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Firm Effect and the Israeli Gender Wage Gap

Shira Buzaglo-Baris*

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Abstract

This paper provides an additional perspective on the well documented gender gap in Israel. Applying methods of firm and worker effects estimation resulted in an overall 29 percent contribution of firm premium to the gender gap. Sorting of women into lower wage-premium firms (also within the same industry) explains a significant part of the gap, while a negligible part is due to within firm inequality, in particular at the bottom 50 percent of the wage distribution. Heterogeneity in the firm premium gap was found across industries and parental status, where non-parents workers face a much lower gap, in line with findings on the "motherhood penalty". Based on these estimates, I suggest that policy should focus on ensuring equal opportunities rather than regulating equal pay within a firm.

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1 Introduction

The gender pay gap in Israel is among the highest in OECD countries (OECD, 2020). One common explanation in the literature is gender segregation in industries and occupations. In this paper, I offer intra-industry analysis and examine, through various empirical methods, the question - what is the role of firm heterogeneity in understanding the gender pay gap in Israel? Using administrative Employee-Employer data I analyze the firm-specific wage premium[1] and assess its contribution to the gender gap. I build directly on the work of Card et al. (2016) (CCK, henceforth) and emphasize heterogeneity patterns related to the notion of "motherhood penalty".

Unlike a perfectly competitive labor market framework, firms might have some wage-setting power. Such an imperfect competition potentially generates both between and within firm wage premium differentials. The first channel raises the question of whether firms offering a high wage premium have a lower probability of employing women. considered as a sorting channel. The second channel examines whether observably similar men and women within the same firm enjoy different wage premium associated with their workplace. The availability of administrative Employee-Employer panel data in Israel makes it possible to identify the component of the wage gap that comes from the effect of a firm on its employees' wages and to assess the contribution of the above two channels. In the Israeli context, a firm-related gender gap has recently aroused interest following the publication of reports on gender pay gaps by virtue of the 2021 amendment to the "Equal Wages for Female and Male Workers" law. The results of this analysis can shed some light on the expected contribution of such within-firm wage regulation to reducing the Israeli gender wage gap.

I found that firm's premiums gap account for 29% of the gender gap in Israel, mostly driven by the sorting of women to lower paying firms. A much smaller effect is due to different premium within the same firm. Heterogeneity in the wage premium gap and the contribution of the within and between channels was found across industries and across levels of childcare responsibilities, where non-parent workers face a much lower gap. I provide supportive evidence to the "motherhood penalty" studied in the literature, documenting a widening gap associated with parenthood (first child birth), mostly through sorting. The relatively small contribution of within-firm gender differentials suggests that a policy of regulating equal pay within firms (e.g., transparency laws) might be less effective in narrowing the gender gap.

This paper lies between two fields in the economic research: the effect of firm hetero-

[1] I estimated firm premium with a firm fixed effect in the wage equation. For that reason, along the analysis, I use the terms "firm wage premium" and "firm effect" interchangeably.

geneity on workers' wages and the gender pay gap. This section will briefly survey the main literature in both fields and suggest two channels in which they intersect and contribute to each other.

The rest of the paper is organized as follows: Section 2 presents the methodology and the data used is described in Section 3. Descriptive statistics, baseline estimation along with heterogeneity analysis on motherhood penalty appears in Section 4. Finally, Section 5 concludes.

1.1 Firm Effect

Wage heterogeneity for observably similar individuals in the literature was mainly attributed to one of the two classes of explanations: permanent unmeasured individual effect and firm effect. Studies in the "person effect" field related changes in the market-level return to unobserved skills and changes in wage inequality (Card and Lemieux, 1996; Juhn et al., 1993; Katz et al., 1999). Although in the literature the person effect accounts for most of the wage variation (around 60%), in this study I emphasize the sizable effect of a firm on its workers' wages.

In standard competitive labor market models, wages are determined in a market-level supply and demand system and taken as given by each firm. A recent paper by Card (2022) surveys the historical development in the research on firm effect on wages. Several explanations departing from the perfect competitive framework developed over time, and Card (2022) divides them into two strands: information frictions and idiosyncratic preferences for different jobs. The latter can rationalize phenomena of sorting and segregation in the labor market. The sorting literature suggests that different workers, in terms of observed and unobserved characteristics, sort into different firms. In their seminal work "High wage workers and high wage firms", Abowd et al. (1999) (hereafter AKM) found a positive correlation between estimated person and firm fixed effects, which they interpreted as assortative matching between firm and individuals. Their model pioneered the ongoing research on firm effect and will be an important tool in my empirical work. Recent studies used this method to study wage inequality (see Song et al., 2019) and in particular to examine wage gaps: Arellano-Bover and San (2020) for native-immigrant gap in Israel; Gerard et al. (2021) for racial gaps in Brazil; Card et al. (2016) and Sorkin (2017) for gender gaps in Portugal and the US, respectively.[2]

Although it has been widely used for many applications and different topics, the model

[2] Sorkin (2017) also offers a search model framework to examine the source of the sorting channel. Under some assumptions, he found that most of the gap related to sorting can be explained by the fact that women search from a different set of jobs opportunity and not by preferences.

as specified in the AKM framework has been criticized for several drawbacks. Moreover, several studies of firm and worker fixed-effect models in different countries found small, sometimes insignificant, or even negative correlation between worker and firm effects, in contrast to the novel result of AKM. These studies pointed to potential bias coming from limited mobility bias. The model, as specified in the AKM framework, is solely identified by workers who move between firms, which creates a connected set of firms (see detailed explanation in Section 2). As a result, if these connections are weak, some bias will arise. In fact, estimates of the contribution of firm effects to wage variation are biased upward while estimates of the contribution of sorting are biased downward. Abowd et al. (2004) and Jochmans and Weidner (2019) showed that the magnitude of the bias is related to the amount of movers linking the firms in the connected set. Bonhomme et al. (2020) aimed to assess the sensitivity of the estimated firm effect to the mobility level. They implement fixed-effects methods for bias correction, originally proposed by Andrews et al. (2008) and developed further by Kline et al. (2020) and found that limited mobility bias is more severe in shorter panels. Based on data from several countries' Employee-Employer records, accounting for bias correction makes the sorting component always positive and typically strong and lowers the share of wage variation attributed to firms. As mentioned above, literature suggest that limited mobility bias is more relevant in short panels where mobility is rare. Since I analyze 12-years data, the bias is less of a concern. Moreover, bias corrected estimators are still rarely used in this literature. As with many other Employee-Employer datasets, working hours are unobserved. Bonhomme et al. (2020) repeat the baseline analysis for different measurements of wages (annual/ monthly/ daily/ hourly) for Norway and found that using less frequent data serves as a lower bound of the true contribution of firm effect.[3]

1.2 Gender Gap

Although having been studied for decades, the research on the gender gap is still an ongoing discussion in the economic literature. Along with theoretical work on discrimination, pioneered by Becker (1957), many papers tried to provide different explanations for the gender gap in earnings, based on observable data.

A suggested mechanism generating a gender gap is that the norms regarding the household division of work see women as the main person responsible for household work, caregiv-

[3]Bias-corrected estimators were found to yield similar results regardless of the frequency of the data, hence should be desirable in that case. Unfortunately, the implementation of the correction is computationally demanding and failed to be executed with this big-data structure. The estimates are considered as a lower bound of the true contribution of firms to the gender gap. Supportive evidence for the small bias generated by the absence of hours is available in Section A in the appendix.

ing, and child-raising. Subject to these norms, women make different career choices which create gender sorting and segregation resulting in the gender pay gap. A recent paper by Blau and Kahn (2017) summarizes decades of gender literature and suggests that while in the past, human capital variables played an important role in explaining the gender pay gap, today, with a significant increase in labor force attachment and women's education, the contribution of these variables is much smaller. At the same time, the role of occupations and industries in explaining the wage gap has increased significantly. Similarly, in Israel, Hasson and Dagan-Buzaglo (2013) and Fuchs (2016) found that occupations and industries are main drivers of the gender gap. Thus, an essential part of the explanation today should be based on understanding gender segregation in industries and occupations. In this paper, I go one step further and examine the effect of firms on the Israeli gender pay gap. I contribute to the above literature by expanding the empirical evidence on gender labor market segregation, finding large wage gap heterogeneity even within the industry level.

