Occupational segregation, skills, and the gender wage gap

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Summary

This report offers evidence of the role of skills and occupational gender segregation in explaining the gender wage gap in Canada. We use Canada's Labour Force Survey (1997-2015) combined with detailed skills information from the Occupational Information Network (O*Net) in our assessment of Canadians' hourly wages. We measure the extent to which gender differences in job skills (specifically interpersonal, analytical, physical strength, visual, and fine motor skills,) can explain gender wage differentials. We estimate this economy-wide, and within industrial sectors. Moreover, we compare adjusted wage gaps that account for gender differences in skills to more standard adjusted wage gaps that account for gender differences in occupations. The difference is referred to as a net segregation wage gap, representing that part of the gender wage gap that is associated with occupational segregation, net of the gender wage gap accounted for by gender differences in skills used in occupations.

We highlight the following results:

- Accounting for gender differences in skills does little to explain the gender wage gap
- The net segregation gap varies across industries and is largest in male-dominated industries
- Gender wage gaps within occupation are partly explained by gender differences in skills and other productive characteristics, however vertical segregation and related pay structures require further investigation

We suggest consideration be given to policy development in regards to:

- Achieving pay equity at an industry level
- Addressing occupational gender segregation within broad occupation categories
- Reducing employer costs associated with part-time schedules within high gender wage gap occupations

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1. Introduction

In 2016, the average hourly wage of women in Ontario was 87% of men's average hourly wage rate. In Ontario, and in the rest of Canada, there has been steady progress in closing the gender wage gap as the female-male wage ratio increases over time (see Figure 1).

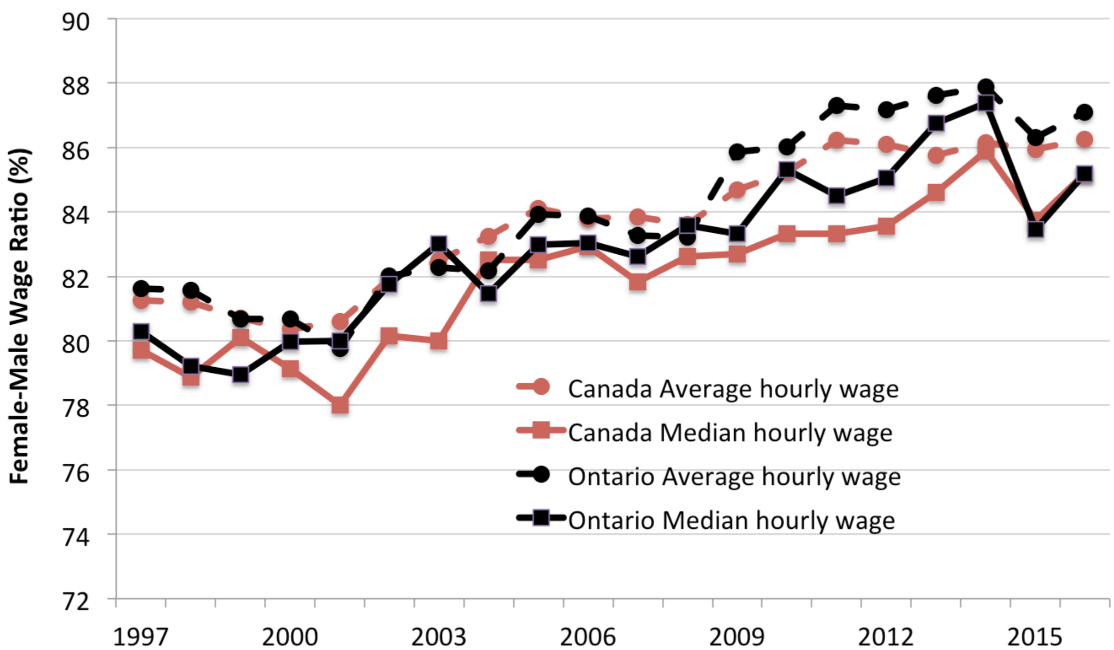

Figure 1. Female-Male Wage Ratios, 1997-2016.
Source: Authors' tabulations based on CANSIM table 282-0074. Wages represent those of all workers aged 25-54.

A large Canadian literature has examined the gender wage gap and attempted to account for factors driving the gap.[1] Overall the literature demonstrates that while the gap between men's and women's wages has decreased over time, the extent to which the remaining gap can be explained as representing differences in productive skills has fallen. Schirle (2015) has shown that across the Canadian provinces, very little of the gender wage gap reflects gender differences in family status, education, or job characteristics such as union status or job tenure. For the most part, the bulk of the wage gap cannot be explained by observable personal and job characteristics. However, large parts of the gender wage gap are associated with occupational and industrial

[1] This includes Fortin et al. (2017), Baker and Cornelson (2016), Fortin (2004), Baker and Fortin (2004), Drolet and Mumford (2012), Schirle and Vickers (2014), Arcila et al. (2016), Vincent (2013).

gender segregation. Simply put, as men and women tend to move into different types of jobs, and the jobs largely occupied by men tend to pay higher wages, men will on average have higher wages.

Whether or not this is a satisfactory explanation of the gender wage gap depends on what we think the wage differential due to gender segregation represents. It has been common to summarize the wage differential associated with such occupational segregation as a compensating differential. In particular, there is an expectation that some occupations require more productive skills, and such skills will be rewarded with a higher wage.

The purpose of this study is to examine further the nature of the gender wage gap associated with occupational gender segregation. Does the wage premium offered in male-dominated occupations actually reflect a gender difference in skills used on the job? What else might underlie this part of the wage gap? In what industries will a skills gap help explain the wage gap, and in what industries is there something else underlying the premium found in male-dominated occupations?

We use data from Canada's Labour Force Survey (LFS, 1997-2015) to investigate this question. We match the detailed occupation information available in the confidential files of the LFS to detailed information about each occupation in the Occupational Information Network Database (O*NET). We begin with a standard exploration of adjusted gender wage gaps, examining how different factors play a role in the gender wage gap. We construct a measure of the extent to which occupational segregation may explain the gender wage gap, net of the role that differences in the skills involved in detailed occupations can explain the gap. We refer to this as the net segregation wage gap.

This report proceeds as follows: In the next section we describe the data used in this study and our sample of interest. We then provide a description of men and women in terms of their personal and job characteristics, as well as the skills used in their jobs. In section 4 we describe our empirical strategy for measuring adjusted wage gaps, and the net segregation wage gap. We investigate these gaps within industries and explore potential relationships with industry characteristics. In Section 5 we examine gender wage gaps within broad occupation categories and the extent to which gender differences in skill can explain these gaps. Finally, we discuss the policy relevance of our estimates and the need for further research for policy development.

2. Data

Labour Force Survey

We use the confidential files of the Labour Force Survey (LFS) from 1997-2015. The Labour Force Survey is administered as longitudinal survey, interviewing all individuals in sampled households for 6 months. Since 1997, the LFS has reported hourly wages of all paid employees as well as personal and job characteristics.[2]

To avoid repeating observations of the same individuals in our sample, we restrict ourselves to using information from the individual's first (birth) interview in the LFS. We then restrict our sample to employed individuals who are not self-employed between the ages of 25 and 54. These basic restrictions leave us with 1,507,991 observations.

The most important information we require from the LFS is occupation. The available LFS files report the National Occupational Classification codes for 2011 (NOC-2011). Each occupation is assigned 4 digits: the first digit represents a broad skill type category, the second generally represents a skill level category, the third and fourth digits define minor occupation groups. These codes are not uniformly applied internationally and have changed over time. As such, it was not possible to match all occupations found in the LFS with skills information from O*NET (described below). As a result, our sample excludes 27,742 observations because their LFS occupation could not be matched with our skills information. (See Appendix A for more detail.)

Given our interest in factors explaining gender wage gaps within industry groups, we also want to ensure large enough samples of men and women within each industry. We chose to exclude any industries whereby fewer than 200 men or 200 women were sampled. Only a handful of industries were excluded, dropping 7080 observations from our sample. Notably, more than half of these dropped observations represented individuals employed in private households. (See Appendix B for more detail.)

Given these restrictions, we are left with 1,473,168 observations in our sample. This sample represents employed men and women in Canada, aged 25-54, over the years 1997-2015.

O*NET based skills measures

The O*NET is a U.S.-based database containing information on detailed occupations, including the abilities and knowledge required of workers who hold the occupations.[3]

[2] Since we are pooling data since 1997, we adjusted wage rates for inflation using the Canadian all-items consumer price index (CANSIM Table 326-0020) so that wages are in 2015 dollars.
[3] More information can be found at https://www.onetonline.org

Increasingly, labour economic studies use the information contained in O*Net to better characterize the implicit heterogeneity in occupational choice (see for example Imai et al. 2014 and Adsera and Ferrer 2014). Typically, the job skills information is collected into a small set of indices, using Factor Analysis, which summarizes the skill requirements for each occupation into a more easily interpretable index. We construct five indices covering both cognitive and non-cognitive job skills that line up with previous work in the area to facilitate comparison. Specifically, we use two cognitive indices representing interpersonal (social) skills and analytical (quantitative) skills and three indices for non-cognitive or manual skills, including fine motor skills, physical strength, and visual skills. We use Confirmatory Factor Analysis (CFA) (following the work of Imai et al 2014) to construct the index values; the technical details of its implementation can be found in the Appendix.

To connect the information regarding skills required of occupations found in O*Net to occupations in the LFS, we rely primarily on a series of crosswalks designed to match occupation codes from O*NET to Standard Occupation Codes (SOC) used in the United States and then from SOC to the NOC codes now used in Canada. Using these crosswalks, we are able to match most occupations. We then manually reviewed unmatched LFS occupations to find appropriate matches in O*NET. As noted in the Appendix A, only a few occupations are left unmatched.

To facilitate interpretation of the skill variables the factor analysis uses as weights the distribution of the skills in the Canadian workforce (all ages) over our sample period (1997-2015). As such, a skill score of zero describes the level of skill used by the average worker in the Canadian workforce. Also, a unit of the skill score (with mean zero) can be interpreted as one standard deviation in the skill distribution of the Canadian working population.

3. Characteristics of men and women

In this section we provide a description of our main samples of men and women used in this study, in terms of their average characteristics.

