females and are higher in 2008 than in 1995. Compared to public service industries, wages are higher in financial industries and the gap is larger for females than for males and increases from 1995 to 2008. Wages in production, sales and private service industries are lower (higher) than in public services in 1995 (2008).

Figures 2 and 3 show the counterfactual log-wage densities for males and females, respectively. It can be seen that the residual distribution did not change markedly over the years and its contribution to the change in the wage distribution is negligible (simulation A). The same is true about the change in attributes (simulations C and E) for males, while for females the change in attributes leads to a slight shift of the wage distribution to the right. The change in the coefficients shifted the wage distribution to the right (simulations B and F) for both males and females. The changes in attributes and coefficients combined accounts for virtually the entire shift of the wage distribution (simulation D).

Decomposition results

Table 3 describes the changes in the gender-specific wage distribution from 1995 to 2008, as obtained from the simulation results. It can be seen that most of the increase in mean wage is attributed to the changes in the regression coefficients (simulation B), while the changes in population attributes (simulation C) and residual distribution (simulation A) have led to only small increases in mean wage. This result is in line with most of the empirical literature on wage gap decompositions (e.g., Lemieux, 2002). From 1995 to 2008, the standard deviation of wages increased by 0.5% for males and by 16% for females. In both cases the increase was dominated by the changes in the regression coefficients (simulation B). The changes in the residual distributions (simulation A) also contributed to the increase in the standard deviation. Interestingly, the changes in attributes (simulation C) had a negative effect on the standards deviation of wages, especially in the case of males, where the negative effect of attributes and the positive effect of coefficients and residuals canceled each

[10] Since both recent immigrants and non-recent immigrants have the same coefficient for the ethnic origin dummy, the recent immigrant dummy measures the wage gap between them.

other almost completely. In the case of females, but the negative effect of attributes was small compared to the much larger positive effects of coefficients and residuals.[11]

All three inequality measures, namely the coefficient of variation, the Gini coefficient and the Theil index, declined between 1995 and 2008, and the decline was more pronounced in the case of males. Both the changes in attributes (simulation C) and the changes in coefficients (simulation B) contributed to the decline in wage inequality (except for the case of the effect of attributes on the Gini coefficient for females), while the changes in the residual distribution (simulation A) worked in the opposite direction but were not as strong. The exception is the case of the Gini coefficient for females, in which the effects in the opposite directions canceled each other almost completely. The finding that changes in coefficients account for the bulk of changes in inequality has been found in many earlier regression-based studies of changes in wage inequality, e.g. Juhn, Murphy, and Pierce (1993), Devicienti (2010), Papps (2010), and Lemieux (2002).

In table 4, we demonstrate the "path dependency" of the decomposition results. In particular, we report the four different ways of computing each of the decomposed components of the distributional changes, as in equation 6, using the different simulation results in table 3. While the differences among the different ways of computation are not dramatic, and in most cases do not display qualitative contradictions, they do diverge by a few percentage points. For example, the contribution of changes in male attributes to the CV and Theil inequality indices ranges from -9% to -11%. This is where the Shapley approach becomes useful.

The Shapley decomposition results appear in table 5. For each indicator we present three measures. The first is the level change in the indicator from 1995 to 2008. The second is a bootstrapped standard error of this change, and the third is the percentage change in the indicator. We first observe that all components, namely attributes, coefficients and residuals contributed positively to the change in mean wage. However, about 80% of the change is due to the changes in coefficients, for males and females alike. The changes in coefficients favored the mean female wage compared to the mean male wage, thereby lead to a decline in the gender wage gap. This is similar to the finding of Mussida and Picchio (2014) for Italy. In the case of the three inequality measures, the results of the Shapley decompositions indicate that the decline in wage inequality was driven by both changes in attributes and changes in coefficients. Changes in attributes were more important than changes in coefficients in the case of the coefficient of variation, while the opposite was true in the case of the Gini index. Changes in attributes and changes in coefficients contributed more equally to the decline of the Theil index. The contributions of the changes in residual inequality to the change in wage inequality were positive but smaller in magnitude so they were dominated by the changes in attributes and coefficients.

[11] Simulations D-F reinforce the findings of simulations A-C and hence we do not discuss them in detail to avoid repetition.

Table 6 shows a further decomposition of the contributions of the changes in coefficients into three parts: the coefficients of demographic attributes (age, schooling, ethnic origin and immigration status), the coefficients of geographic variables (region and size of locality), and the coefficients of professional attributes (industry and occupation). The changes in the professional coefficients accounted for most of the increase in mean wage for males. This is due to the increase in the returns to most occupations compared to skilled and unskilled workers and the increase in the returns to most industries compared to public and private services (table 2). For females, the changes in the coefficients of the demographic attributes were responsible for most of the increase in mean wage, while the changes in the professional coefficients also contributed positively but their contribution was relatively small. The changes in the coefficients of the geographic variables worked in the opposite direction, due to the increasing wage gaps between center and periphery (with the exception of the south – see table 2). Ehrl (2017) also found that changes in the returns to occupations were pivotal in explain wage inequality, but did not differentiate between males and females.