I found supportive evidence for an accumulated gender gap and mobility patterns related to childcare responsibilities from the perspective of between and within-firm differentials. Recent work on the "motherhood penalty", a wage decline associated with the first child birth, was documented by Kleven et al. (2019b). Yachin (2021) used Israeli administrative data to show similar effects in Israel. Kleven et al. (2019a) survey estimates from different countries and provide some institutional explanations for their differences. Lucifora et al. (2021) used french administrative panel data to show a within-firm effect of child birth on mothers' outcomes. They found an evidence for a “mommy track”, a slower and flatter career path with lower probability of upward move in the job ladder and lower probability of becoming a manager.

1.3 Firm Effect and Gender Gap

In the Israeli context, a firm-related gender gap has recently aroused interest following the publication of reports on gender pay gaps by virtue of the amendment to the "Equal Wages for Female and Male Workers" law from 2021. The available reports, published in 2022, show large heterogeneity in the relative pay of women across firms, which gives greater motivation to my analysis. Moreover, the results of this analysis can shed some light on the expected contribution of such regulation to reducing the Israeli gender wage gap. Similar laws were adopted in many countries, including Denmark (2006), US (2016), UK (2017) and Canada (2019). However, the literature on the effect that such laws have on the gender gap is rare. Studies of pay transparency laws typically found reductions in the gender wage gap when the obligation to publish gender gap reports, unlike the case of

Israel, is accompanied by the threat of sanctions (Bennedsen et al., 2022; Blundell, 2020; Kim, 2015) and covers a large share of the firms in the country.

I conclude this part by emphasizing the channels through which firms can contribute to the gender gap. The between-channel, sorting, raises the question of whether firms offering a high wage premium have a lower probability of employing women. This may be a result of different preferences or gender-specific barriers that unfortunately cannot be separately identified in this paper.[4] Exploring the within channel, I ask whether, in the same firm, similar female workers gain less from the premium associated with their workplace. Allowing for different sorting patterns and different gains from the firm premium, firms can explain a sizable part of the gender gap.

Heinze and Wolf (2010) examined the within-firm gender gap, controlling for different human capital variables, and found that the gender gap varies tremendously across firms. This heterogeneity is linked to firm and institutional characteristics such as collective wage agreement coverage and competition. More recently, integrating the gender gap with the firm effect literature, CCK introduce a rent-sharing design into the known AKM model. I use their methodology as part of my analysis and contribute to the literature with new heterogeneity patterns and policy implications. It is worth noting that they refer to the within-channel as a bargaining effect and point to the relatively small bargaining (or negotiation) power of women. I prefer to keep the general notion of a within-firm channel that can be attributed to many factors rather than only bargaining ability.[5]

2 Methodology and Empirical Strategy

Adopting the methodology of CCK, I follow the wage of individual $i \in \{1, 2, ..., I\}$ who worked at firm $j \in \{1, 2, ..., J\}$ during period $t \in \{1, 2, ..., T\}$.

I assumes that wages of individual i in time t, w_{it}, are determined according to

$$w_{it} = \alpha_i + \psi^{G(i)}_{J(i,t)} + X_{it}\beta^{G(i)} + r_{it} \tag{1}$$

Where $G(i) = \{F, M\}$ is a function identifying individual i's gender and $J(i, t)$ is a function identifying in which firm individual i works in time t. As described in CCK, the

[4] Estimating a stractural search model, Sorkin (2017) finds that women search from a different set of job offers. He concludes that most of the sorting channel is related to different opportunities in the labor market rather than different preferences.

[5] One interesting explanation offered by Caldwell and Danieli (2020) is that women have a smaller set of job opportunities (mostly due to willingness to commute), resulting in smaller leverage at the wage setting process.

time invariant firm premium, $\psi^{G(i)}_{J(i,t)}$ is shared differentially by gender according to each gender's relative gain from working at the firm. The error component, r_{it}, is an unobserved time-varying error capturing shocks to human capital, person-specific job match effects, and other factors. Equation 1, which has the known AKM structure of person and firm fixed effects together with year effect and time-varying covariates, is estimated separately for male and female workers following CCK. Hence, it allows for different firm effect and returns to covariates by gender.

The separate identification of the person and firm effects, α_i and $\psi^{G(i)}_{J(i,t)}$, requires the presence of individuals who move between firms in the sample. Formally, I require observations of individual i working in firm j that also employs some other individual who moved from a different firm. This structure generates a connected set of firms and individuals, linked by job mobility. To use the same firms for both genders, I focus on the dual connected set, the intersection between the two connected sets generated by females and males movers.

As in the classic AKM methodology, the underlying assumption is exogenous mobility. That is, patterns of mobility are uncorrelated with unobservables (r_{it}). Following Card et al. (2013) (CHK henceforth) I will present an event study to support the exogenous mobility and the symmetric moves structure of the model based on the wage path of movers between firms with high and low co-workers' wages. An additional assumption is that firm-specific pay premiums are additively separable (in logarithms) from other pay components, which implies a common time-invariant firm effect to all workers in the same firm. To check for complementarities, a wage gain associated with a mutual match between employer and employee, match effect models are estimated controlling for the interaction between worker and firm effect.

Estimation of equation 1 yields estimates of firm and person fixed effects by gender. Following Card et al. (2018) I decompose the overall variation in wage to assess the contribution of person and firm effect:

$$\begin{aligned} Var(w_{it}) &= Var(\widehat{\alpha}_i) + var(X'_{it}\widehat{\beta}) + \overbrace{2cov(\widehat{\alpha}_i, \widehat{\psi_{J(i,t)}})}^{assortative-matching} \\ &\quad +2cov(\widehat{\alpha}_i, X'_{it}\widehat{\beta}) + 2cov(\widehat{\psi_{J(i,t)}}, X'_{it}\widehat{\beta}) + var(\widehat{r_{it}}) \end{aligned} \tag{2}$$

An alternative representation uses the statistical identity:

$$Var(w_{it}) = Cov(w_{it}, \widehat{\alpha}_i) + Cov(w_{it}, \widehat{\psi_{J(i,t)}}) + Cov(w_{it}, X'_{it}\widehat{\beta}) + Cov(w_{it}, \widehat{r_{it}}) \tag{3}$$

The overall contribution of firm to wage variation is therefore:

$$\frac{Cov(w_{it}, \widehat{\psi_{J(i,t)}})}{Var(w_{it})} \tag{4}$$

Equations 2-4 are gender-specific decompositions since equation 1 was estimated separately for men and women. To use and compare the estimated firm effect, normalization should be applied. Since men and women firm effects are estimated separately, we need to define a common firm/group of firms to which estimates are being related. In their work, CCK showed that compared with other normalization methods, which require more data, results are robust to the choice of food and restaurant firms as the base group, an assumption I adopt here. That is, I substract from each firm's $\psi^{G(i)}_{J(i,t)}$ the average firm effect in the food and restaurant industry by gender. Then, I define the gap between the average normalized firm effect for male and female workers, $\psi^M - \psi^F$, as the firm-related gender gap.

Both between and within firm inequality drives the contribution to the firm-related gender gap. Following CCK, I use an Oaxaca (1973) style twofold decomposition of the overall contribution of firms to the gender gap into two parts:

$$\begin{aligned} E(\psi^M_{J(i,t)}|male) - E(\psi^F_{J(i,t)}|female) \; &= \; E(\psi^M_{J(i,t)} - \psi^F_{J(i,t)}|male) \\ &\quad + E(\psi^F_{J(i,t)}|male) - E(\psi^F_{J(i,t)}|female) \end{aligned} \tag{5}$$

With the first RHS term referring to within wage gap and the second term is the between (sorting) effect. I use $male$ or $female$ as a shorthand for the distribution of jobs held by men/women.

3 Data

The research population comprises individuals born between 1950 and 1995, matched with their firm's co-workers along 2008-2019.[6] The main dataset used is Israeli administrative Employee-Employer records (2008-2019) collected from tax records. I combine it with a rich set of demographic variables from the Population Registry (e.g. age, marital status, and children's year of birth), tenure at current employer and educational attainment records. Each observation is an individual-year combination at her most valued job in that year.[7]

[6] This period was chosen subject to different data constraints and computational consideration. For example, education records are available only from 2008.

[7] Valued job is defined as the job she worked for the longer period in the given year. In case of duplicates, we took the one with the highest monthly wage.