In Table 1 we summarize some of the demographic characteristics of men and women. The age distribution of men and women is quite similar, though men appear more present in the workforce at younger ages than women. In terms of the number of children in one's household, men are more likely to have younger children than women and women are more likely to have older children included in their household. Among employed men and women, this will in part reflect the management of childcare (as women are more likely not employed when children are young) and child custody arrangements whereby older children are more likely primarily with mothers than fathers. As these factors may reflect differences in lifecycle work arrangements of men and women they are important to account for in our analysis of wages.

Table 1. Demographic characteristics (Mean)

	Men	Women
Age (proportion in each group)		
25-29	0.177	0.172
30-34	0.174	0.164
35-39	0.171	0.165
40-44	0.174	0.176
45-49	0.160	0.172
50-54	0.144	0.150
Married/common-law (proportion)	0.692	0.693
Number of own children aged:		
0-3	0.145	0.123
4-5	0.083	0.076
6-12	0.211	0.228
13-15	0.110	0.132
16-17	0.073	0.092
Number of observations	740,173	732,995

Note: Sample includes employed Canadians aged 25-54, 1997-2015.

In Figure 2 we present the distribution of men and women across educational attainment categories. It is clear that women are more likely to attend university and college than men, and are less likely to leave school before finishing high school. However, men are more likely to pursue a trades certificate than women. As the training offered by formal education affects a worker's productivity, education must be accounted for in our analysis of gender wage gaps.

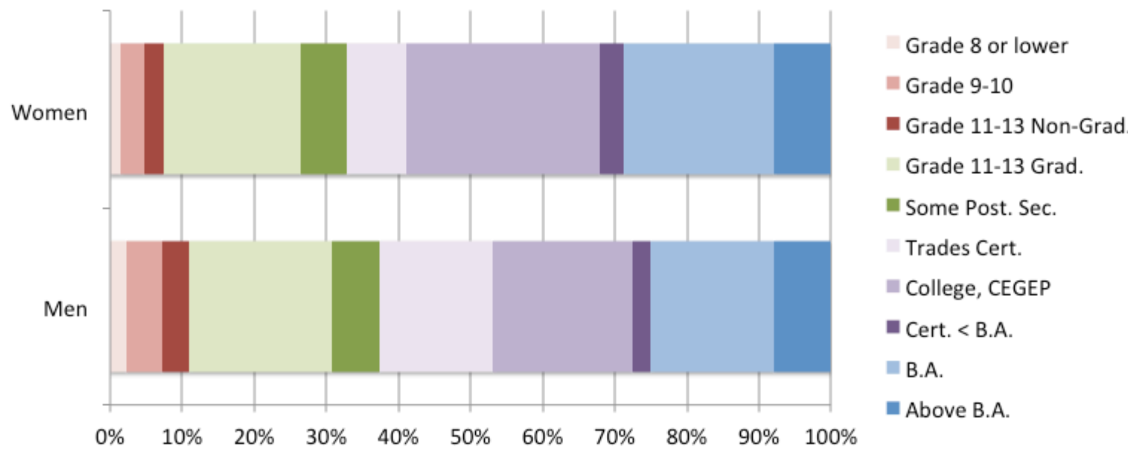

Figure 2. Distribution of men and women across education categories
Note: Each segment represents the percent of men or women with each level of education.

In Table 3 we consider the average job characteristics of men and women. On average, men have slightly more seniority in their jobs (just over four months). Men are more likely to work in full time positions (95.7%) than women are (81.6%). Despite this, nearly as many women are working in permanent positions as men. Women are slightly more likely to be unionized than men are, which in part reflects their much higher likelihood of being employed in the public sector. Finally, women are more likely than men to work with very small employers (less than 20 employees) than men are.

Table 3. Job characteristics

	Men	Women
Tenure (years)	7.923	7.557
Full time	0.957	0.816
Permanent	0.918	0.904
Union (covered)	0.337	0.354
Public Sector	0.188	0.318
Establishment size		
Less than 20	0.290	0.321
20-99	0.330	0.327
100-500	0.238	0.213
More than 500	0.142	0.140

Note: Sample includes employed Canadians aged 25-54, 1997-2015.

In Figure 3 we summarize the skills used by men and women in their jobs. Recall that the skills measures are standardized so that a value of zero represents the skills used by the average Canadian employee (without age restrictions). A skill value of one tells us individuals' skills are one standard deviation away from the average.

In Figure 3 we see men and women typically use very different skills in their jobs. Jobs held by women tend to use more interpersonal skills than average, while men use slightly less interpersonal skills than average. Both men and women in our sample use more analytical skills than the average worker in Canada. Given our sampling structure, this implies men and women 25-54 are using more analytical skills than workers outside this age range. It is also clear that men use substantially more physical strength, visual skills, and fine motor skills in their jobs than women use.

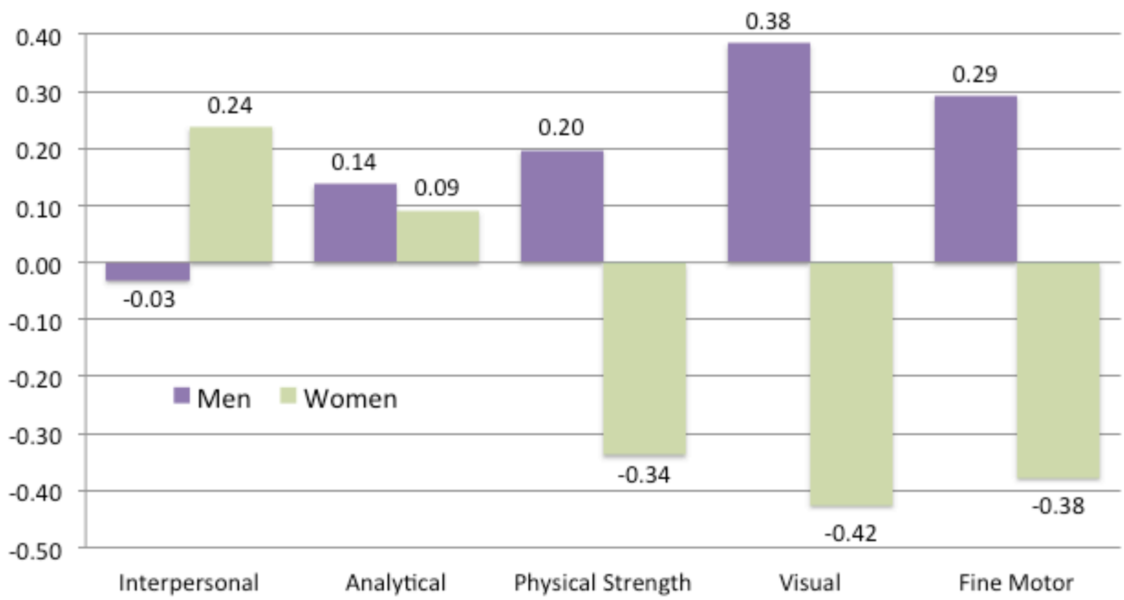

Figure 3. Average job skills of men and women
Note: Sample includes employed Canadians aged 25-54, 1997-2015

From Figures 4 and 5 we also see that men and women tend to segregate into different occupational categories (at a 2-digit NOC level). Men heavily dominate the workforce in trades-related occupations, as equipment operators, labourers, and professional occupations in science. Women tend to dominate in nursing, office administration and support, and care providers. It is clear the skills used in each of these occupations are quite different. (See Appendix C for a list of occupation groups with more detailed average skills information and the portion of employees that are male.)

Overall, we see several dimensions along which men and women appear quite different in terms of their position in the labour market, the characteristics of their jobs, their training, and the skills they use in their jobs. In the next sections we investigate the extent to which these differences in characteristics and skills can explain differences in hourly wages.

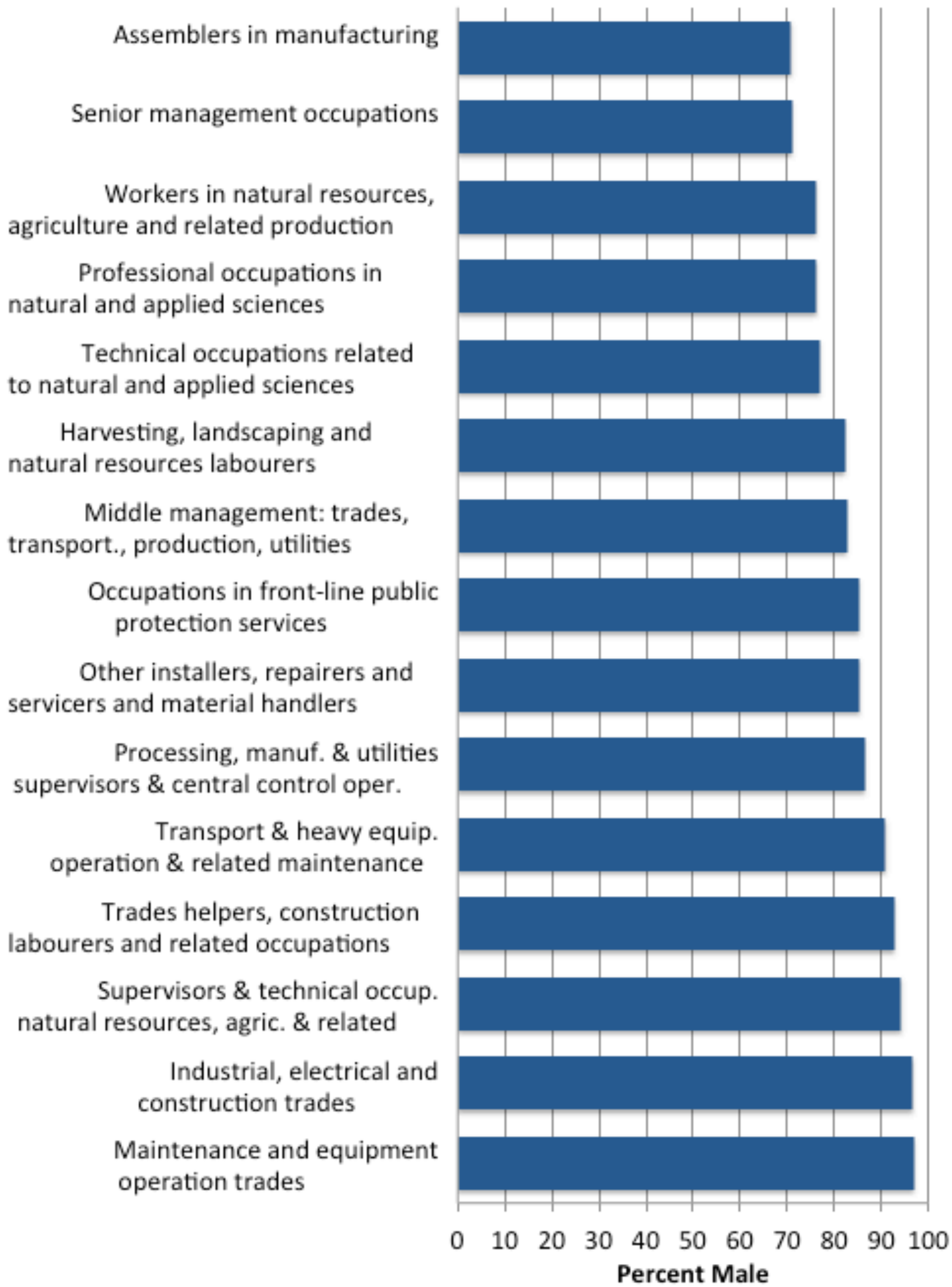

Figure 4. Percent male, by occupation (more than 70% male)
Note: See Appendix C for more information