For both males and females, the changes in the demographic coefficients contributed to the decline in wage inequality, while the changes in the geographic and professional coefficients contributed to wage inequality in the opposite direction but to a smaller extent. Further decomposition of the contributions of the coefficients of the demographic attributes (table 6) reveals that the decrease in the returns to schooling and the catching-up of immigrant wages were the main drivers (among the changes in coefficients only) of the decrease in male wage inequality. In the case of females, the decrease in the wage penalty of immigrants was the most important factor among the changes in coefficients, while the decrease in the returns to schooling and the changes in the ethnicity coefficients also contributed negatively to wage inequality but to a lower magnitude. The changes in the age coefficients (interpreted as returns to experience) worked in the opposite direction and moderated the decrease in wage inequality due to changes in coefficients.

Returning to the case of mean wages, the further decomposition of the demographic coefficients reveals that for males, the small contribution of these coefficients was due to two opposite trends that moderated each other, namely a decline in mean wage due to the decline of the education premium and an increase in mean wage due to the increase in the experience premium. For females, the picture is qualitatively similar, but in this case the positive effect on mean wage resulting from the increase in the experience premium was much more dominant, rendering an overall positive effect of the changes in the demographic coefficients on mean wage. These results indicate that changes in work experience are likely to be important drivers of gender wage convergence, as indicated by earlier studies (e.g., Gayle and Golan, 2012; Blau and Kahn, 2017).

Conclusion

In this paper, we have analyzed the changes in the gender-specific wage distributions of full-time salaried employees in Israel, during a period of shrinking gender wage disparities (as in many developed countries) and declining wage inequality (as opposed to most developed countries). Between 1995 and 2008, the increase in mean wage was much stronger for females, while the decline in wage inequality, which was initially larger for males, was stronger for males. Altogether, the male and female wage distributions converged to each other.

In order to understand the drivers of these changes in the gender-specific wage distributions, we performed a decomposition exercise based on counterfactual distributions using the Shapley approach. In particular, we decomposed the changes in mean wages and in wage inequality into several components: changes in personal attributes, changes in the returns to these attributes, and changes in residual inequality. We found that most of the increase in male wages was due to the increase in the returns to specific occupations and industries, while female wages increased mostly due to the increase in the returns to experience. The decline in wage inequality was driven mostly by changes in attributes, the decline in the returns to education, and the catching-up of immigrant workers, and each of these components was stronger for males than for females.[12] Therefore, we conclude that the convergence of the male and female wage distributions was due to both changes in the supply of labor (especially among females) and changes in the demand for labor (that has resulted in changes in the returns to various skills).

This research can be extended in several directions. First, several authors (e.g., Neuman and Oaxaca, 2005; Chzhen and Mumford, 2011; Picchio and Mussida, 2011; Onozuka, 2016; Machado, 2017) have found that gender-specific changes in selection into full-time employment are potentially important to changes in wage distributions. Hence, we can add a labor supply module to our decomposition procedure, and thereby account for changes in hours of work as well as well as participation. This can also enable analyzing gender difference in total earnings distributions. Second, in many cases it was found that wage changes could be very different at different parts of the wage distribution (e.g., Papps, 2010; Kassenboehmer and Sinning, 2014; Blau and Kahn, 2017; Bertrand, 2018). The use of quantile regression results to simulate counterfactual wage distributions could be useful in that regard. Finally, we can extend the analysis to the household level and examine the changes in the household income distribution, accounting for the different roles of male and female wages and labor supply decisions.

[12] Ferro Luzzi and Silber (1998) used a different approach: decomposing the differences between male and female wages and then taking the difference across time periods. They found that in Switzerland most of the change in the male-female wage differential was due to the unobserved components of the wage equations.

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Table 1. Descriptive statistics