Log monthly wages, expressed in 2010 prices, were computed using data on the number of months worked each year. This data allows tracking individuals' wages through the research period and estimating the AKM model using firm and individual identifiers, as described above. On the firm side, the Employee-Employer dataset includes information on firm size in terms of employment and industry in 2 digits classification.[8] Data is made available by the Israeli Central Bureau of Statistics.[9]

Many registered firms (based on registered Tax Deduction File Numbers) are very small, such that mobility and gender variety is rare and identification of their wage premium will be biased. For that reason, I drop firms with less than 15 workers, a total of about 400,000-500,000 workers, 13% of the entire research population. To focus on main working ages and exclude workers who are less attached to the labor market, I further limit my main analysis sample. I include only non-Arab workers due to two main reasons. There is a well-documented wage gap between Jews and Arabs in Israel, comprehensive analysis of it is beyond the scope of this study. That is, parts of the racial gap should not be attributed to the gender gap. Moreover, Arab women are less likely to participate in the labor market, hence are less likely to be included in my database which may cause some bias in estimation. I focus on main working ages and include individuals aged 25-64 (approx. 75% of Jewish workers in large enough firms) who worked for at least 6 months in a year (remove 13% more). It is worth noting, however, that I characterize a firm based on all its workers and not only the subgroup mentioned above. Meaning, firm size (in terms of employment), firm average wage and female share in employment are constructed before subsetting the sample. As a benchmark, I repeat the estimation in the appendix, using the full sample of Israeli workers aged 25-64. Table 1 presents sample characteristics, comparing the entire population (excluding workers in small firms, column 1) and the main sample described above (column 2).

Compared with the unique dataset used by CCK, one important limitation of my dataset is the absence of working hours. As noted above, women work on average fewer hours compared to men, and the gender gap in hourly wages is smaller, compared with its monthly counterpart. Nevertheless, many applications of the AKM model used annual data and didn't account for hourly wages. Estimates based on such an analysis serve as a lower bound for the true share of variation attributed to firms. Furthermore, combining data from the last Israeli Census (2008) allows bringing some evidence for the negligible bias generated by the absence of working hours (see section A in the appendix).

[8]See Central Bureau of Statistics documentation on the unified 2011 classification Central Bureau of Statistics (2015).

[9]This study was performed in the Israel Central Bureau of Statistics (ICBS) research room using de-identified Microdata (direct identifiers removed from data) in files prepared specifically for this project.

Table 1: Sample Characteristics

	(1) Entire Population Full sample		(2) Jews 25-64 6+ working months a year		(3) Dual Largest Connected Set Constructed from (2)	
	Male	Female	Male	Female	Male	Female
ln wage	8.7	8.4	9.2	8.8	9.3	8.8
Married (%)	56	56	70	68	70	68
Youngest Child Age	6.5	6.8	6.8	7.3	6.8	7.3
Age	38	38	42	42	42	42
Above 45 years (%)	31	30	38	39	38	39
Tenure (years)	4.6	5.0	6.0	6.7	6.0	6.7
Education						
Years of Schooling	12.9	13.3	13.6	13.9	13.7	13.9
No Bagrut (%)	46	35	37	29	37	29
Bagrut or Non-Academic Diploma (%)	26	29	26	24	26	24
BA (%)	15	21	21	27	21	27
MA or Phd (%)	9	12	13	16	14	17
Firm Characteristics						
ICT Industry (%)	10	5	17	8	17	8
Firm Size	4,102	13,709	4,523	16,161	4,584	16,304
Female Share (%)	37	65	38	64	38	64
Number of Firms	108,436		85,343		65,793	
Number of Workers	2,534,452	2,542,999	1,423,383	1,571,118	1,399,174	1,553,831

An additional important limitation is the lack of detailed occupational records. I found limited variation across time in the academic background of workers, a proxy to their class of occupation. Still, within 12 years of working records there are potential changes in occupations within and between firms that are not captured by either education field, firm, or person fixed effect. Specifically, moving to a managerial position might result in a significant wage increase that will be measured improperly. The results should be taken while considering this caveat.

4 Results

I begin with some descriptive statistics reflecting the gendered environment during the sample period. The background figures describe the labor market in Israel in general, hence they include the entire research population. At the main analysis part, as mentioned above, I focus on a subset of Jewish workers aged 25-64 who worked for at least 6 months in a year.

Figure 1 shows the raw and covariates-adjusted relative pay of women through 2008-2019. To do so, I compute the average female residual from a male standard log wage equation and take the exponential of this residual to obtain a simulated female-to-male wage ratio, adjusted for indicated covariates (see Blau and Kahn, 2017). This residual corresponds to an experiment where I compare a woman's actual wage with her predicted wage from the male equation. The relative pay of women increased over the research period and in 2019 women earn 30% less than men. The covariates I account for in the red line are Arabic indicator, age, age squared, industry, tenure and number of months worked as a measure of attachment to the employer/ labor force, indicator for married and youngest child age. When I adjust for the characteristics of workers I still obtain a 20% gender gap.

4.1 Gender Segregation in The Labor Market

In this part, I provide several indicators for gender segregation in the labor market over the research period. Over the sample period, women worked at firms with 46% females on average while men worked at firms with only 28% females. Figure 2 plots the correlation between male and female average wage and the female share in their firm. Both males and females earn less when they work in a firm with higher share of female workers.

What characterizes firms in which women are highly represented? I define a firm as female-dominated firm if there are more than 60% female workers and a male-dominated firm if there are less than 40% female workers. Table 2 presents a comparison between female firms and male firms. Female firms have lower wages as described before, workers

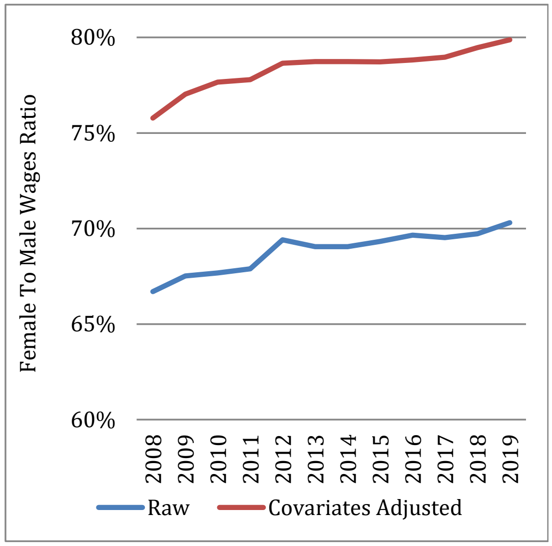


Figure presents raw and adjusted gender gap from 2008 to 2019, estimated over the full sample. See text for details.

Figure 1: Gender Gap Evaluation, 2008-2019.

tend to be married, more educated, have more years of tenure and are represented less in the ICT industry. An interesting result is that female firms are much larger, and a larger share of them operate in less competitive industries.[10] That is, female firms might have higher monopsonistic power.

To complete the descriptive background, I compute the Duncan and Duncan (1955) segregation index[11] for 2-digits industrial segregation. The index was roughly stable around 33% between 2008-2019. As noted by Blau and Kahn (2017), industrial and occupational segregation became extremely important in the last two decades to understanding the gender wage gap. In the appendix, I show the 15 most "female"/"male" industries in 2019, documenting slightly younger workers who earn lower wages in more "female" industries. That is, the documented segregation is characterized by a disproportional allocation of women into low-wage industries, therefore contributing to the overall gender gap.

[10] Firms were clustered into three groups by the competition level at the industry they operate in. The competition level is based on the HHI index which sums the squared market share (in terms of employment) of all firms in the industry. HHI value of less than 1500 is considered as high competition level in the industry, 1500-2500 as moderate and more than 2500 as low competition level.

[11] The Duncan and Duncan (1955) segregation index provides a useful summary measure, giving the percentage of females (or males) who would have to change jobs for the industrial distribution of women and men to be the same, with a value of 0 indicating no segregation and a value of 1 indicating complete segregation.