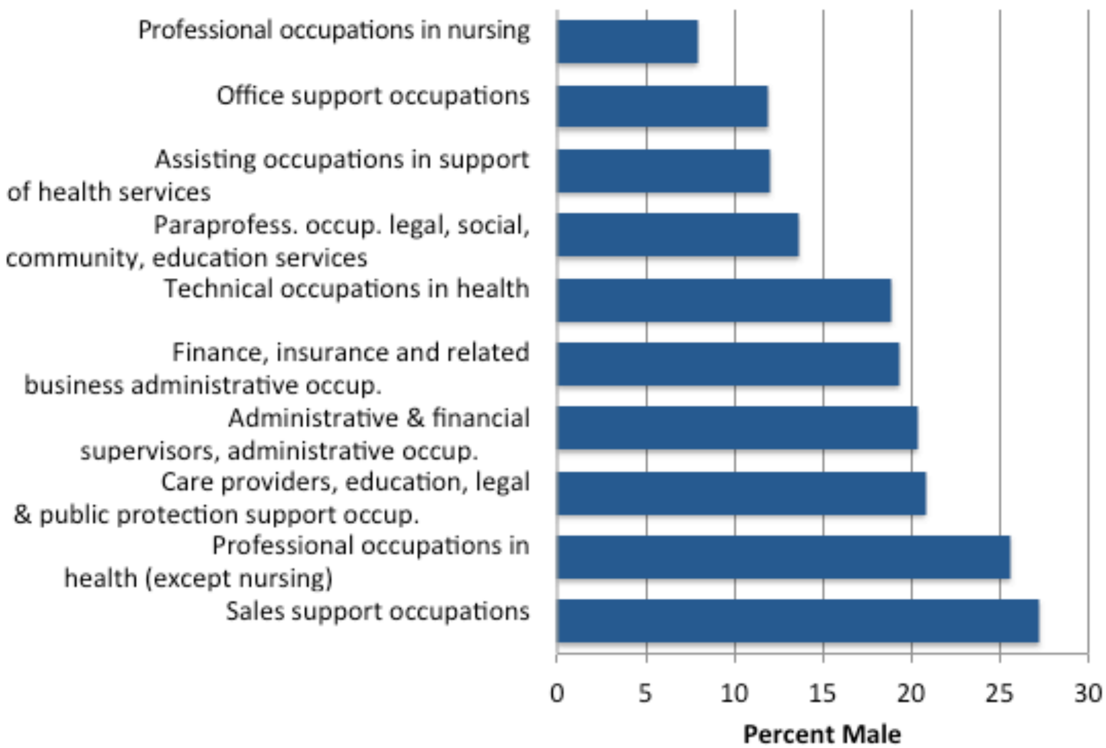

Figure 5. Percent male, by occupation (more than 70% female)
Note: See Appendix C for more information.

4. Gender wage gaps and the net segregation wage gap

Methodology

In our analysis we use four regression models, each accounting for different factors, as follows:

(1) $\ln(w_i) = \alpha + \delta F_i + \varepsilon_i$

(2) $\ln(w_i) = \alpha + \gamma F_i + X_i B + \varepsilon_i$

(3) $\ln(w_i) = \alpha + \lambda F_i + X_i B + \Sigma_j \varphi_j Occup_{ji} + \varepsilon_i$

(4) $\ln(w_i) = \alpha + \phi F_i + X_i B + \Sigma_k \eta_k Skill_{ki} + \varepsilon_i$

Where $\ln(w_i)$ is the natural logarithm of the real hourly wage and F_i is an indicator variable equal to one when individual *i* is female, and 0 when male. In the first equation, the regression coefficient δ will represent the unadjusted, or raw, gender wage gap: the percent difference in hourly wages between men and women, without controlling for anything else.[4] In the general case where men on average earn more than women, this coefficient will be negative.

In the second equation, the term X_i represents the main variables we control for, and are modeled as affecting wages according to the parameter B. In our study, the control variables include indicators for 5-year age group, marital status, the number of own children by age of the child, education levels, tenure on the job, whether one's job is full time, permanent, unionized, and in the public sector, and the size of the establishment one works in, as well as indicators for province of residence and the year one is observed. When using our full sample of individuals we also include a set of indicator variables for industry. The coefficient on the indicator for female, γ, now represents an adjusted gender wage gap: after accounting for gender differences in these control variables, what is the percent difference in hourly wages between men and women. By comparing the values of γ and δ, we can get a sense of how much of the raw gender wage gap is due to gender differences in these characteristics.

In the third equation, the terms $Occup_j$ represent indicator variables for each of *j* occupation categories. In our main specification we include 40 occupation categories. When estimating the equation with our full Canadian sample, we are able to include a finer set of categories, breaking occupations into 140 groups. The coefficient λ represents the adjusted wage gap that further accounts for the tendency of men and

[4] The coefficient multiplied by 100 is roughly the percent difference in hourly wages between men and women.

women to enter different categories of occupations, as well as the set of covariates described in the second equation. The difference (γ–λ) describes the extent to which the gender wage gap can be attributed to this occupational gender segregation.[5]

Finally, the fourth equation replaces the occupation indicator variables with our more direct measures of skills used in the individual's occupation (recalling finer classifications of the 4-digit NOC are used when matching skills of individual jobs). From this regression, the coefficient ϕ represents the adjusted wage gap that accounts for any gender differences in skills, as well as the set of covariates used in previous specifications.

There are two comparisons from this final equation that are interesting. First, as with our third specification, the difference between ϕ and γ describes the extent to which the gender wage gap can be attributed to gender differences in skills used on the job.[6] If gender differences in skills help explain the gender wage gap, we expect ϕ to be closer to zero than γ. The difference (γ–ϕ) indicates how much of the gender wage gap is attributed to gender differences in skills.

Second, we are interested in the difference between λ and ϕ. Where results suggest λ is closer to zero than ϕ is, we have a situation in which occupational gender segregation appears to explain more of the gender wage gap than gender differences in skills used in an occupation. We create the measure (λ-ϕ) to capture the extent to which this is true. This difference (λ-ϕ) can be interpreted as the part of the gender wage gap that can be explained by occupational gender segregation net of any gender wage gap associated with gender differences in the skills used in occupations. A positive number will indicate that occupational gender segregation explains more of the gender wage gap than gender differences in job skills. We refer to this difference (λ-ϕ) as a ***net segregation wage gap***.

Generally this could represent gender differences in any undesirable job attributes that employers must compensate employees for (such as risk of injury), as well as any systemic bias in workplaces that tend to favour wage schedules in male-dominated occupations. We return to a discussion of what this difference may indicate in later sections.

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[5] We note there are important relationships between the occupation indicators we include in the regressions and other covariates included in X. We do not directly account for more complex interactions between these variables that could affect our estimated coefficients. There are also many factors we are not able to observe, that if accounted for may affect our regression estimates. This should be kept in mind when interpreting results.

[6] As with our use of occupation indicators, there will be important relationships between skills and other factors (only some of which are accounted for) in our analysis.

Model Results – All industries

In Table 4 we present the regression results based on the full sample of Canadians aged 25-54, across all industries combined. Each column represents a different regression model, corresponding to the equations (1-4) described in the previous section. The first row of the table provides the coefficient on the female indicator variable in these regressions, representing the unadjusted or adjusted wage gap.

In the first column of Table 4, our estimates indicate an unadjusted wage gap (δ) of -.175, indicating that the average wages of women are roughly 17.5% less than the average wages of men. This forms the baseline against which our estimated adjusted wage gaps are compared.

In the second column of Table 4, we include our baseline set of control variables. Perhaps surprisingly, the adjusted wage gap appears slightly larger than the unadjusted wage gap. This in part relates to a common finding in the gender wage gap literature, whereby women in this sample are more educated, on average, than men, and would therefore expect to receive higher wages as a result. As such, the wage gap that is not accounted for by the included variables appears larger. In the next column of Table 4 (2b), we extend our baseline set of control variables to include a set of indicator variables for industry (at the 3-digit NAICS level). This accounts for industrial gender segregation. The adjusted wage gap estimate is much smaller as a result, at 14.7 percent.

In the next two columns of Table 4 (3a and 3b) we include indicators for occupational categories, accounting for occupational gender segregation. The estimates suggest that when using a broader set of (40) occupation categories, the adjusted wage gap is 12.3 percent. A finer set of (140) occupation categories are used in specification in column (3b) as a robustness check, resulting in a very similar estimate for the adjusted wage gap.

Finally, the last column of Table 4 (column 4) replaces the occupation indicator variables with our measures of job skills in the regression. First, we compare the resulting adjusted gender wage gap (at 14.4%) to that in column (2b) (at 14.7%) which includes all the same control variables except for skills. Accounting for gender differences in skills does little, if anything, to reduce the gender wage gap. Given other regression coefficients in Table 4 and the average skills of men and women (Figure 3), we see a situation where men tend to use more of the skills that receive the lowest wage premiums. For example, in Table 4 we see that interpersonal skills are associated with much higher wages (a one standard deviation increase in skill is associated with wages that are 7.1 percent higher) and in figure 3 we see that women use more interpersonal skills in their jobs. Moreover, men use more fine motor skills and these are associated with lower wages on average. This balances against men's slightly higher use of analytical skills in their jobs and the higher wage associated with the use of those skills.