Variable	Males 1995 mean	Males 1995 Mean wage	Males 2008 mean	Males 2008 Mean wage	Females 1995 mean	Females 1995 Mean wage	Females 2008 mean	Females 2008 Mean wage
Age (years)	41.24		41.89		40.40		41.65	
Schooling (years)	12.74		13.74		13.32		14.38	
Country of origin								
Asia/Africa	0.19	47.55	0.08	54.95	0.17	35.55	0.08	44.81
Europe/America/Oceania	0.25	49.92	0.22	53.70	0.29	40.20	0.27	45.04
Israel, parents Asia/Africa	0.19	43.66	0.20	58.89	0.22	36.10	0.23	49.22
Israel, parents Europe/America/Oceania	0.14	71.78	0.10	76.45	0.14	51.54	0.10	60.82
Israel, Mixed (parents from different origins)	0.08	58.09	0.14	64.38	0.10	43.53	0.16	52.46
Israel, parents Israel/Jewish	0.04	56.76	0.11	63.26	0.05	43.70	0.12	50.68
Israel, parents Israel/Arab	0.11	31.45	0.16	36.60	0.02	28.82	0.04	37.79
Immigration status								
Immigrant since 1990 who acquired education abroad	0.13	30.13	0.16	45.07	0.13	26.98	0.20	38.31
Other	0.87	53.16	0.84	59.60	0.87	42.40	0.80	51.85
District								
Jerusalem	0.08	51.52	0.09	48.24	0.10	43.74	0.08	49.46
North	0.15	38.11	0.18	45.58	0.10	32.74	0.14	41.58
Haifa	0.15	51.17	0.12	56.46	0.14	40.21	0.11	47.18
Center	0.25	54.09	0.26	65.33	0.25	41.19	0.28	52.74
Tel Aviv	0.22	55.95	0.17	61.01	0.27	44.21	0.20	52.54
South	0.13	44.12	0.14	50.84	0.12	34.17	0.15	41.72
Judea & Samaria	0.02	53.33	0.04	61.87	0.02	39.00	0.04	48.37
Size of municipality								
200 thousand and above	0.19	55.84	0.26	56.78	0.23	45.08	0.28	50.55
100-200 thousand	0.26	49.95	0.15	52.90	0.28	39.24	0.18	45.48
50-100 thousand	0.13	53.75	0.12	63.70	0.12	41.70	0.12	52.02
20-50 thousand	0.19	47.91	0.20	52.49	0.18	37.86	0.19	45.46
10-20 thousand	0.08	40.92	0.07	55.47	0.06	35.45	0.05	50.36
2-10 thousand	0.09	47.58	0.07	64.12	0.06	41.06	0.05	53.65
Under 2,000	0.06	49.48	0.14	62.52	0.07	37.33	0.15	50.94
Occupation								
Managers and academic professionals	0.22	78.50	0.24	82.99	0.16	60.51	0.22	68.20
Associate professionals and technicians	0.09	55.85	0.12	65.04	0.14	47.18	0.17	53.59
Agents, sales workers and service workers	0.11	50.35	0.09	55.60	0.40	37.96	0.32	47.08
Clerical workers	0.09	41.20	0.13	45.47	0.13	29.70	0.18	35.35
Skilled and unskilled workers	0.47	37.44	0.38	42.06	0.15	28.10	0.10	29.70
Unknown occupation	0.02	57.36	0.04	61.09	0.01	47.24	0.02	55.67
Industry								
Manufacturing, construction, agriculture, electricity, water	0.37	47.17	0.35	55.38	0.20	35.20	0.15	46.67
Trade, repairs, transport, storage, communication	0.25	41.79	0.25	48.19	0.17	32.88	0.19	40.09
Banking and business activities	0.12	62.59	0.17	70.37	0.14	47.97	0.21	58.09
Public and private services	0.25	57.93	0.19	58.12	0.49	43.06	0.42	49.02
Unknown industry	0.02	43.70	0.04	60.52	0.01	34.71	0.03	51.13

Table 2. Regression results, log hourly wage

	Males		Females	
	1995	2008	1995	2008
Age (years)	0.0625***	0.0684***	0.0492***	0.0665***
	(48.89)	(53.27)	(28.62)	(47.78)
Age (years) squared	-0.0006***	-0.0007***	-0.0005***	-0.0006***
	(-40.26)	(-45.44)	(-22.88)	(-39.10)
Schooling (years)	0.0372***	0.0248***	0.0410***	0.0364***
	(66.45)	(45.66)	(50.83)	(56.81)
Asia/Africa	-0.0918***	-0.00659	-0.0631***	0.0202*
	(-10.58)	(-0.85)	(-6.11)	(2.54)
Europe/America/Oceania	-0.0354***	0.00442	-0.0163	0.0109
	(-4.06)	(0.62)	(-1.63)	(1.54)
Israel, parents Asia/Africa	-0.0786***	-0.0258***	-0.0340***	-0.0177**
	(-9.39)	(-4.18)	(-3.54)	(-2.89)
Israel, parents Europe/America/Oceania	0.0531***	0.0408***	0.0403***	0.0299***
	(6.12)	(5.69)	(3.97)	(4.11)
Israel, Mixed (parents from different origins)	0.0138	0.00298	0.0132	0.00155
	(1.48)	(0.47)	(1.25)	(0.25)
Israel, parents Israel/Arab	-0.245***	-0.260***	-0.194***	-0.142***
	(-25.82)	(-36.92)	(-12.19)	(-14.66)
Immigrant since 1990 / education abroad	-0.516***	-0.266***	-0.410***	-0.238***
	(-88.35)	(-45.00)	(-56.30)	(-40.01)
Jerusalem	-0.0516***	-0.0928***	-0.0374***	-0.0480***
	(-7.13)	(-13.35)	(-4.52)	(-6.75)
North	-0.0670***	-0.109***	-0.135***	-0.150***
	(-10.13)	(-16.69)	(-15.35)	(-21.22)
Haifa	0.0057	-0.0316***	-0.0741***	-0.0991***
	(0.99)	(-5.19)	(-10.48)	(-15.98)
Center	0.0124*	0.0426***	-0.0233***	-0.00917
	(2.49)	(8.91)	(-3.88)	(-1.95)
South	-0.0124*	-0.0286***	-0.105***	-0.107***
	(-2.11)	(-4.92)	(-14.39)	(-18.30)
Judea & Samaria	0.000158	-0.106***	-0.0137	-0.0922***
	(0.01)	(-10.33)	(-0.92)	(-8.79)
100-200 thousand	-0.00743	-0.0492***	-0.0233***	-0.0453***
	(-1.24)	(-9.71)	(-3.34)	(-9.11)
50-100 thousand	0.0197**	0.0574***	-0.00416	0.0187***
	(2.87)	(10.66)	(-0.50)	(3.42)
20-50 thousand	0.00379	0.0174***	-0.00600	0.00315
	(0.63)	(3.54)	(-0.82)	(0.62)
10-20 thousand	-0.0309***	0.0746***	-0.0364***	0.0430***
	(-4.04)	(10.55)	(-3.56)	(5.29)
2-10 thousand	0.0432***	0.123***	0.0247*	0.0598***
	(5.51)	(16.84)	(2.31)	(7.23)
Under 2,000	-0.0878***	0.0225**	-0.162***	-0.0170*
	(-10.51)	(3.27)	(-16.21)	(-2.38)