Table 2: Female-Dominated Firms' Characteristics

	Male Firms Female Share < 40%	**Female Firms** Female Share > 60%
Workers Characteristics		
Average Log Wages	8.9	8.5
Median Log Wages	9.0	8.7
Age	38.1	40.3
Above 45 (%)	30.4	36.4
Married (%)	55.3	60.4
Youngest Child Age	6.7	6.9
No Kids (%)	40.7	31.2
Years of Schooling	12.8	13.6
No Bagrut (%)	46.8	34.3
Bagrut or Non-Academic Diploma (%)	28.3	24.4
BA (%)	14.3	22.9
MA or Phd (%)	7.0	15.4
Worked Months	9.2	9.4
Tenure	4.9	6.4
Firm Characteristics		
ICT Industry (%)	14.1	1.5
Joiners Out of Total Employees (%)	17.6	13.4
Up To 50 Workers (%)	26.9	10.6
51-100 Workers (%)	14.0	6.8
101-250 Workers (%)	16.3	9.5
More Than 250 Workers (%)	42.8	73.1
Number of Firms	24089	14006
Number of Workers	1224554	1502875

Competition level is based on the HHI index where market share is in terms of employment (monopsony), see footnote 9 for details

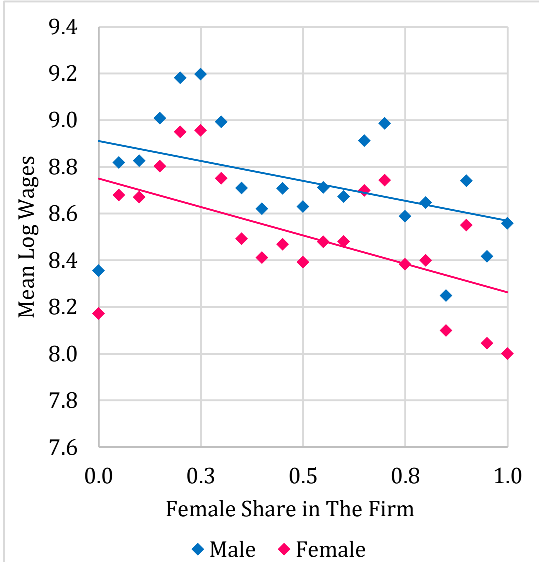


Figure presents the average log wages of female and male workers by the share of females in their workplace. Analysis includes all workers in the full sample at 2019.

Figure 2: Female Share and Average Wage

4.2 Exogeneity

As described in CHK and CCK, an exogenous mobility assumption might not be satisfied due to different reasons. The relation between the error term and mobility can go via a firm negative or positive shock, inducing people to leave or join. In that case, I expect a drop in movers' earnings just before they leave and unusual growth for joiners. Moreover, if there are no idiosyncratic match effects correlated with mobility, I would expect symmetric wage gain/loss for movers between two firms. In the absence of transitory wage shock correlated with the direction of move, I would expect no significant difference between the wage evaluation of workers who move to a higher/lower paying firm. It should be noted that the structure of the model, as shown in equation 1, allows for mobility based on time-varying observables (e.g., children's age) and sorting. In fact, sorting of high skilled workers into high paying firms is an inherent part of the model.

In Figure 3, I apply CHK's event study analysis by gender, plotting the wage path three years before and after the move of job changers of different ranked firms. Ranking is based on co-workers' average wage in the last year at the origin firm and the first year at the new firm. That is, moving from 1 to 4 means moving from a firm where your co-workers are at the top quartile of wage distribution to a firm with co-workers' wages at the bottom quartile. Wages were detrended by substracting the time varying component from the AKM model ($X\beta$) in such a way that changes in individual's wage are attributed to the unobserved residual components and in the case of job switching also to the difference between $\psi^{G(i)}_{J(i,t)}$ to $\psi^{G(i)}_{J(i,t+1)}$.

In Figure 3, I define movers by their job starting year from administrative data.[12] Wage changes occur mostly around period t = 0, the first year at the new workplace, and there seems to be no pre-trend or post-trend. Moreover, a move between firm ranked 1 to firm ranked 4 exhibits a wage change which is similar in magnitude and in the opposite sign compared with move from 4 to 1, supporting the symmetric structure of the model. The results indicate that the exogenous mobility assumption seems to be relatively satisfied and fits the data well. In that sense, I join many other papers supporting the validity of the AKM framework.

4.3 Estimation

The model is estimated within a dual connected set of firms and individuals, all linked by the set of movers. The use of relatively long panel data increases the number of movers, which can potentially reduce the estimated bias. Figure C.3 in the appendix shows the distribution of firms according to the number of moves. To ensure my dual connected set is representative of the research population, in Table 1 I present a comparison between the main sample and the dual connected set constructed from it. In general, the dual connected set is a good representation of the population of Jewish workers aged 25-64 who worked for at least 6 months in a year.

Estimation of equation 1 is reported in Table 3. The covariates included are age (in quadratic and cubic terms[13]), an indicator for married, youngest child age[14], tenure (in years), years of schooling, and the highest diploma acquired. Following the AKM framework, I control for year, person and firm fixed effects.

[12]Due to the data structure, in the AKM regression analysis I use a less restrictive job definition which increases the number of moves. That is, mover is one that changed his main workplace which is the job you worked for the longest period along a year. For that reason, the exact job switching year (for people holding more than 1 job in a year) might be inaccurate. For example, a job switching might occur along time -1 but the new workplace will be identified as the individual's employer only in the next period. Nevertheless, results of the event study analysis under the unrestricted job switch definition are qualitatively the same, positing no threat of a bias in the results.

[13]Since year and age are perfectly colinear when we include person effects, we exclude the linear age term. Following CCK we center age around 40 and include the centered variable in a quadratic and cubic terms.

[14]Entered the regression as dummy variables for grouped youngest child age: 0-1 (born this year), 1-2, 2-3 and 4-18. That is, I consider as the reference group children older than 18 as well as having no children.

Table 3: Estimation Results

Dependent Variable: Log Wages

	Male	Female
Age^2	-0.001***	-0.001***
	(0.000)	(0.000)
Age^3	0.000***	0.000***
	(0.000)	(0.000)
Years of Schooling	0.009***	0.016***
	(0.000)	(0.000)
Tenure	0.013***	0.016***
	(0.000)	(0.000)
Married	0.040***	0.019***
	(0.001)	(0.001)
Youngest Child Age		
Reference: No kids and kids older than 18		
0-1	0.019***	-0.093***
	(0.001)	(0.001)
1-2	0.025***	-0.060***
	(0.001)	(0.001)
2-3	0.025***	-0.032***
	(0.001)	(0.001)
3-18	0.011***	-0.034***
	(0.000)	(0.000)
Highest Diploma		
Reference: No Bagrut Diploma		
Bagrut or Non-Academic Diploma	-0.072***	-0.080***
	(0.001)	(0.001)
BA	0.146***	0.079***
	(0.001)	(0.002)
MA or Phd	0.282***	0.186***
	(0.002)	(0.002)
Constant	9.122***	8.587***
	(0.003)	(0.004)
Person-Years Observations	8,985,561	10,360,369
R-squared	0.902	0.870
Adjusted R-squared	0.886	0.849

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Table 3 presents results from an estimation of equation 1 by gender. The sample includes Jews aged 25-64 in the dual connected set who worked for at least 6 months. Year, person and firm fixed-effects are included.

Coefficients of the control variables are with expected sign. Years of schooling contribute to individual's wage, as well as tenure in the current employer. It is interesting to note that variables related to individual's parental status are negatively correlated with wages of female only, in line with the literature of a "Motherhood Penalty". In addition, the estimated coefficients on youngest child age suggest that mothers of younger children are more affected in terms of wage decrease.

A match effect model was estimated to check for complementarities between employee and her employer. I found a similar small contribution (in terms of R squared) of about 0.06 for both male and female. Appendix Figure A.2 suggests that some of the match component is due to working hours, especially for workers at the lower tail of the person effect distribution.

To assess the contribution of firm effect to the overall wage variance, I follow equations 3 and 2 to decompose the variance of log wages. Most of the variance is indeed attributed to person effect (about 50%) which represents unobserved fixed characteristics of the worker such as her ability, unobserved skills, and in some sense even the probability of working in a certain employment arrangement (full time versus part time). Thus, at least part of the variation in hours of work is captured by person effect and hence limits the bias caused by their absence. This issue is discussed in more detail in appendix A. Firms account for 30% and 24% share of the variation in the male and female equations, respectively, slightly higher than results in the literature. The correlations between the estimated person and firm effects are positive for both female and male workers and 7% of wage variation is attributed to positive assortative matching in which high-skilled workers (in terms of person effect) are highly represented in firms that pay higher wage premium to all their worker. The contribution of this phenomena is intensified when I compare men and women, as discussed in the next part.