Table 4: Regression results (all industries)

	(1)	(2a)	(2b)	(3a)	(3b)	(4)
Female	-0.175	-0.184	-0.147	-0.123	-0.121	-0.144
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Interpersonal	-	-	-	-	-	0.071
						(0.001)
Analytical	-	-	-	-	-	0.091
						(0.001)
Physical	-	-	-	-	-	0.021
						(0.001)
Visual	-	-	-	-	-	-0.015
						(0.001)
Motor	-	-	-	-	-	-0.002
						(0.001)
Industry (93)	No	No	Yes	Yes	Yes	Yes
Occupation (40)	No	No	No	Yes	No	No
Occupation (140)	No	No	No	No	Yes	No
Education (Gr. 11-13, non graduate omitted)						
Grade 8 or lower	-	-0.097	-0.076	-0.046	-0.043	-0.04
		(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Grade 9-10	-	-0.036	-0.03	-0.017	-0.016	-0.015
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Grade 11-13 Grad.	-	0.072	0.056	0.037	0.036	0.033
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Some Post. Sec.	-	0.133	0.105	0.059	0.055	0.058
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Trades Cert.	-	0.176	0.123	0.077	0.075	0.081
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
College, CEGEP	-	0.223	0.169	0.086	0.081	0.094
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cert. < B.A.	-	0.304	0.242	0.117	0.107	0.143
		(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
B.A.	-	0.404	0.328	0.153	0.141	0.2
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Above B.A.	-	0.497	0.41	0.192	0.193	0.243
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure (years)	-	0.012	0.011	0.009	0.008	0.009
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Full Time	-	0.16	0.108	0.063	0.06	0.08
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Permanent	-	0.079	0.093	0.073	0.066	0.075
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Union (covered)	-	0.045	0.035	0.084	0.088	0.077
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Public sector	-	0.125	0.098	0.082	0.089	0.089
		(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Other covariates	No	Yes	Yes	Yes	Yes	Yes

Note: Other covariates include indicators for each 5 year age group, the number of children by age of the childe, marital status, establishment size, province of residence, year. The 93 industry categories correspond to 3-digit NAICS categories. The 40 occupations correspond to occupation categories based on the first two NOCS digits, 140 categories on the first 3 digits with some groups collapsed to address small samples.

We then compare the difference between the adjusted gender wage gap accounting for skills (ϕ in column 4) to the adjusted wage gap accounting for occupational gender segregation (λ in column 3a). The difference, 2.1 percentage points, represents the net segregation wage gap. That is, we suggest that 2.1 percentage points of the gender wage gap is associated with occupational gender segregation after accounting for the part of the gap that is associated with gender differences in the skills used in detailed occupations.

Adjusted gaps and the net segregation wage gap within industries

In this section we investigate gender wage gaps within industries, with the expectation that the gap and our measure of the net segregation wage gap will vary widely across industries. Estimating the adjusted wage gaps and net segregation wage gap within industry also allows us to recognize that each type of skill may be valued differently in different industries. As discussed in later sections, policy makers may want to recognize and identify how these wage gaps vary across industrial sectors.

We repeat the regressions specified in equations (1)-(4) to obtain estimates of δ, γ, λ, and ϕ. These gender wage gaps are estimated within samples of workers, by industry group (3-digit NAICS). Results are presented in Table 5, with each row representing regressions for the specified industry and each column representing our gender wage gap estimates of δ, γ, λ, and ϕ, respectively. The net segregation wage gap can be found by finding the difference between the third and fourth column results ($\lambda - \phi$).

First, consider the results in column (1) for the unadjusted wage gap (δ), where we see a high degree of variation across industries. For example, in the industry of specialty trade contractors, women on average earn roughly 28.9 percent less than men. In real estate, the unadjusted gender wage gap is 10.4 percent and in nursing and residential care facilities, the gap is only 5.5 percent. Within broader industry categories, there is a wide range of wage gaps observed and few generalizations can be made. Looking across industries there are also few generalizations, although industries dominated by the public sector appear to have average or lower than average gender wage gaps.

In Figure 6 we relate the extent to which an industry is male-dominated (i.e. the percent of workers in that industry that are male) to the unadjusted wage gap in the industry. Perhaps surprisingly, there is no clear correlation between the two industry level statistics. Moreover, we see that even within broader categories of industries that are male- or female-dominated there is a wide variation in the unadjusted gender wage gap.

Table 5: Adjusted Wage Differentials, by Industry

Industry	Covariates include: (1) None	(2) Basic	(3) Occupation+	(4) Skills+
All industries	-0.175	-0.147	-0.123	-0.144
Agriculture, forestry, fishing, hunting (11)				
Crop production	-0.168	-0.171	-0.176	-0.182
Animal production and aquaculture	-0.096	-0.131	-0.144	-0.135
Forestry and logging	-0.191	-0.203	-0.203	-0.227
Fishing, hunting and trapping	-0.137	-0.224	-0.237	-0.250
Support activities for agriculture and forestry	-0.180	-0.187	-0.177	-0.172
Mining, quarrying, and oil and gas extraction (21)				
Oil and gas extraction	-0.218	-0.244	-0.183	-0.200
Mining and quarrying (except oil and gas)	-0.104	-0.171	-0.130	-0.161
Support for mining, oil and gas extract.	-0.165	-0.223	-0.205	-0.241
Utilities (22)				
Utilities	-0.182	-0.185	-0.147	-0.160
Construction (23)				
Construction of buildings	-0.172	-0.177	-0.184	-0.231
Heavy and civil engineering construction	-0.158	-0.191	-0.154	-0.197
Specialty trade contractors	-0.289	-0.204	-0.191	-0.271
Manufacturing (31-33)				
Food manufacturing	-0.220	-0.182	-0.149	-0.169
Beverage and tobacco product manufacturing	-0.105	-0.088	-0.107	-0.114
Textile mills	-0.177	-0.140	-0.126	-0.163
Textile product mills	-0.215	-0.190	-0.169	-0.191
Clothing manufacturing	-0.257	-0.185	-0.129	-0.146
Leather and allied product manufacturing	-0.277	-0.170	-0.157	-0.177
Wood product manufacturing	-0.145	-0.148	-0.146	-0.173
Paper manufacturing	-0.219	-0.182	-0.175	-0.198
Printing and related support activities	-0.279	-0.241	-0.217	-0.239
Petroleum and coal product manufacturing	-0.195	-0.198	-0.182	-0.192
Chemical manufacturing	-0.189	-0.167	-0.164	-0.192
Plastics and rubber products manufacturing	-0.269	-0.218	-0.179	-0.204
Non-metallic mineral product manufacturing	-0.184	-0.179	-0.186	-0.219
Primary metal manufacturing	-0.131	-0.121	-0.117	-0.149
Fabricated metal product manufacturing	-0.202	-0.191	-0.187	-0.230
Machinery manufacturing	-0.187	-0.188	-0.178	-0.211
Computer & electronic product manuf.	-0.378	-0.244	-0.172	-0.193
Electrical equip., appliance, and comp. manuf.	-0.253	-0.202	-0.171	-0.194
Transportation equipment manufacturing	-0.214	-0.161	-0.133	-0.165
Furniture and related product manufacturing	-0.128	-0.137	-0.154	-0.165
Miscellaneous manufacturing	-0.266	-0.209	-0.184	-0.198

Industry	Covariates include:			
	(1) None	(2) Basic	(3) Occupation+	(4) Skills+
Wholesale trade (41)				
Farm product merchant wholesalers	-0.188	-0.194	-0.149	-0.171
Petroleum and petro products merch. wh.	-0.244	-0.246	-0.242	-0.253
Food, beverage, tobacco merch. wh.	-0.148	-0.144	-0.155	-0.168
Personal and household goods merchant wh.	-0.141	-0.135	-0.127	-0.139
Motor vehicle/parts/accessories merch. wh.	-0.218	-0.219	-0.166	-0.205
Building material and supplies merch. wh.	-0.194	-0.194	-0.169	-0.201
Machinery, equipment & supplies merch. wh.	-0.224	-0.207	-0.164	-0.186
Miscellaneous merchant wholesalers	-0.160	-0.169	-0.163	-0.171
Retail trade (44-45)				
Motor vehicle and parts dealers	-0.202	-0.195	-0.149	-0.189
Furniture and home furnishings stores	-0.189	-0.149	-0.191	-0.194
Electronics and appliance stores	-0.160	-0.158	-0.152	-0.167
Building material, garden equip/supply dealers	-0.186	-0.175	-0.158	-0.173
Food and beverage stores	-0.241	-0.138	-0.117	-0.129
Health and personal care stores	-0.272	-0.151	-0.128	-0.158
Gasoline stations	-0.127	-0.132	-0.086	-0.087
Clothing and clothing accessories stores	-0.231	-0.145	-0.144	-0.146
Sporting goods, hobby, book and music stores	-0.234	-0.164	-0.159	-0.160
General merchandise stores	-0.303	-0.201	-0.170	-0.185
Miscellaneous store retailers	-0.267	-0.205	-0.191	-0.190
Non-store retailers	-0.145	-0.178	-0.169	-0.154
Transportation and warehousing (48)				
Air transportation	-0.298	-0.303	-0.200	-0.204
Rail transportation	-0.074	-0.120	-0.094	-0.102
Water transportation	-0.179	-0.174	-0.090	-0.130
Truck transportation	-0.099	-0.138	-0.144	-0.184
Transit and ground passenger transportation	-0.188	-0.055	-0.067	-0.087
Support activities for transportation	-0.222	-0.193	-0.152	-0.220
Postal service	-0.072	-0.034	-0.037	-0.043
Couriers and messengers	-0.145	-0.094	-0.107	-0.128
Warehousing and storage	-0.203	-0.174	-0.160	-0.178
Information and cultural industries (51)				
Publishing industries (except internet)	-0.281	-0.170	-0.130	-0.139
Motion picture and sound recording ind.	-0.123	-0.086	-0.055	-0.083
Broadcasting (except internet)	-0.080	-0.085	-0.058	-0.076
Telecommunications	-0.200	-0.159	-0.097	-0.113
Data processing, hosting, and related services	-0.404	-0.229	-0.085	-0.099
Other information services	-0.196	-0.112	-0.071	-0.090