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Table 2 (continued)

	Males		Females	
	1995	**2008**	**1995**	**2008**
Managers and academic professionals	0.386***	0.445***	0.430***	0.528***
	(76.80)	(89.61)	(51.35)	(72.65)
Associate professionals and technicians	0.206***	0.308***	0.302***	0.400***
	(33.73)	(54.69)	(37.41)	(55.05)
Clerical workers	0.0944***	0.158***	0.143***	0.282***
	(17.07)	(27.17)	(21.53)	(43.98)
Agents, sales workers and service workers	-0.000338	0.0120*	-0.0187*	0.0941***
	(-0.06)	(2.29)	(-2.34)	(13.72)
Unknown occupation	0.205***	0.246***	0.294***	0.394***
	(15.94)	(29.44)	(13.91)	(29.08)
Manufacturing, construction, agriculture, etc.	-0.00158	0.133***	-0.0155**	0.140***
	(-0.34)	(27.88)	(-2.63)	(26.50)
Trade, repairs, transport, storage, etc.	-0.00672	0.0329***	-0.0462***	0.0337***
	(-1.32)	(6.65)	(-7.70)	(7.16)
Banking and business activities	0.0738***	0.111***	0.0920***	0.178***
	(12.55)	(21.16)	(16.06)	(39.37)
Unknown industry	-0.0241*	0.0943***	-0.0102	0.101***
	(-2.55)	(11.11)	(-0.78)	(9.56)
Intercept	1.757***	1.749***	1.783***	1.358***
	(61.98)	(62.07)	(48.05)	(44.90)
Number of cases	85,464	98,323	44,501	71,897
R^2	0.410	0.341	0.376	0.356

t-statistics in parentheses; * significant at 5%; ** significant at 1%; *** significant at 0.1%.

Table 3. Changes in wage density characteristics

	X	b	U	Mean wage	Standard deviation	Inequality measures CV	Gini	Theil	N
Males									
1995	95	95	95	50.258	37.015	0.737	0.349	0.208	85,464
Simulation A	95	95	08	50.797	38.781	0.763	0.358	0.220	85,464
				(1.06%)	(4.71%)	(3.61%)	(2.52%)	(5.71%)	
Simulation B	95	08	95	55.899	39.252	0.702	0.334	0.191	85,464
				(11.20%)	(5.97%)	(-4.70%)	(-4.35%)	(-8.45%)	
Simulation C	08	95	95	51.130	33.769	0.660	0.341	0.187	98,323
				(1.73%)	(-8.61%)	(-10.16%)	(-2.55%)	(-9.99%)	
Simulation D	08	08	95	56.405	35.690	0.633	0.327	0.172	98,323
				(12.30%)	(-3.33%)	(-13.91%)	(-6.49%)	(-17.14%)	
Simulation E	08	95	08	51.617	35.049	0.679	0.349	0.197	98,323
				(2.69%)	(-5.16%)	(-7.65%)	(-0.29%)	(-5.52%)	
Simulation F	95	08	08	56.489	41.194	0.729	0.343	0.203	85,464
				(12.36%)	(11.16%)	(-1.07%)	(-1.74%)	(-2.85%)	
2008	08	08	08	56.939	37.118	0.652	0.335	0.182	98,323
				(13.35%)	(0.51%)	(-11.33%)	(-4.13%)	(-12.68%)	
Females									
1995	95	95	95	40.313	25.895	0.642	0.309	0.163	44,501
Simulation A	95	95	08	40.533	26.663	0.658	0.315	0.169	44,501
				(0.55%)	(2.93%)	(2.37%)	(1.73%)	(3.84%)	
Simulation B	95	08	95	46.724	29.541	0.632	0.304	0.157	44,501
				(15.86%)	(13.89%)	(-1.70%)	(-1.86%)	(-3.47%)	
Simulation C	08	95	95	41.752	25.515	0.611	0.313	0.159	71,897
				(3.31%)	(-1.39%)	(-4.54%)	(0.92%)	(-2.15%)	
Simulation D	08	08	95	48.539	29.052	0.599	0.304	0.151	71,897
				(20.10%)	(12.28%)	(-6.51%)	(-1.99%)	(-7.02%)	
Simulation E	08	95	08	41.961	26.142	0.623	0.318	0.165	71,897
				(3.82%)	(1.04%)	(-2.68%)	(2.49%)	(1.13%)	
Simulation F	95	08	08	46.980	30.447	0.648	0.309	0.164	44,501
				(16.49%)	(17.33%)	(0.72%)	(-0.10%)	(0.38%)	
2008	08	08	08	48.785	29.807	0.611	0.309	0.157	71,897
				(21.04%)	(15.83%)	(-4.30%)	(-0.34%)	(-3.51%)	

Note: All wages expressed in 2008 prices. Percentage changes from 1995 values in parentheses.