Estimates of firm effect from the male and female equations are also strongly positively correlated (linear fit slope of 0.74), indicating that firms that pay higher wage premiums to men tend to pay more to women as well. Note, however, that a coefficient of 0.74 is significantly different than 1, meaning women still get smaller premiums on average. In Figure 4, I grouped firms by industries and plot the average firm effect of male against female. The estimated slope is 0.82, similar to the results in the literature.

Ordering firms by their average wage indicates that most of the gap is driven by the top 50% of the wage distribution, while there is no difference in the wage premium enjoyed by workers at the lower part of firm wage distribution (Figure 5). One potential mechanism can be coverage by collective bargaining agreement or minimum wage in lower paying firms, limiting the possibility of gender wage dispersion within firm. Nevertheless, the close relation between the overall female and male firm effect suggests that most of the gender

Table 4: Wage Variance Decomposition

	Men	Women
$Var(w)$	0.76	0.63
Share of Overall Variance (%)		
$Var(w)$	100	100
$Var(\alpha)$	43	44
$Var(\psi)$	24	19
$Var(X\beta)$	8	9
$2Cov(\alpha, \psi)$	7	8
$2Cov(\alpha, X\beta)$	3	4
$2Cov(\psi, X\beta)$	4	4
$Var(r)$	10	13

pay gap related to firms is due to the between firms channel. A formal decomposition assessing this finding can be found in the next section.

4.4 Between and within channels

The average gender wage gap among Jews aged 25-64 is 0.43 log points, of which 0.13 log points are firm-related gap, i.e., the gap between the average firm premium of male and female workers. That is, the firm premium gap accounts for 29% of the raw gender gap. Calculation based on equation 5 suggests that sorting accounts for most of the firm-related gender gap, while the within-firm gap explains only a very small part. This, in turn, translates into 27% of the total gender gap accounted by sorting and negligible within component, about 2%. Results are in line with the findings in the literature that found a relatively small "within effect" in many countries (see Palladino et al., 2021). In that sense, it is clear that most of the gap is coming from the disproportional representation of women in lower-paying firms rather than unequal pay within firm. In this part, I would like to examine some heterogeneity patterns in the within and between components. Motivated by literature on the "motherhood penalty", in Figure 6 I study heterogeneity by time since first birth to uncover the firm-related parental inequality. The firm-related wage gap, as well as the raw gender wage gap, is smaller for workers with no childre and continues to increase even after 5-6 years following the birth of their first child. Decomposition suggests that the sorting into lower-paying firm is the dominated effect driving the firm-related motherhood penalty. Even 16 years after becoming a parent there is a stable gap in wage premiums between male and female workers. This might reflect an accumulated gap from the time they had younger children and made career decisions in favor of more flexible jobs. Table 5 offers some explanation of these findings. Comparing mobility patterns of male and female workers shows that women move to higher ranked firm when their youngest child age is older and 2 years later than men after becoming a parent. That is, men improve their firm premium earlier by moving to a higher ranked firm. Along with the negative coefficient on family-related variables reported in Table 3 for female workers, These findings provide supporting evidence to the notion of motherhood penalty.

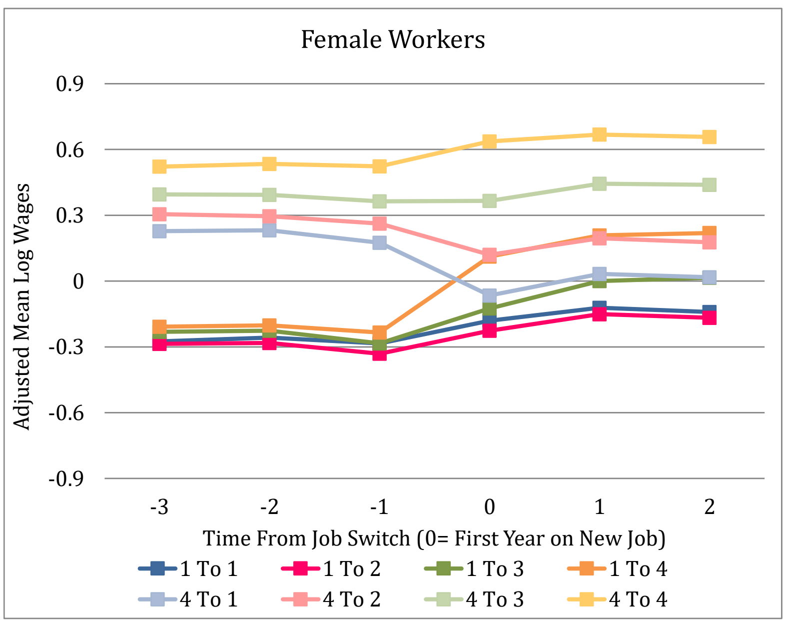
Table 5: Mobility Patterns of Male and Female Workers

	Males	**Females**
Number of Moves	991,243	1,004,042
To Higher-Ranked Firm (%)	44	46
To Same-Ranked Firm (%)	27	23
To Lower-Ranked Firm (%)	30	32
Move To Higher-Ranked Firm:		
Age	37.4	37.4
Wage Gain ($\Delta lnwage$)	0.4	0.4
Tenure at Origin Firm	2.9	3.3
Youngest Child Age	5.5	6.7
Time Since First Birth	8.9	11.0

Note: Firms were grouped to deciles of wage premium distribution. Move to better-ranked firm is move to a higher decile.

A natural question is whether there is some heterogeneity across industries. An extreme scenario can be that the sorting between firms documented above is solely sorting into different industries, which makes the results less novel. I study this more broadly in appendix B where I repeat the analysis using industry fixed effect rather than firm fixef effect. Results point to a smaller contribution to the variance of wages along with an increase in the share of the person effect. That is, there is extra information coming from sorting into firms rather than sorting into industries. The increase of the person effect part might suggest that sorting into firms within the same industry has a systematic manner. Moreover, Figure 7 reports the firm wage premium gap, composed of within and between contributions by industries. Industries were sorted according to their raw gender gap with the lowest on the left. The firm premium gap is different across industries, ranging from -0.35 log points in Education (gap in favor of women) to 0.24 log points gap among agriculture and mining workers. Overall, results suggest that sorting is prominent within industries as well.

I conclude this section by suggesting that policy should focus on the between-firm channel rather than within-firm. The cost of regulating equal pay within a firm is high and according to the above findings, will contribute slightly to reducing the gender gap. It is worth noting that the data used in this study end before the requirement to publish the gender gap in a firm-level reports came into effect. In that sense, the results of this study question the effectiveness of this law in narrowing the gender gap. There is much more to do, in fact, to eliminate some of the unequal sorting phenomena. Sorkin (2017) suggests that most of the sorting effect is coming from unequal opportunities in the labor market. Caldwell and Danieli (2020) point to a main source of the difference in opportunities: the lower willingness of females to commute due to family responsibilities. A policy of encouraging hours flexibility and remote work in firms might be highly effective.



Figures present the wage path of male and female job changers three years before and after the move (denoted as Time = 0, first year at the new job). Firms were classified by quartile of mean co-worker wages at origin and destination firm. Analysis based on Jews aged 25-64 in the dual connected set who worked for at least 6 months in a year. Wages are detrended by substracting the time-varying component from the AKM estimation.

Figure 3: Wages of Male and Female Job Changers

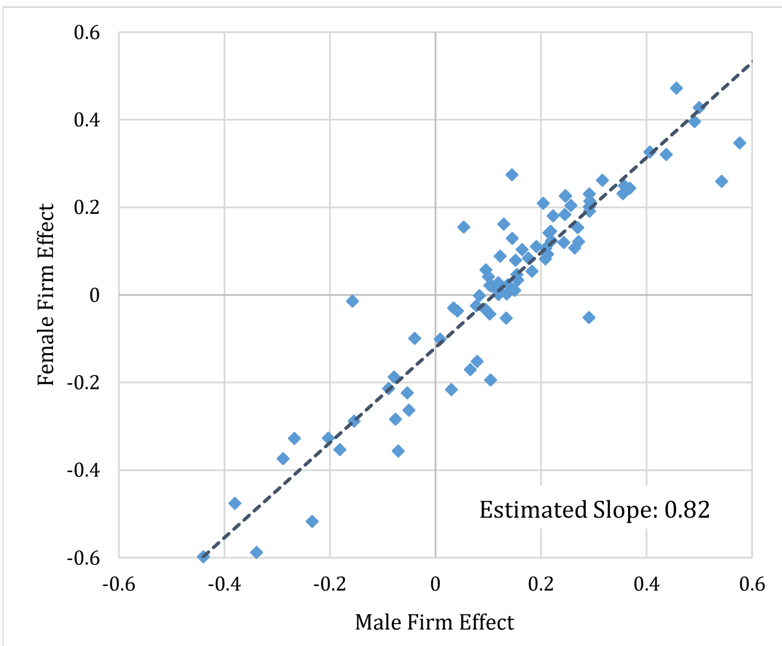


Figure plots estimated firm effect by gender, grouped by 2-digit industry classification.