Industry	Covariates include:			
	(1) None	(2) Basic	(3) Occupation+	(4) Skills+
Finance and insurance (52)				
Credit intermediation and related services	-0.354	-0.216	-0.130	-0.148
Securities, commodity contracts, other service	-0.293	-0.214	-0.128	-0.138
Insurance carriers and related activities	-0.263	-0.196	-0.137	-0.145
Real estate and rental and leasing (53)				
Real estate	-0.104	-0.093	-0.150	-0.159
Rental and leasing services	-0.266	-0.166	-0.168	-0.167
Professional, scientific and technical services (54)				
Professional, scientific and technical services	-0.290	-0.199	-0.127	-0.161
Admin. & support, waste management & remediation services (56)				
Administrative and support services	-0.101	-0.086	-0.082	-0.107
Waste management and remediation services	-0.087	-0.165	-0.152	-0.225
Educational services (61)				
Educational services	-0.077	-0.073	-0.061	-0.059
Health care and social assistance (62)				
Ambulatory health care services	-0.221	-0.107	-0.032	-0.163
Hospitals	0.042	0.016	-0.010	-0.028
Nursing and residential care facilities	-0.055	-0.043	-0.052	-0.062
Social assistance	-0.097	-0.071	-0.055	-0.061
Arts, entertainment and recreation (71)				
Performing arts, spectator sports and related	-0.158	-0.150	-0.106	-0.147
Heritage institutions	-0.076	-0.063	-0.074	-0.075
Amusement, gambling and recreation	-0.167	-0.124	-0.122	-0.123
Accommodation and food services (72)				
Accommodation services	-0.221	-0.130	-0.102	-0.093
Food services and drinking places	-0.167	-0.124	-0.115	-0.113
Other services (except public admin.) (81)				
Repair and maintenance	-0.252	-0.224	-0.200	-0.250
Personal and laundry services	-0.249	-0.194	-0.204	-0.160
Religious, grant-making, civic, prof. org.	-0.088	-0.026	-0.029	-0.008
Public administration (91)				
Federal government public admin.	-0.121	-0.102	-0.069	-0.085
Provincial and territorial public admin.	-0.158	-0.124	-0.082	-0.098
Local, municipal and regional public admin.	-0.134	-0.136	-0.091	-0.102
Aboriginal public admin.	-0.108	-0.116	-0.094	-0.095

NOTE: Results presented are coefficients on the female indicator for regressions represented by equations (1) – (4), estimated within each industry.

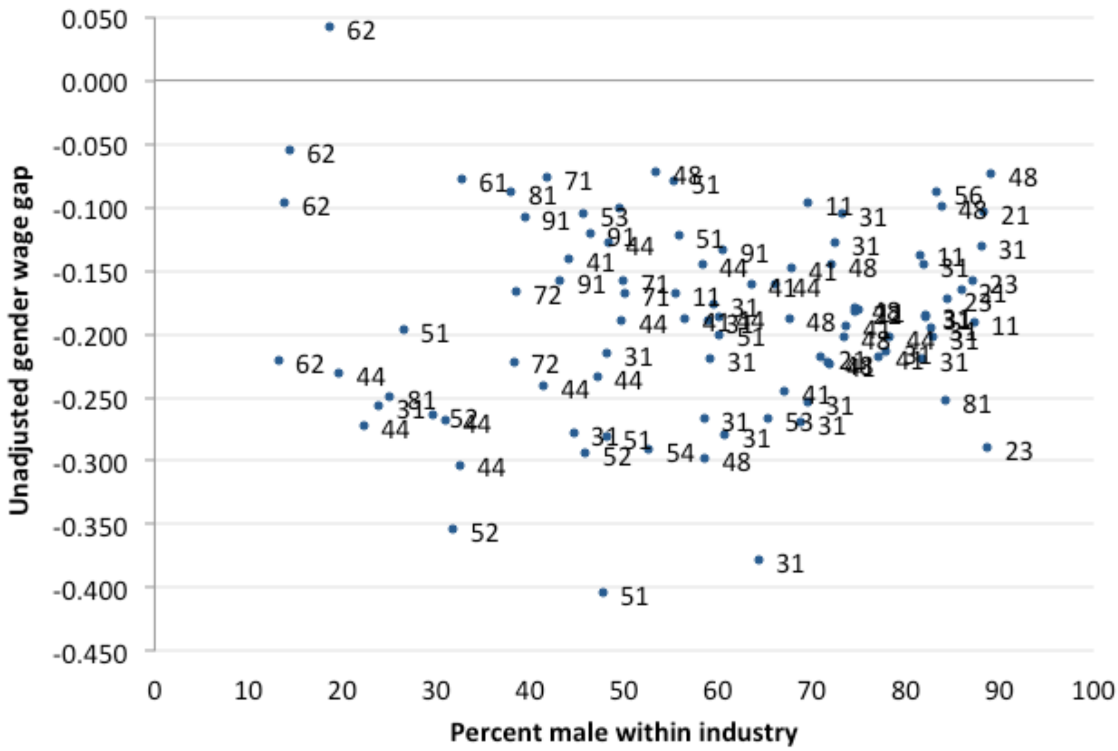

Figure 6. Unadjusted gender wage gaps and the percent of the workforce that is male, by industry.

Note: Each point in the scatterplot represents an industry at the 3-digit NAICS, labeled by the number for its broader 2-digit NAICS, as provided in Table 5.

We now turn to our estimates of the adjusted gender wage gaps in Table 5 (columns 2-4), and the resulting net segregation wage gaps. Consider, for example, the oil and gas extraction industry. The unadjusted gender wage gap in this industry is relatively high, at 21.8 percent. After accounting for gender differences in our main control variables and occupation categories, our results suggest an adjusted gender wage gap that is slightly smaller, at 18.3 percent. Notably, the difference between the results in column (2) and column (3), at 6.1 percentage points, suggests that occupational segregation can explain a substantial portion of the gender wage gap. Moving from columns (3) to (4), however, we see that gender differences in skills will account for less of the gender wage gap than gender differences in occupation. Our estimate of the net segregation wage gap for the oil and gas extraction industry is 1.7 percentage points.

Generally speaking, the results across industries are similar in that gender segregation into occupations tends to explain a larger portion of the gender wage gap than gender differences in skills used in detailed occupations. In some industries the resulting net segregation wage gap is quite large: for example in specialty trade contractors, the net segregation wage gap is 8 percentage points; in professional, technical and scientific services, the net segregation wage gap is 3.4 points; in fabricated metal product manufacturing the net segregation wage gap is 4.3 points. We note an unusually large net segregation wage gap in ambulatory health care services, at 13.1 percentage points, that is worthy of special consideration and a more detailed examination given the range of services included in this industry.

In contrast, there are some industries in which the net segregation wage gap is nearly zero, or even positive. Accommodation services, which has a fairly high unadjusted gender wage gap at 22.1 percent, has a small negative net segregation wage gap at -0.9 percent. This indicates that the part of the gender wage gap accounted for by gender differences in occupations is also reflecting gender differences in skill. Other examples where this appears to be true include educational services, rental and leasing services, several industries involved in retail trade, and support activities for agriculture and forestry.

Comparing the net segregation wage gap across industries

We have described the net segregation wage gap as representing that part of the wage gap accounted for by occupational segregation net of the wage gap accounted for by gender differences in skills. What might this part of the gender wage gap represent?

There are two key factors we want to consider here. The first factor is generally known as compensating differentials. While we have accounted for skills, there are many other job attributes that employees are compensated for - such as risk, instability, or other undesirable job attributes. The second factor represents a systemic bias favouring male wage structures, maybe maintaining an historical relative position of men in the labour market. It may also represent a tendency to reward full time work schedules at a higher hourly rate of pay than part time work.[7]

For the most part, the factors we are most interested in cannot be directly accounted for given the data we have available. In this section we provide some correlations between industry characteristics and the net segregation wage gap, hoping to give a better sense of what this may or may not represent.

In Figure 7 we present a scatterplot of industries' net segregation wage gap (based on industry wage gap results in Table 5) and the percent of workers that are male in each industry. While there was no clear relationship between the total unadjusted gender

[7] Typically, we see full time workers earning a higher wage rate than those working part time (as our estimates in Table 4 suggest). However, we need to further consider wage schedules within occupations. For example, Goldin and Katz (2016) studied the evolution of part-time wage penalties among pharmacists and point to the importance of technology that facilitates the substitutability of workers for closing the gender wage gap. Further examination of work schedules is part of the authors' future research agenda.

wage gap and the percent male in each industry (Figure 6), in Figure 7 we see a clear positive relationship between the net segregation wage gap and the percent male in the industry.

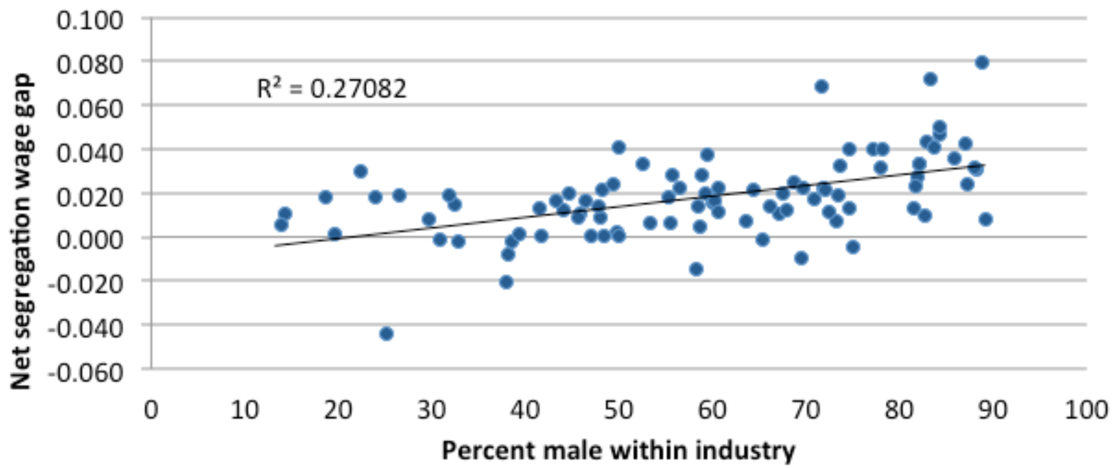

Figure 7. The net segregation wage gap and percent male within industries.
Note: Each point represents a single industry (3-digit NAICS), with one outlier (ambulatory health care) omitted.