Table 4. All possible computations of wage density decomposition

	Mean wage	Standard deviation	Inequality measures		
			CV	Gini	Theil
Males					
<u>Attributes</u>					
Simulation C	1.73%	-8.61%	-10.16%	-2.55%	-9.99%
D-B	1.10%	-9.30%	-9.21%	-2.14%	-8.69%
E-A	1.63%	-9.87%	-11.26%	-2.81%	-11.23%
2008-C	0.99%	-10.65%	-10.26%	-2.39%	-9.83%
<u>Coefficients</u>					
Simulation B	11.20%	5.97%	-4.70%	-4.35%	-8.45%
D-C	10.57%	5.28%	-3.75%	-3.94%	-7.15%
F-A	11.30%	6.45%	-4.68%	-4.26%	-8.56%
2008-E	10.66%	5.67%	-3.68%	-3.84%	-7.16%
<u>Residuals</u>					
Simulation A	1.06%	4.71%	3.61%	2.52%	5.71%
E-C	0.96%	3.45%	2.51%	2.26%	4.47%
F-B	1.16%	5.19%	3.63%	2.61%	5.60%
2008-D	1.05%	3.84%	2.58%	2.36%	4.46%
Females					
<u>Attributes</u>					
Simulation C	3.31%	-1.39%	-4.54%	0.92%	-2.15%
D-B	4.24%	-1.61%	-4.81%	-0.13%	-3.55%
E-A	3.27%	-1.89%	-5.05%	0.76%	-2.71%
2008-C	4.55%	-1.50%	-5.02%	-0.24%	-3.89%
<u>Coefficients</u>					
Simulation B	15.86%	13.89%	-1.70%	-1.86%	-3.47%
D-C	16.79%	13.67%	-1.97%	-2.91%	-4.87%
F-A	15.94%	14.40%	-1.65%	-1.83%	-3.46%
2008-E	17.22%	14.79%	-1.62%	-2.83%	-4.64%
<u>Residuals</u>					
Simulation A	0.55%	2.93%	2.37%	1.73%	3.84%
E-C	0.51%	2.43%	1.86%	1.57%	3.28%
F-B	0.63%	3.44%	2.42%	1.76%	3.85%
2008-D	0.94%	3.55%	2.21%	1.65%	3.51%

Table 5. Shapley decomposition results

	Attributes	Coefficients	Residuals	Total
Males				
Mean wage	0.682**	5.492**	0.533**	6.707**
S.D.	0.1804	0.0188	0.0046	0.1797
% change	(1.36%)	(10.93%)	(1.06%)	(13.35%)
CV	-0.075**	-0.031**	0.023**	-0.083**
S.D.	0.0041	0.0006	0.0002	0.0041
% change	(-10.22%)	(-4.20%)	(3.09%)	(-11.33%)
Gini	-0.009**	-0.014**	0.009**	-0.014**
S.D.	0.0011	0.0002	0.0000	0.0011
% change	(-2.47%)	(-4.10%)	(2.44%)	(-4.13%)
Theil	-0.021**	-0.016**	0.011**	-0.026**
S.D.	0.0016	0.0002	0.0001	0.0016
% change	(-9.93%)	(-7.82%)	(5.07%)	(-12.68%)
Females				
Mean wage	1.564**	6.660**	0.278**	8.502**
S.D.	0.1421	0.0423	0.0404	0.1790
% change	(3.87%)	(16.48%)	(0.69%)	(21.04%)
CV	-0.031**	-0.011**	0.014**	-0.028**
S.D.	0.0049	0.0011	0.0010	0.0054
% change	(-4.83%)	(-1.71%)	(2.24%)	(-4.30%)
Gini	0.001	-0.007**	0.005**	-0.001
S.D.	0.0012	0.0003	0.0003	0.0015
% change	(0.33%)	(-2.35%)	(1.68%)	(-0.34%)
Theil	-0.005**	-0.007**	0.006**	-0.006**
S.D.	0.0016	0.0004	0.0003	0.0018
% change	(-3.06%)	(-4.09%)	(3.64%)	(-3.51%)

Notes: the results are based on a bootstrap of 500 repetitions.
* (**) statistically significant at the 5% (1%) level.

Table 6. Shapley decomposition results including sub-groups of coefficients

A. Males

	Attributes	Demographic Coefficients	Geographic Coefficients	Professional Coefficients	Residuals	Total
Males						
Mean wage	0.673**	-0.647**	0.418**	5.733**	0.517**	6.695**
S.D.	0.1825	0.0157	0.0085	0.0140	0.0045	0.1829
% change	(1.34%)	(-1.29%)	(0.83%)	(11.41%)	(1.03%)	(13.33%)
CV	-0.072**	-0.047**	0.009**	0.009**	0.023**	-0.078**
S.D.	0.0040	0.0004	0.0003	0.0003	0.0002	0.0040
% change	(-9.74%)	(-6.46%)	(1.23%)	(1.22%)	(3.15%)	(-10.60%)
Gini	-0.007**	-0.021**	0.003**	0.004**	0.009**	-0.012**
S.D.	0.0011	0.0001	0.0001	0.0001	0.0000	0.0011
% change	(-2.15%)	(-5.93%)	(0.77%)	(1.26%)	(2.49%)	(-3.56%)
Theil	-0.019**	-0.024**	0.004**	0.005**	0.011**	-0.024**
S.D.	0.0015	0.0002	0.0001	0.0001	0.0001	0.0015
% change	(-9.21%)	(-11.58%)	(1.76%)	(2.34%)	(5.17%)	(-11.52%)
Females						
Mean wage	1.882**	13.444**	-7.854**	0.770**	0.266**	8.508**
S.D.	0.1945	0.0301	0.0167	0.0150	0.0030	0.1723
% change	(4.66%)	(33.26%)	(-19.43%)	(1.91%)	(0.66%)	(21.05%)
CV	-0.031**	-0.013**	0.002**	0.000	0.014**	-0.028**
S.D.	0.0055	0.0004	0.0004	0.0005	0.0002	0.0054
% change	(-4.78%)	(-2.03%)	(0.26%)	(0.01%)	(2.17%)	(-4.37%)
Gini	0.000	-0.008**	0.0003**	0.001**	0.005**	-0.0014
S.D.	0.0014	0.0001	0.0001	0.0001	0.0000	0.0014
% change	(0.10%)	(-2.52%)	(0.10%)	(0.17%)	(1.68%)	(-0.47%)
Theil	-0.005**	-0.007**	0.0004**	0.000	0.006**	-0.006**
S.D.	0.0018	0.0001	0.0001	0.0002	0.0001	0.0018
% change	(-3.32%)	(-4.48%)	(0.28%)	(0.18%)	(3.60%)	(-3.74%)