Figure 4: Male and Female Firm Effects

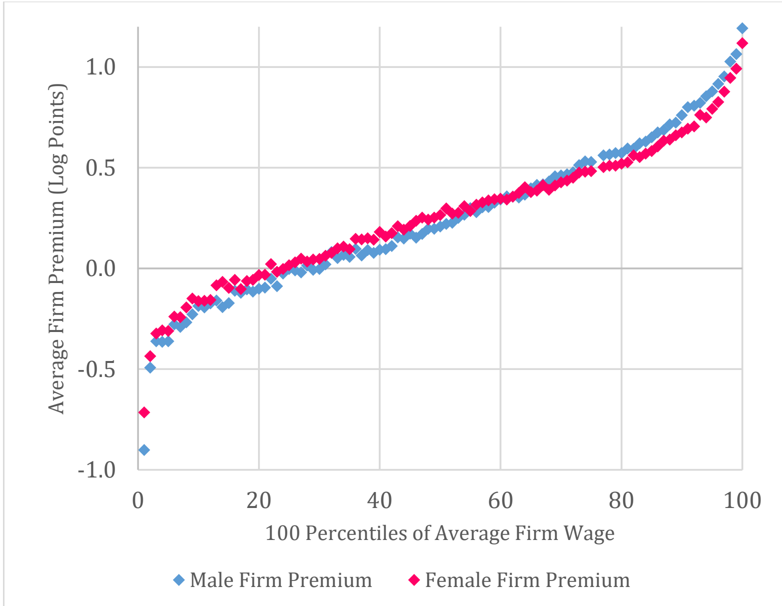


Figure plots male and female estimated firm effect, grouped by 100 percentiles of firm average wage.

Figure 5: Firm Effect by Firm Average Wage

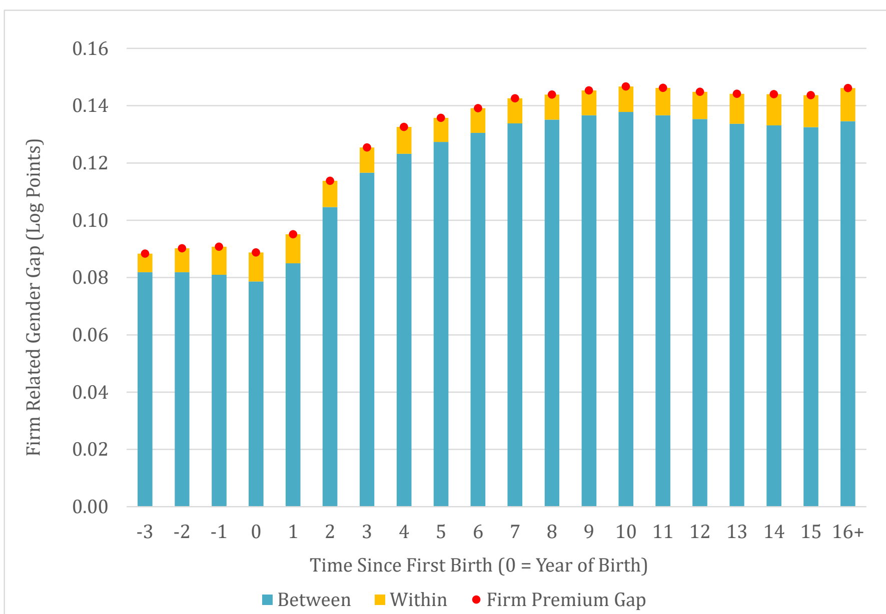


Figure 6: Decomposition to Between and Within Channels, by Time from First Birth

Figure presents decomposition to between and within firm-related gender gap. Industries were sorted in ascending order from left to right by their raw gender gap.

Figure 7: Decomposition to Between and Within Channels, by Industries

5 Conclusion

In this paper, I provide additional perspective on the Israeli gender gap and assess the part of the gap related to firms' heterogeneity. I depart from the competitive labor market framework and model wages as contributed from an individual's specific workplace. Allowing for such wage determination, I suggest two channels in which firms can contribute to the gender gap: a within channel, where female workers enjoy smaller share of the wage premium a firm shares with its workers, and a between channel where female workers are highly represented in firms with smaller firm effect. Based on an Israeli Employee-Employer dataset, the results presented in this paper support the latter and find negligible evidence for within firm gaps, in particular at the bottom 50% of average firm wage distribution. Heterogeneity in the firm-related gap and its drivers (between or within firm differentials) was found across levels of childcare responsibilities, where non-parents workers face a much lower gap which rises with the time from first birth. Part of it is due to female workers making job switch to better-ranked firms when their children are older. That is, males improve their firm premium earlier. A stable gap is present even after 16 years into parenthood, which might point to an accumulated gap. This finding goes in line with the negative coefficients on family-related variables in the estimated wage equation, characterizing female workers only. In that sense, one main contribution of this paper is providing supportive evidence of the "motherhood penalty" documented in the literature.

The focus on firms' sorting, rather than industries, improves our understanding of the gender gap and provides some extra information of sorting even within the same industry. In that sense, it highlights the importance of a specific workplace on individual's wages.

One caveat mentioned throughout the analysis is the absence of working hours. Combining data from the Israeli 2008 Census, I found small difference between the baseline estimation and estimation using hourly wages. That is, results are robust and suggest that there is still a "pure" firm effect on wages.

As documented in Section 4, the gender gap in Israel is declining. A future analysis assessing the role of firm in closing the gap and decomposing its drivers into within and between firm channels will be interesting and useful. The dominating effect of sorting can be a result of different preferences or different opportunities by gender. Examining the sources of sorting in a future analysis will be an important contribution to both policy and academic research regarding the gender gap.

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Appendices

Appendix A Hours bias

Employee-Employer datasets often lack the availability of observed working hours. One might think it should be more of a concern when the analysis focuses on gender disparities. In this section, I will try to bring some evidence of how different the estimated firm effects would have been had I observed hourly wage data. Using data from the last Israeli Census conducted in 2008, employees from the research population were merged with their answers to the survey, in particular regarding weekly working hours. Around 13% of the research population in 2008 can be found in the census too. The raw gender gap in 2008 is smaller by 24 log point using hourly wages from the Cencus. Nevertheless, my goal is to examine the change in the contribution of firm-related gender gap to the overall gender gap, using different wage measurement units. I repeat my estimation of equation 1 twice: once using log monthly wages as the dependent variable and once using log hourly wage. To adjust to the new structure, I omit the year and person fixed effect since I analyze single-year data. The first supportive evidence of relatively small bias caused by the less frequent data is the fact that ranking firms based on their estimated firm effect yields similar results for both wage measurement units, with a correlation of 90% on average.[15] That is, the relative position of a firm is very similar. The share of the gap associated with firms (firm wage premium gap) when hourly wages are used, is similar (16% versus 13%). However, decomposition of the gap to between and within channels is very similar, suggesting that most of the gap is coming from sorting. Comparison is summarized in Table A.1.

Hours absence can also be considered as an omitted variable from the RHS of equation 1, which can make the estimated coefficients upward biased. The amount of bias is related to the covariance between hours and the rest of the explanatory variables. I suggest that conditional on individuals' covariates (education, tenure, age, marital status and kids age), as well as person fixed-effect, the bias in the firm effects will be limited since hours are well captured by the former. A regression of working hours explained by individual's observables and person effect yields R^2 of 11% for males and 17% for females. Based on the above, I conclude that there is still a pure firm effect on wages, generating a gender pay gap due to sorting.

Do hours solely differentiate between higher and lower-premium firms? In Figure A.1, I plot average working hours against 100 percentiles of firm effect and report a positive

[15] Average between the correlations from the male and female equations. The correlation of monthly and hourly firm effect estimated from the female equation is a little lower.