In Figures 8 and 9 we consider the potential relationship between industries' job risk and the net segregation wage gap, as risk would represent an important reason to compensate employees apart from the skills used in their jobs. We use the available incidence of fatal and non-fatal occupational injuries from the U.S. within each 3-digit NAICS (which is unfortunately not readily available from Canadian sources) as a proxy for industry risk.

In Figure 8 we show there is a small positive correlation between the risk of fatal injury and our measure of the net segregation gap, however we must stress that the correlation is near zero. Similarly, when we consider the risk of non-fatal injuries (Figure 9), there is virtually no relationship with our measure of the net segregation wage gap.

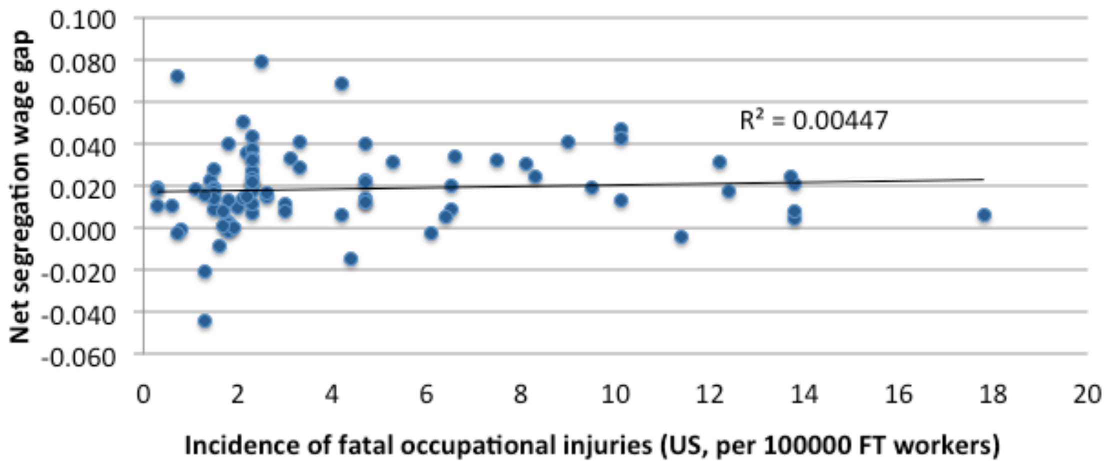

Figure 8. The net segregation wage gap and risk of fatal injury
Note: The incidence of fatal occupational injuries is based on the U.S. Census of fatal occupational injuries in 2015, found at https://www.bls.gov/iif/oshcfoi1.htm#2015 . The figure above excluded four outliers of most fatal occupations representing forestry, fishing and truck transportation.

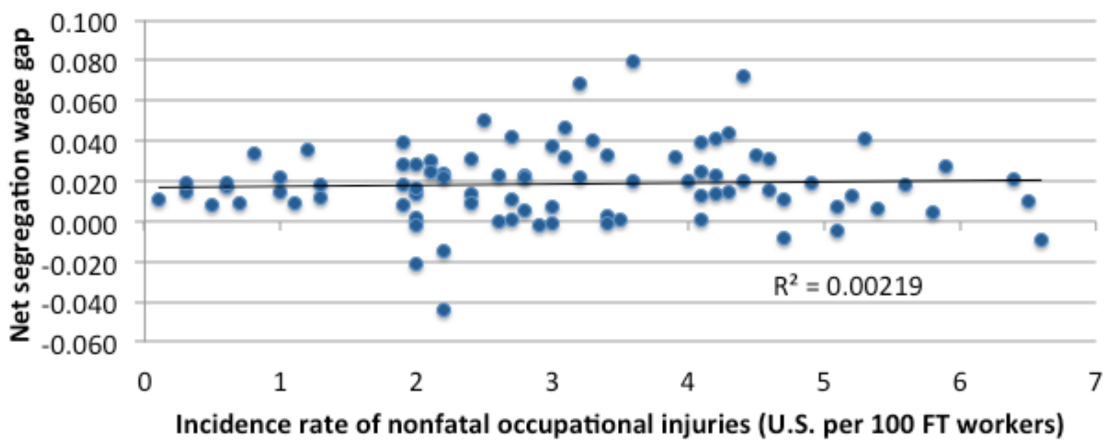

Figure 9. The net segregation wage gap and risk of non-fatal injury
Note: Incidence rates are based on BLS data available at https://www.bls.gov/iif/oshwc/osh/os/ostb4740.pdf , and largely represents the private sector.

While a more rigorous assessment of jobs in Canada is required, this suggests that gender differences in job risks will not explain that part of the wage gap associated with occupational segregation net of gender differences in skills. This is perhaps unsurprising given evidence that the risks facing men and women are not as large as once believed. For example, Hersch (1998) showed that women face a job risk that is 71 percent of men's and similarly receive a wage premium for that risk.

We then consider how competitive an industry is in relation to the net segregation wage gap. Generally, theories of discrimination would suggest that the more competitive an industry, the less employers are able to discriminate against women and pay lower wages than for equally skilled men. In Figure 10 we relate values of the net segregation wage gap and the Herfindahl-Hirschman Index (HHI) for each industry (at the 3-digit NAICS level, Canada, based on total revenues and number of enterprises). Note that higher values of the HHI suggest an industry is less competitive, having few enterprises holding a relatively large market share. Perhaps surprisingly, there is no correlation between this measure of market concentration our net segregation index. It is unclear, however, that measuring industry concentration at this high level of aggregation is the most relevant measure for our purposes.

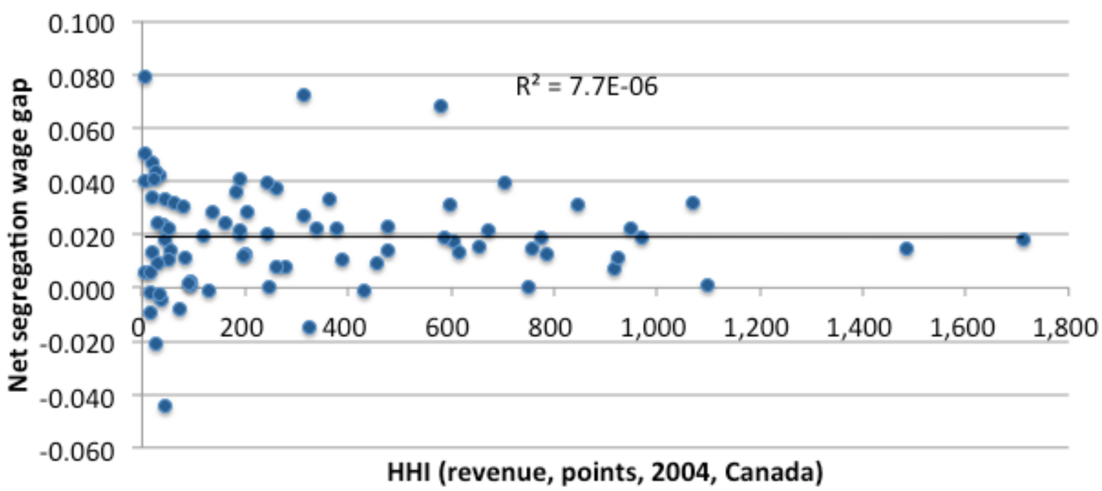

Figure 10. The net segregation wage gap and industry concentration
Note: HHI values represent custom tabulations by Statistics Canada.

Overall, then, we are left with the knowledge that male-dominated industries tend to be those with larger net segregation wage gaps. With the information presented here, however, we are not able to speak to which factors underlie the net segregation wage gap.

5. Occupations and skills

As the net segregation wage gap is not easily explained, we further investigate gender wage gaps within broad occupation categories. Specifically, within each of 10 broad occupation categories, we estimate the following regressions:

(5) $\ln(w_i) = \alpha + \delta F_i + \varepsilon_i$

(6) $\ln(w_i) = \alpha + \omega_1 F_i + \Sigma_k \eta_k Skill_{ki} + \varepsilon_i$

(7) $\ln(w_i) = \alpha + \omega_2 F_i + \Sigma_k \eta_k Skill_{ki} + \Sigma_j \varphi_j Industry_{ji} + \varepsilon_i$

(8) $\ln(w_i) = \alpha + \omega_3 F_i + \Sigma_k \eta_k Skill_{ki} + \Sigma_j \varphi_j Industry_{ji} + X_i B + \varepsilon_i$

Equation (5) is directly comparable to equation (1), in that the coefficient δ will represent an unadjusted gender wage gap in the occupation category. The adjusted wage gap estimate from equation (6), ω_1, represents the gender gap within the broad occupation category after accounting for the skills used within each detailed occupation category. The adjusted gap estimates based on the models in equations (7) and (8) are provided for completeness, further adjusting the gap to account for the industry in which individuals work and other individual and job characteristics X_i, as in the previous section.

We also conduct a Oaxaca-Blinder (OB) decomposition to estimate the extent to which gender differences in skills are a factor driving the gender wage gap within each occupation group. Specifically, we estimate regressions with the full set of covariates similar to that specified in equation (8), but within samples of men and women (rather than pooling the two groups together and including the indicator for female). The resulting gender specific coefficients and averages of covariates (subscripted with M and F) are used to estimate the percent of the gender wage gap ($\ln(w_M) - \ln(w_F)$) attributed to gender differences in skill as follows:

(9) $\text{OB \% skills} = 100^*(\Sigma_k(Skill_{kM} - Skill_{kF})\, \eta_{kM})/ (\ln(w_M) - \ln(w_F))$

The results are presented in Table 6. As a starting point, consider management occupations. Within this broad class of occupations, we see that women earn a wage that is approximately 19.4 percent less than men on average. When we account for skills used in detailed occupations, the adjusted wage gap is much smaller at 16.3 percent. This suggests roughly 3 percentage points of the 19 point gap (or 16%) can be attributed to gender differences in skill. In the third and fourth columns, we further adjust the wage gap for Industry and other variables we can control for, noting there may be important interactions between the additional variables and our skills measures. After accounting for observable gender differences in characteristics, we find an adjusted wage gap of 13.7 percent remains. In the last column, we provide the estimated explanatory power of gender differences in skills. The result suggests that gender differences in skills used across all management occupations can explain 4.8 percent of the gender wage gap within this broadly defined occupation group.