Notes: the results are based on a bootstrap of 500 repetitions.

* (**) statistically significant at the 5% (1%) level.

Table 7. Shapley decomposition results including sub-groups of demographic coefficients

	Attributes	Age Coefficients	Education Coefficients	Ethnicity Coefficients	Immigrant Coefficient	Other Coefficients	Residuals	Total
Males								
Mean wage	0.721**	5.973**	-9.604**	1.290**	1.378**	6.291**	0.536**	6.711**
S.D.	0.1691	0.0103	0.0202	0.0058	0.0096	0.0172	0.0046	0.1678
% change	(1.44%)	(11.89%)	(-19.12%)	(2.57%)	(2.74%)	(12.53%)	(1.07%)	(13.36%)
CV	-0.072**	-0.001**	-0.022**	-0.004**	-0.020**	0.015**	0.023**	-0.079**
S.D.	0.0042	0.0001	0.0002	0.0002	0.0002	0.0005	0.0002	0.0043
% change	(-9.84%)	(-0.10%)	(-2.96%)	(-0.59%)	(-2.69%)	(2.04%)	(3.11%)	(-10.70%)
Gini	-0.008**	0.000**	-0.009**	-0.001**	-0.010**	0.006**	0.009**	-0.013**
S.D.	0.0011	0.0000	0.0001	0.0001	0.0001	0.0001	0.0000	0.0011
% change	(-2.20%)	(-0.02%)	(-2.69%)	(-0.33%)	(-2.75%)	(1.79%)	(2.44%)	(-3.59%)
Theil	-0.019**	0.000**	-0.011**	-0.002**	-0.011**	0.007**	0.011**	-0.024**
S.D.	0.0016	0.0000	0.0001	0.0001	0.0001	0.0002	0.0001	0.0016
% change	(-9.34%)	(-0.09%)	(-5.47%)	(-0.81%)	(-5.14%)	(3.54%)	(5.09%)	(-11.62%)
Females								
Mean wage	1.947**	18.383**	-8.952**	-4.106**	-3.883**	4.712**	0.276**	8.515**
S.D.	0.2019	0.0383	0.0183	0.0110	0.0139	0.0179	0.0032	0.1706
% change	(4.82%)	(45.50%)	(-22.16%)	(-10.16%)	(-9.61%)	(11.66%)	(0.68%)	(21.08%)
CV	-0.030**	0.012**	-0.007**	-0.005**	-0.014**	0.001	0.014**	-0.028**
S.D.	0.0056	0.0002	0.0001	0.0002	0.0003	0.0006	0.0002	0.0055
% change	(-4.72%)	(1.80%)	(-1.04%)	(-0.75%)	(-2.12%)	(0.13%)	(2.17%)	(-4.38%)
Gini	0.001	0.005**	-0.003**	-0.002**	-0.007**	0.001**	0.005**	-0.0014
S.D.	0.0015	0.0001	0.0000	0.0001	0.0001	0.0001	0.0000	0.0015
% change	(0.18%)	(1.52%)	(-0.96%)	(-0.76%)	(-2.38%)	(0.24%)	(1.68%)	(-0.46%)
Theil	-0.005**	0.005**	-0.003**	-0.002**	-0.007**	0.001**	0.006**	-0.006**
S.D.	0.0018	0.0001	0.0001	0.0001	0.0001	0.0002	0.0001	0.0018
% change	(-3.20%)	(3.14%)	(-1.97%)	(-1.45%)	(-4.38%)	(0.33%)	(3.60%)	(-3.73%)

Notes: the results are based on a bootstrap of 500 repetitions. * (**) statistically significant at the 5% (1%) level.