(but far from 1) slope for both genders. Since average wages in a firm are affected by the amount of hours worked, it is reasonable that a higher firm effect is associated with higher working hours. Conditional on person effect decile, I show in Figure A.2 that the positive correlation is smaller for high-skilled workers, who are more likely to be employed in a full-time position. To summarize, higher-premium firms are likely to be more than just higher-working-hours firms.

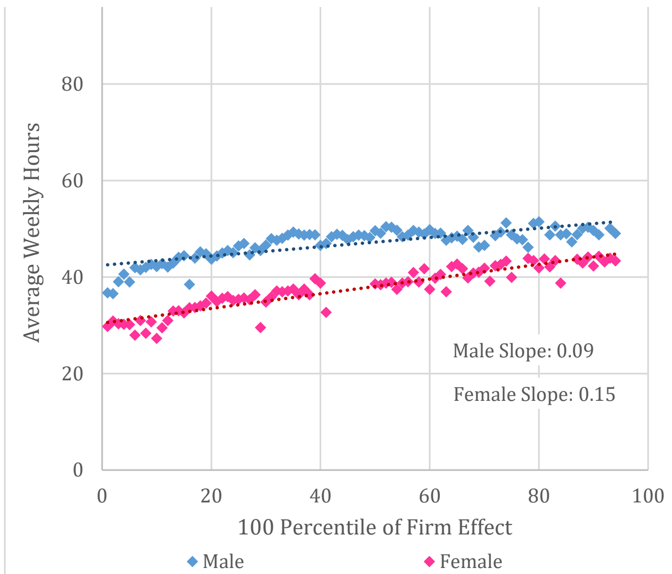
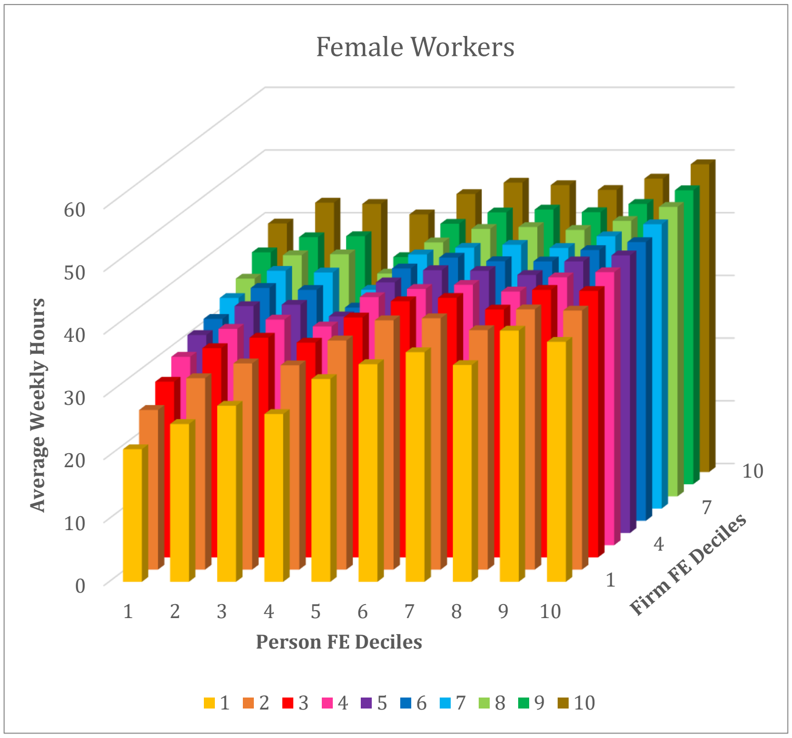


Figure presents average weekly hours, by 100 percentiles of firm effect. Hours data from 2008 Israeli census.

Figure A.1: Average Weekly Hours by Firm Effect Percentiles

Table A.1: Models Comparison

	Baseline (Table 3)	Israeli 2008 Census Monthly Wages	Israeli 2008 Census Hourly Wages
Sample Period	2008-2019	2008	2008
Raw Gender Gap (log points)	0.43	0.52	0.27
Firm-Related Gender Gap (%)	29	16	13
Between Firm Channel (%)	27	48	49
Within Firm Channel (%)	2	-32	-36
Person×Year Observations	19,345,930	178,304	178,304
Firm Effect	V	V	V
Person Effect	V	X	X
Year Effect	V	X	X



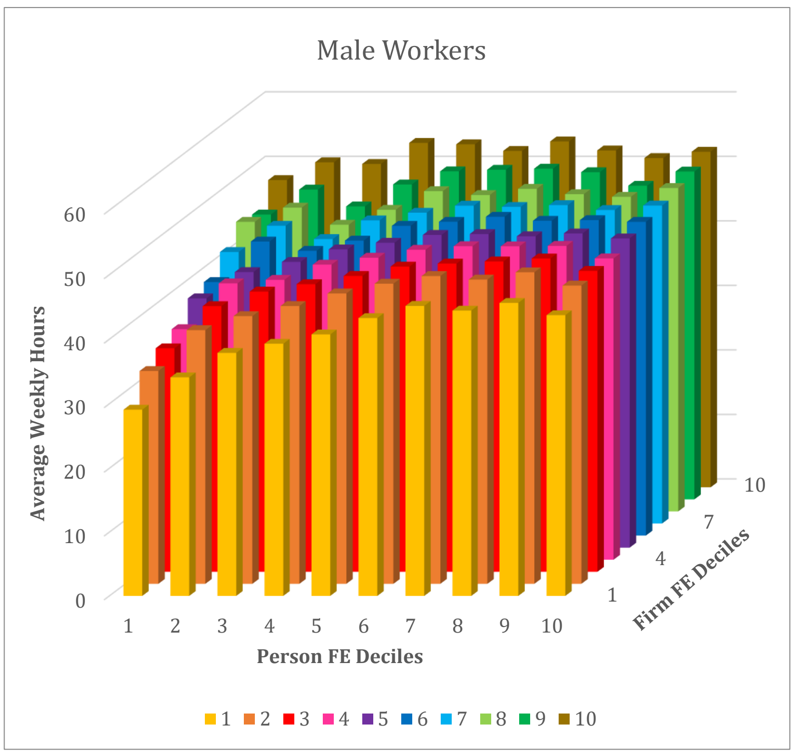


Figure presents average weekly hours, classified by person and firm effect deciles. Hours data from 2008 Israeli census .

Figure A.2: Average Weekly Hours by Firm and Person Effect Deciles

Appendix B Industry-Level Robustness Check

Segregation by industries is a well documented phenomena. Table B.2 describe the most female/male industries in Israel. . The main specification of equation 1 includes a firm fixed effect. An extreme scenario can be that the sorting between firms documented above is solely sorting into different industries, which makes the results less novel. In this part I repeat equation 1 estimation, replacing the firm fixed effect with an industry fixed effect. The share of wage variation associated with industries is less than half of the share attributed to firms, 13%-10% versus 30%-24% (based on male or female equation). In the industry-level analysis, the residual share was found to be twice as large as the residual share observed in thefirm-level analysis. The overall contribution of industries to the raw gender gap is similar in an industry-level analysis and decomposition of the industry-related gap still points to the gap being driven by sorting mostly.