Table 6. Wage gaps within occupation categories

	Adjusted wage gaps accounting for:				OB %
Occupation category	None	Skills	Industry	Controls	Skills
Management occupations	-0.194	-0.163	-0.154	-0.137	4.8
Business, finance & admin.	-0.152	-0.113	-0.121	-0.102	16.8
Natural & applied science	-0.114	-0.120	-0.126	-0.123	-1.2
Health	-0.039	-0.087	-0.062	-0.049	-46.5
Education, law, social, community, gov.	-0.159	-0.078	-0.047	-0.053	17.9
Art, culture, recreation and sport	-0.071	-0.081	-0.064	-0.068	-0.7
Sales & service	-0.229	-0.212	-0.177	-0.141	3.5
Trades, transport, equipment oper.	-0.289	-0.205	-0.184	-0.170	16.4
Natural resources, agriculture, related	-0.417	-0.234	-0.144	-0.168	11.4
Occup. In manufacturing & utilities	-0.374	-0.305	-0.227	-0.187	10.1

NOTE: Results in the first columns presented are coefficients on the female indicator for regressions represented by equations (5) – (8), estimated within each industry. Results in the last column represent estimates of equation (9).

Looking across the occupation categories in Table 6, we see a fair amount of variation in results. For example, in some occupations, skill differentials will account for fairly large parts of the gender wage gap. This is clearly the case for business, finance and administration, or trades, transport and equipment operators. In others, such as occupations in natural and applied sciences, skills will explain very little of the gap. Some occupation groups, such as health, appear more complex as accounting for skills substantially increases the size of the gap that needs to be explained.[8]

What do the adjusted wage gaps tell us? The adjusted wage gaps in the fourth column of Table 6 will in part reflect any other gender differences in job attributes that cannot be accounted for in our data. In many occupation categories, however, a substantial gap remains. Given what we know from the current literature, it is difficult to imagine a list of job attributes with sufficient gender differences to account for this gap.

[8] As with our discussion of the ambulatory health services industry in the previous section, we believe health occupations require a more detailed examination than provided here. Here, Autor and Handel's (2013) work regarding the fact that tasks within detailed occupation groups may vary could be important.

The adjusted wage gap may reflect some degree of vertical segregation. Vertical segregation is the segregation of men and women along hierarchical levels of work and in this case occurs in similar lines of work (broad occupation categories).[9] Typically, we would think of this hierarchy as representing different levels of skills, education, or experience. However, in our analysis presented in Table 6 we have accounted for a variety of measures that reflect such differences.

Evidence in the literature suggests important gender differences in the propensity to receive job offers, training, or promotion opportunities, unrelated to one's productive characteristics. In particular, there is a growing evidence of evaluators' bias in the evaluation of women that reduces women's likelihood of being hired and promoted relative to equally qualified male candidates.[10] This bias that impedes women's ability to reach the top levels of the occupational hierarchy, often labeled as the "glass ceiling", has been cited as a determinant of the gender wage gap.[11]. Given the unobservable nature of productivity in many senior management positions, we would like to consider whether similar forms of evaluator bias also affect wage structures in ways that tend to favour men.

6. Discussion and policy relevance

Closing the gender wage gap has long been a goal for policy makers at many levels of government. The results presented in this study suggest two distinct approaches to policy to consider: (i) the development of pay equity policies at an industry level, and (ii) development of policies to address vertical occupational segregation within occupation groups.

The first suggested approach to policy derives from our estimates of the net segregation wage gap within industries. This represented the part of the gender wage gap that is associated with occupational segregation net of the gender wage gap accounted for by gender differences in skills used in occupations. The factors driving the net segregation wage gap are likely to vary by industry and require more detailed study within smaller geographic regions and industry groups. The evidence provided in this study suggests industries that could be targeted for further investigation. Here, we are interested in

[9] This is differentiated from vertical segregation that represents hierarchical levels of work across different lines of work, and horizontal segregation, which would be segregation into jobs with similar skill requirements, but different fields such as teachers and engineers. See Fortin and Huberman (2002) for more on this.

[10] For examples, see Wenneras and Wold (1997), Bagues and Esteve-Volart (2010), Rouse and Goldin (2000) and Sarsons (Forthcoming)

[11] See for example "The Glass ceiling", The Economist, May 5th, 2009

industries with large net segregation gaps, particularly industries that are heavily male dominated. Within industries, job attributes and pay structures within male and female dominated occupations could be compared at an industry level in a manner similar to methods outlined in current pay equity policies for large employers.

The second approach to policy – addressing vertical occupational segregation – derives from our analysis of wage gaps within broad occupation categories. Our evidence demonstrates that within occupation categories, some of the gender wage gap will relate to differences in the productive characteristics of detailed occupations – such as education, experience and skills. However, large parts of the gender wage gap within broad occupation categories are not explained by such factors. While some unobserved job attributes may (or many not) rationalize the remaining gender wage gap, we are more generally concerned that barriers remain preventing many women from entering the higher paid jobs within broad occupation groups.

Finally, we have highlighted a need to further investigate wage schedules within occupations in light of evidence that the elimination of part-time wage penalties can reduce the gender wage gap. Evidence from Goldin (2016) based on the occupation of pharmacist suggests that reducing employers' costs associated with offering greater 'temporal flexibility' (part time work schedules) is necessary to reduce the part-time wage penalty. The importance of flexible work schedules within Canadian occupations remains an important part of future research.

Appendix A. Excluded occupations

The following are occupation categories (4-digit NOCS) that are dropped from our sample due to difficulty matching with O*NET occupations. This required dropping 27742 observations from a sample of 1507991 observations.

NOCS	Occupation
11	Legislators
212	Architecture and science manager
413	Government managers - education
414	Other managers in public administration
433	Commissioned officers of the Canadian Forces
822	Managers in horticulture
1122	Professional occupations in business management consulting
2115	Other professional occupations in physical sciences
2234	Construction estimators
2255	Technical occupations in geomatics and meteorology
2283	Information systems testing technicians
3011	Nursing co-ordinators and supervisors
3215	Medical radiation technologists
3221	Denturists
3237	Other technical occupations in therapy and assessment
4165	Health policy researchers, consultants and program officers
4313	Non-commissioned ranks of the Canadian Forces
5223	Graphic arts technicians
5226	Other technical and co-ordinating occupations in motion picture, broadcasting and the performing arts
5227	Support occupations in motion picture, broadcasting and the performing arts
5232	Other performers, n.e.c.
6533	Casino occupations
6562	Estheticians, electrologists and related occupations
6721	Support occupations in accommodation, travel and facilities set-up services
7303	Supervisors, printing and related occupations
8252	Agricultural service contractors
9471	Plateless printing equipment operators
9472	Camera, platemaking and other prepress occupations
9527	Machine operators and inspectors, electrical apparatus manufacturing
9614	Labourers in wood, pulp and paper processing
	Total observations = 27742

Appendix B. Excluded Industries

We do not include the following industries in our main sample, nor do we assess the industry separately, because of small samples of either men or women (less than 200 men or 200 women). Notably, just over half of observations dropped here are represented in the industry of private households.

NAICS	Industry
110	Unknown
210	Unknown
419	Business-to-business electronic markets, and agents and brokers
486	Pipeline transportation
487	Scenic and sightseeing transportation
521	Monetary authorities - central bank
526	Funds and other financial vehicles
533	Lessors of non-financial intangible assets (except copyrighted works)
551	Management of companies and enterprises
814	Private households
919	International and other extra-territorial public administration
	Total observations = 7080

Appendix C. Occupation categories, average skills, and percent male.

Skills:	Inter-personal	Analy-tical	Physical	Visual	Fine Motor	% male
Maintenance and equipment operation trades	-0.412	0.231	1.106	1.368	1.485	96.86
Industrial, electrical and construction trades	-0.605	-0.001	1.206	1.295	1.219	96.65
Supervisors & technical occup. natural resources, agric. & related	-0.223	0.037	0.914	1.583	1.242	94.22
Trades helpers, construction labourers and related occupations	-1.535	-1.110	1.654	1.487	1.201	92.69
Transport & heavy equip. operation & related maintenance	-0.607	-0.727	0.919	2.363	1.597	90.89
Processing, manuf. & utilities supervisors & central control oper.	0.049	0.289	0.600	0.479	1.008	86.41
Other installers, repairers and servicers and material handlers	-1.056	-1.019	1.522	1.241	1.224	85.35
Occupations in front-line public protection services	0.598	0.228	1.451	2.610	1.702	85.19
Middle management: trades, transport., production, utilities	0.860	1.167	-0.227	-0.102	-0.204	82.57
Harvesting, landscaping and natural resources labourers	-1.775	-1.235	1.246	1.380	1.172	82.2
Technical occupations related to natural and applied sciences	0.345	0.736	0.035	0.320	0.420	76.83
Professional occupations in natural and applied sciences	0.943	1.726	-1.111	-0.496	-0.798	76.23
Workers in natural resources, agriculture and related production	-1.539	-1.200	1.148	1.733	1.417	76.08
Senior management occupations	1.932	1.872	-1.220	-0.354	-0.919	70.93
Assemblers in manufacturing	-1.073	-0.764	0.614	0.294	0.883	70.87
Processing & manuf. machine oper. & related production workers	-1.427	-0.794	0.793	0.400	1.071	65.05
Distribution, tracking and scheduling co-ordination occup.	-0.470	-0.442	0.256	0.303	0.039	63.22
Middle management: retail, wholesale trade, customer services	1.054	0.986	-0.910	-0.591	-0.867	56.56
Labourers in processing,	-1.619	-1.037	0.855	0.242	0.739	53.77