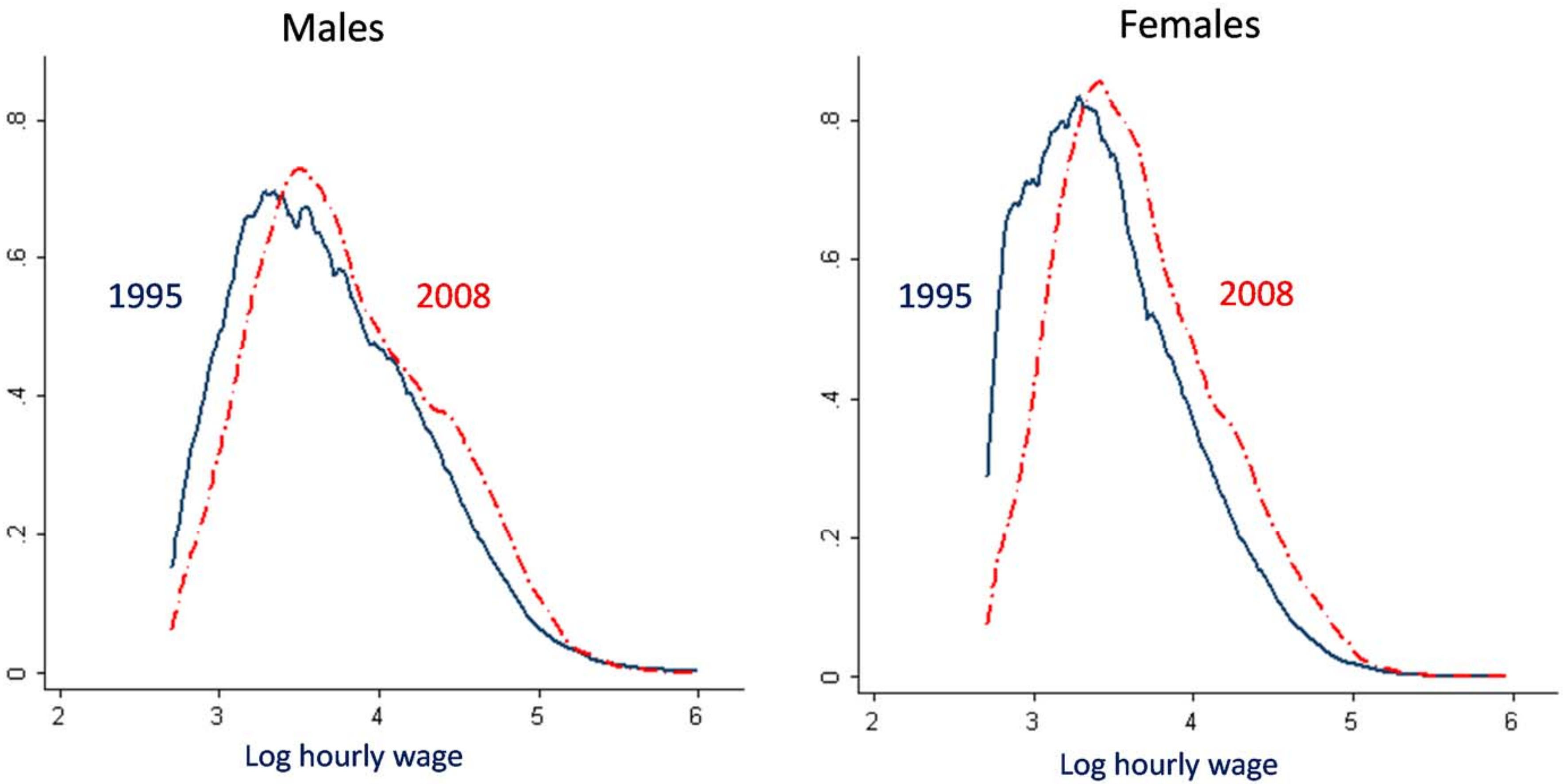
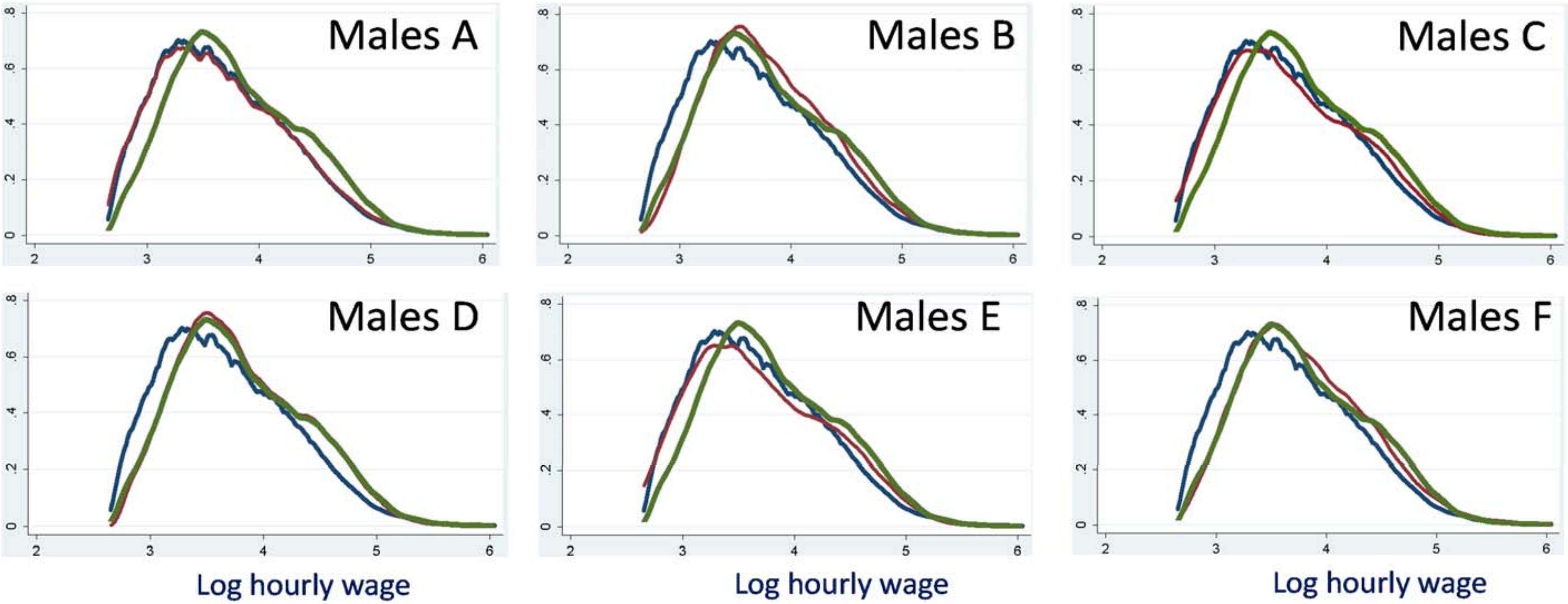