Table B.2: Most Male and Female Industries, 2019

	Industry Name	Industry Code	Female Share	Average Log Wage	Years of Schooling	Average Age
1	Manufacture of textiles	13	11%	9.8	13	43
2	Creative, arts and entertainment activities	90	12%	9.1	11	42
3	Programming and broadcasting activities	60	13%	9.2	12	45
4	Manufacture of electrical equipment	27	16%	9.3	13	47
5	Wholesale trade, except motor vehicles and motorcycles	46	17%	9.3	12	40
6	Manufacture of tobacco products	12	18%	9.5	12	50
7	Forestry and logging	2	19%	9.0	12	38
8	Manufacture of other non-metallic mineral products	23	19%	9.9	14	46
9	Manufacture of computer, electronic and optical products	26	19%	9.4	12	44
10	Wholesale and retail trade and repair of motor vehicles and motorcycles	45	21%	9.2	13	41
11	Electricity, gas, steam and air conditioning (cooling) supply	35	21%	9.7	14	46
12	Manufacture of motor vehicles, trailers and semi-trailers	29	22%	9.5	13	45
13	Manufacture of machinery and equipment n.e.c.	28	22%	9.2	13	45
14	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	16	24%	9.3	13	41
15	Manufacture of pharmaceutical products, including homeopathic preparations	21	24%	9.2	12	44
1	Other professional, scientific and technical activities	74	60%	8.1	12	40
2	Manufacture of coke and refined petroleum products	19	62%	8.8	12	39
3	Activities of extraterritorial organizations and bodies	99	62%	9.4	14	48
4	Libraries, archives, museums and other cultural activities	91	65%	8.4	13	36
5	Travel agency, tour operator, reservation service and related activities	79	65%	9.3	15	43
6	Security and investigation activities	80	66%	8.6	14	40
7	Other personal service activities	96	68%	8.5	12	38
8	Real estate activities	68	71%	9.4	14	38
9	Employment activities	78	73%	8.9	13	44
10	Education	85	73%	9.3	15	43
11	Gambling and betting activities	92	76%	8.1	13	38
12	Rental and leasing activities	77	78%	9.3	15	42
13	Repair of computers and personal and household goods	95	81%	8.7	12	38
14	Human health activities	86	82%	8.2	13	45
15	Printing and reproduction of recorded media	18	85%	8.6	12	41

Table B.3: Firm Vs. Industry Level Estimation

	Firm-Level	Industry-Level
Raw Gender Gap (log points)	0.43	
Firm/Industry-Related Gender Gap (%)	29	29
Between Firm/Industry Channel (%)	27	29
Within Firm/Industry Channel (%)	2	0
share of overall wage variation:		
Person Effect (%)	49-50	38-41
Firm/Industry Effect (%)	24-30	10-13

Appendix C Additional Figures and Tables

C.1 Mobility

Since mobility is crucial for identifying the model in equation 1, I would like to examine how frequent it is and how limited mobility is across firms. About 49% stay in the same firm for 12 years while there is no significant difference between male and female mobility and both genders tend to move in a similar rate.

In Figure C.3 I show that there are many firms with sufficient number of movers allowing to identify them in the regression, although there are about 8% of the firms without movers at all, excluded from the results in Table 3.

C.2 Israeli Transparency Law

The amendment to the "Equal Wages for Female and Male Workers" law from 2021 indeed sets a firm size threshold (518 workers) from which firms are obligated to publish a gender gaps report. I repeat the analysis in section by the firm size in 2019 (the most recent year in my dataset before the law came into effect), comparing firms with more or less than 518 workers. The results points to a slightly smaller firm-related gap but higher within component in the treated firms.

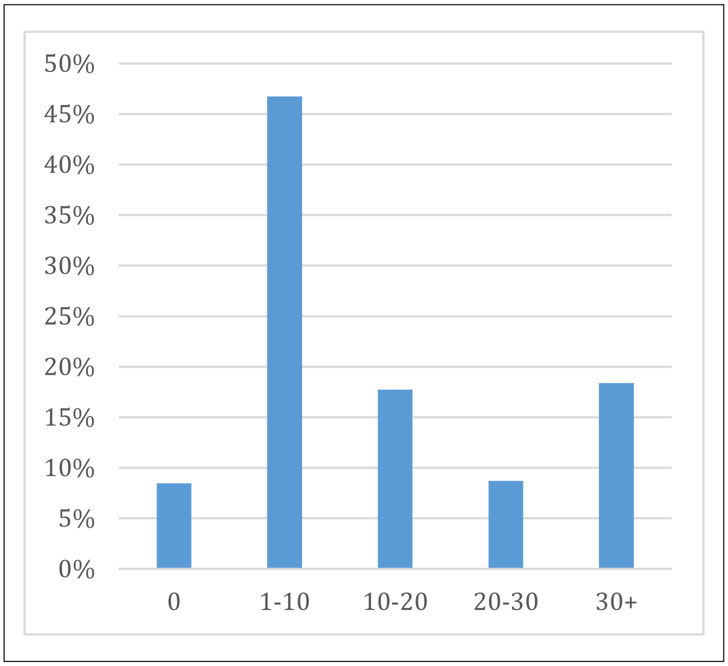


Figure C.3: Distribution of Firms By The Number of Moves.

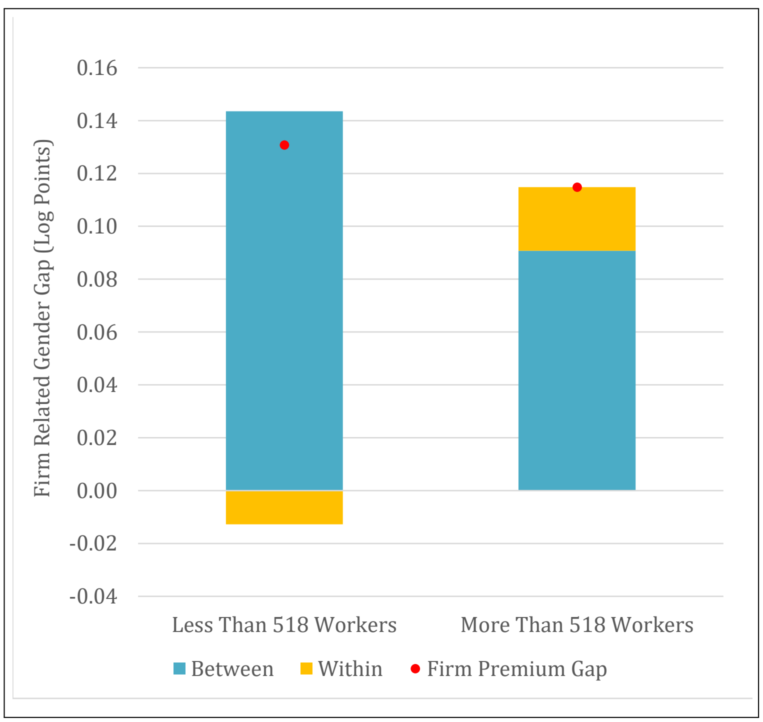


Figure C.4: Decomposition to Between and Within Channels, by Firm Size Threshold of The Transparency Law

Appendix D Benchmark: Full Sample Estimation

As a benchmark, filling a gap in the empirical evidence in Israel, I further estimate the model in equation 1 for the full sample of Israeli workers who worked in firms with more than 15 workers. The covariates are the same as reported in Table 3. Firm effect accounts for 22% and 29% of the wage variation in the full sample, for female and male workers, respectively. This result is slightly smaller than the analysis on Jews aged 25-64 who worked for at least 6 months a year. Assortative matching accounts for 7% of the wage variation. Higher share of variation is attributed to the residual component, compared with my baseline estimation.

Table D.4: Estimation Results

	Male	Female
Age^2	-0.001***	-0.001***
	(0.000)	(0.000)
Age^3	0.000***	0.000***
	(0.000)	(0.000)
Years of Schooling	0.018***	0.021***
	(0.000)	(0.000)
Tenure	0.017***	0.021***
	(0.000)	(0.000)
Married	0.044***	0.013***
	(0.001)	(0.001)
Youngest Child Age		
Reference: No kids and kids older than 18		
0-1	0.020***	-0.106***
	(0.001)	(0.001)
1-2	0.025***	-0.103***
	(0.001)	(0.001)
2-3	0.025***	-0.048***
	(0.001)	(0.001)
3-18	0.011***	-0.040***
	(0.001)	(0.001)
Highest Diploma		
Reference: No Bagrut Diploma		
Bagrut or Non-Academic Diploma	-0.080***	-0.087***
	(0.002)	(0.002)
BA	0.180***	0.107***
	(0.002)	(0.002)
MA or Phd	0.322***	0.216***
	(0.002)	(0.002)
Constant	8.784***	8.338***
	(0.004)	(0.004)
Observations	12,419,212	13,443,031
R-squared	0.839	0.808
Adjusted R-squared	0.813	0.778

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table presents results from an estimation of equation 1 by gender.
Sample includes all workers in the dual connected set.
Year, person, and firm fixed-effects are included.

Table D.5: Wage Variance Decomposition

	Men	Women
$Var(w)$	0.92	0.85
Share of Overall Variance (%)		
$Var(w)$	100	100
$Var(\alpha)$	37	39
$Var(\psi)$	23	18
$Var(X\beta)$	8	8
$2Cov(\alpha, \psi)$	7	7
$2Cov(\alpha, X\beta)$	4	5
$2Cov(\psi, X\beta)$	5	3
$Var(r)$	16	19