Skills:	Inter-personal	Analy-tical	Physical	Visual	Fine Motor	% male
manufacturing and utilities						
Specialized middle management occupations	1.238	1.259	-1.051	-0.554	-0.984	50.7
Sales rep. and salespersons - wholesale and retail trade	0.286	-0.246	-0.128	-0.508	-0.464	48.24
Retail sales supervisors and specialized sales occupations	0.603	0.353	-0.625	-0.607	-0.641	48.1
Technical occupations in art, culture, recreation and sport	0.440	0.163	-0.316	-0.153	-0.227	46.4
Service supervisors and specialized service occupations	-0.674	-0.774	0.329	-0.585	0.267	46.07
Service support and other service occupations, n.e.c.	-1.533	-1.446	0.395	-0.281	0.064	43.59
Professional occupations in art and culture	1.086	0.457	-0.901	-0.575	-0.813	42.36
Professional occupations in business and finance	0.914	1.313	-1.353	-0.763	-1.244	39.56
Professional occup. Law, social, community & gov. services	1.475	0.928	-0.875	-0.568	-1.029	36.9
Professional occupations in education services	1.066	0.579	-0.677	-0.592	-1.059	33.57
Service rep. and other customer and personal services occup.	-0.227	-0.583	-0.141	-0.475	-0.137	31.64
Sales support occupations	-0.706	-0.703	0.269	-0.546	-0.072	27.22
Professional occupations in health (except nursing)	1.116	1.195	0.057	-0.550	0.072	25.58
Care providers, education, legal & public protection support occup.	-0.346	-0.849	0.270	-0.345	-0.451	20.78
Administrative & financial supervisors, administrative occup.	0.617	0.036	-0.971	-0.726	-1.085	20.32
Finance, insurance and related business administrative occup.	0.217	0.551	-1.415	-0.761	-1.004	19.32
Technical occupations in health	0.381	0.562	0.577	-0.240	0.793	18.87
Paraprofess. occup. legal, social, community, education services	0.634	0.318	-0.430	-0.366	-0.779	13.66
Assisting occupations in support of health services	0.745	0.913	1.025	1.406	1.341	12.01
Office support occupations	0.110	-0.201	-1.202	-0.879	-0.982	11.93
Professional occupations in nursing	0.567	0.503	0.941	-0.487	0.733	7.91

Appendix D. Construction of skills indices

We use Confirmatory Factor Analysis (CFA) to create our skills index using the information about abilities required for jobs in the O*NET. We weight each index using the Labor Force Survey (LFS) so that it can be interpreted as standard deviations of distributions of skill in the labor force in Canada. This is exercise is equivalent to Imai et al (2014).

The O*NET data contains very detailed information about skills required for each job; many of these are correlated and represents one underlying skill. Therefore, CFA is a very suitable technique to reduce the dimension of the information and recover everything in one single index. We then generate five skills measure: Interpersonal, Analytical, Physical, Visual, and Motor.

To match the codification of the occupations in the LFS 2015, which uses the Canadian Standard Occupation Classification, and the codification in the O*NET database, we use the crosswalks posted in the O*NET webpage. In some cases, two occupations in the O*NET-SOC codification were matched into one in the Canadian. For these cases, we use two approaches: The first one was to match randomly one of the repeated values in the O*NET-SOC into the Canadian one. The second was averaging the value of the information of those repeated values required for each job and matched it with the Canadian pair. The results presented in the paper do not change conditional on how we matched the information.

Interpersonal

We construct an index that recover Interpersonal skills using ten variables, the first six are listed in the Abilities section in the O*NET database and the remaining four in the job incumbent rating. Table A1 show the variables and Table A2 the principal components (PC) loadings.

Table A1: Variables Used to Construct the Interpersonal skill index

Variable ID	*Variable Name*	*O*NET Description*
1A1a1	Oral Comprehension	The ability to listen to and understand information and ideas presented through spoken words and sentences.
1A1a2	Written Comprehension	The ability to read and understand information and ideas presented in writing.
1A1a3	Oral Expression	The ability to communicate information and ideas in speaking so others will understand
1A1a4	Written Expression	The ability to communicate information and ideas in writing so others will understand.
1A4b4	Speech Recognition	The ability to identify and understand the speech of another person.
1A4b5	Speech Clarity	The ability to speak clearly, so others can understand you.
4A4a1	Interpreting the Meaning of Information for Others	Translating or explaining what information means and how it can be used.
4A4a2	Communicating with Supervisors, Peers, or Subordinates	Providing information to supervisors, coworkers, and subordinates by telephone, in written form, e-mail, or in person.
4A4a3	Communicating with Persons Outside	Communicating with people outside the organization, presenting the organization to customers, the public, government, and other external sources. This information can be exchanged in person, in writing, or by telephone or e-mail.
4A4a4	Establishing and Maintaining Interpersonal Relationships	Developing constructive and cooperative working relationships with others, and maintaining them over time.

Table A2: PC loadings for the Interpersonal skill index

Variable ID	***Factor Loading***
1A1a1	0.9267
1A1a2	0.9260
1A1a3	0.9435
1A1a4	0.9269
1A4b4	0.8444
1A4b5	0.8667
4A4a1	0.7792
4A4a2	0.8360
4A4a3	0.8392
4A4a4	0.8197
Eigenvalue	7.6116
% of Variance	0.7612

Analytical

We construct an index that recover Analytical skills using eigth variables, the first six are listed in the Abilities section in the O*NET database and the remaining two in the job incumbent rating. Table A3 show the variables and A4 the PC loadings:

Table A3: Variables Used to Construct the Analytical skill index

Variable ID	*Variable Name*	*O*NET Description*
1A1b4	Deductive Reasoning	The ability to apply general rules to specific problems to produce answers that make sense.
1A1b5	Inductive Reasoning	The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).
1A1b6	Information Ordering	The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).
1A1b7	Category Flexibility	The ability to generate or use different sets of rules for combining or grouping things in different ways.
1A1c1	Mathematical Reasoning	The ability to choose the right mathematical methods or formulas to solve a problem.
1A1c2	Number Facility	The ability to add, subtract, multiply, or divide quickly and correctly.
4A2b1	Making Decisions and Solving Problems	Analyzing information and evaluating results to choose the best solution and solve problems.
2C4a	Mathematics	Knowledge of arithmetic, algebra, geometry, calculus, statistics, and their applications.

Table A4: PC loadings for the Analytical skill index

Variable ID	*Factor Loading*
1A1b4	0.9373
1A1b5	0.9083
1A1b6	0.9192
1A1b7	0.8858
1A1c1	0.9087
1A1c2	0.8635
4A2b1	0.7656
2C4a	0.8105
Eigenvalue	6.1474
% of Variance	0.7684

Physical

We construct an index that recover Physical skills using six variables, the first four are listed in the Abilities section in the O*NET database and the remaining two in the job incumbent rating. Table A5 show the variables and A6 the PC loadings:

Table A5: Variables Used to Construct the Physical skill index

Variable ID	*Variable Name*	*O*NET Description*
1A3a1	Static Strength	The ability to exert maximum muscle force to lift, push, pull, or carry objects.
1A3a3	Dynamic Strength	The ability to exert muscle force repeatedly or continuously over time. This involves muscular endurance and resistance to muscle fatigue.
1A3a4	Trunk Strength	The ability to use your abdominal and lower back muscles to support part of the body repeatedly or continuously over time without "giving out" or fatiguing.
1A3b1	Stamina	The ability to exert yourself physically over long periods of time without getting winded or out of breath.
4A3a1	Performing General Physical Activities	Performing physical activities that require considerable use of your arms and legs and moving your whole body, such as climbing, lifting, balancing, walking, stooping, and handling of materials.
4A3a2	Handling Moving Objects	Using hands and arms in handling, installing, positioning, and moving materials, and manipulating things.

Table A6: PC loadings for the Physical skill index

Variable ID	*Factor Loading*
1A3a1	0.9413
1A3a3	0.9723
1A3a4	0.9371
1A3b1	0.9569
4A3a1	0.9725
4A3a2	0.9339
Eigenvalue	5.4433
% of Variance	0.9072

Visual

We construct an index that recover Visual skills using five variables listed in the Abilities section in the O*NET database. Table A7 show the variables and A8 the PC loadings:

Table A7: Variables Used to Construct the Visual skill index

Variable ID	*Variable Name*	*O*NET Description*
1A1f1	Spatial Orientation	The ability to know your location in relation to the environment or to know where other objects are in relation to you.
1A4a4	Night Vision	The ability to see under low light conditions.
1A4a5	Peripheral Vision	The ability to see objects or movement of objects to one's side when the eyes are looking ahead.
1A4a6	Depth Perception	The ability to judge which of several objects is closer or farther away from you, or to judge the distance between you and an object.
1A4a7	Glare Sensitivity	The ability to see objects in the presence of glare or bright lighting.

Table A8: PC loadings for the Visual skill index

Variable ID	*Factor Loading*
1A1f1	0.9719
1A4a4	0.9662
1A4a5	0.9722
1A4a6	0.8280
1A4a7	0.9640
Eigenvalue	4.4382
% of Variance	0.8876

Motor

We construct an index that recover Motor skills using eight variables listed in the Abilities section in the O*NET database. Table A9 show the variables and A10 the PC loadings:

Table A9: Variables Used to Construct the Motor skill index

Variable ID	*Variable Name*	*O*NET Description*
1A2a1	Arm-Hand Steadiness	The ability to keep your hand and arm steady while moving your arm or while holding your arm and hand in one position.
1A2a2	Manual Dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
1A2b1	Control Precision	The ability to quickly and repeatedly adjust the controls of a machine or a vehicle to exact positions.
1A2b2	Multilimb Coordination	The ability to coordinate two or more limbs (for example, two arms, two legs, or one leg and one arm) while sitting, standing, or lying down. It does not involve performing the activities while the whole body is in motion.
1A2b3	Response Orientation	The ability to choose quickly between two or more movements in response to two or more different signals (lights, sounds, pictures). It includes the speed with which the correct response is started with the hand, foot, or other body part.
1A2b4	Rate Control	The ability to choose quickly between two or more movements in response to two or more different signals (lights, sounds, pictures). It includes the speed with which the correct response is started with the hand, foot, or other body part.
1A2c1	Reaction Time	The ability to quickly respond (with the hand, finger, or foot) to a signal (sound, light, picture) when it appears.
1A2c3	Speed of Limb Movement	The ability to quickly move the arms and legs.

Table A10: PC loadings for the Motor skill index

Variable ID	*Factor Loading*
1A2a1	0.8830
1A2a2	0.9152
1A2b1	0.9297
1A2b2	0.9373
1A2b3	0.9369
1A2b4	0.9382
1A2c1	0.9394
1A2c3	0.8899
Eigenvalue	6.7925
% of Variance	0.8491

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