Figure 1. Kernel density estimates of the log-wage distribution

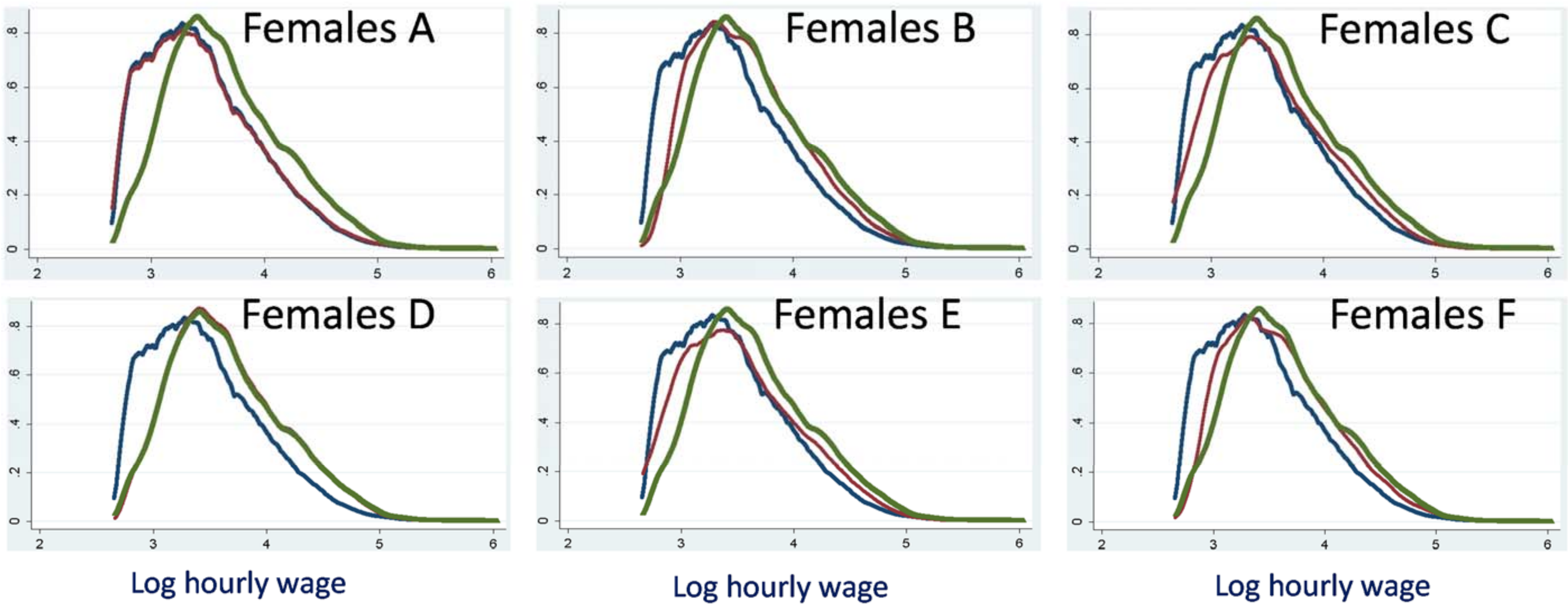


Actual density of 1995 wages
Counterfactual density
Actual density of 2008 wages

Definitions of simulations

	Attributes	Coefficients	Residual
Actual	'95	'95	'95
Simulation A	'95	'95	'08
Simulation B	'95	'08	'95
Simulation C	'08	'95	'95
Simulation D	'08	'08	'95
Simulation E	'08	'95	'08
Simulation F	'95	'08	'08

Figure 2. Actual and counterfactual density estimates of the log-wage distribution: males



Actual density of 1995 wages
Counterfactual density
Actual density of 2008 wages

Definitions of simulations

	Attributes	Coefficients	Residual
Actual	'95	'95	'95
Simulation A	'95	'95	'08
Simulation B	'95	'08	'95
Simulation C	'08	'95	'95
Simulation D	'08	'08	'95
Simulation E	'08	'95	'08
Simulation F	'95	'08	'08

Figure 3. Actual and counterfactual density estimates of the log-wage distribution: females