Working Part-Time: By Choice or By Constraint

by

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Abstract. The selection of workers into part-time jobs, and the wages they earn, are analysed using Canadian data. We focus on the distinction between voluntary and involuntary part-time workers since involuntary part-timers earn substantially lower wages than voluntary part-timers. We find that the selection of individuals into involuntary part-time work is more closely tied to job characteristics such as industry, occupation and region of employment than personal or human capital characteristics. Personal characteristics play a larger role in explaining the lower wages of the involuntary part-timers but results also suggest that selection effects dominate the contribution coming from differences in endowments.

Keywords: involuntary part-time workers, job queue, wage decomposition.

J.E.L. Classification Numbers: J22, J23, J31

1. Introduction

Despite the dramatic increase in the importance of part-time work in the last two decades, there are relatively few studies of the wages and working conditions of part-time workers.[1] Generally a substantial positive wage differential is found between full-time and part-time workers. Several theories have been used to explain this differential. Part-time workers could be compensated for the low wage by their shorter working hours, they may be discriminated against, or the lower wage could reflect lower productivity due to particular characteristics of the workers or the jobs in part-time work. Alternatively, the existence of quasi-fixed costs (e.g. hiring and training costs) could induce firms to offer employees a wage premium in return for working hours above a full-time threshold. These theories also imply differences in the selection of workers into the two types of jobs. Most recent studies of part-time full-time wage differentials correct for selectivity bias due to differences in the unobservable component of wages caused by a nonrandom selection of workers.[2] With few exceptions however, the selection model is used more as a statistical tool in correcting wage regressions rather than as a useful economic model in itself.

In this paper we present an analysis of the selection of part-time workers, and the wages they earn, distinguishing between involuntary and voluntary part-time workers. Involuntary part-time workers are part-time workers who desire to work full-time hours in the current job and at the current wage.[3] That this is an interesting and important distinction is evidenced by the wage differentials between the two types of part-time workers. Based on data from the 1989 Canadian Labour Market Activity Survey (LMAS), we find a much larger wage differential between voluntary and involuntary part-time workers than between voluntary part-time and full-time workers. Specifically, the difference in hourly earnings between full-time workers and voluntary part-time workers is less than 1 dollar (36 cents for females and 92 cents for males) whereas the difference between voluntary and involuntary part-time workers is approximately 3 dollars ($2.55 for females and $3.19 for males).[4]

These observed wage differentials immediately beg the questions of who are the involuntary part-time workers and why are they paid so poorly? The paper addresses these two questions in turn. First, we look at the selection of workers into three groups: full-time, voluntary and involuntary part-time. This is modelled as a two-stage process. An initial labour supply decision is made in which individuals choose between not participating in the labour market, working part-time or joining a queue for full-time work. In the second stage, employers select workers from the queue to fill the full-time jobs. The labour supply decision by individuals is explained by human capital variables, local labour market variables and household characteristics. The employer's choice of the full-time workers depends on human capital variables and characteristics of the job.[5] The selection of workers is a central part of the study and is of independent interest as it distinguishes between demand and supply components of the part-time and full-time work decision.

Results from the selection models show that variations in the characteristics of the job (occupation and industry) and the region are more important in explaining the probability of being constrained to work part-time than the personal characteristics of the worker such as age and education. This is true for both men and women and it is true whether one considers the probability of being chosen from the queue (the marginal probability) or the total probability of being involuntarily part-time which takes into account the decision to join the queue for full-time jobs. For example, considering the choice of individuals from the queue of those who want to work full-time, a job in education and health will have a probability of being involuntary part-time of 5 percentage points higher than manufacturing for women and 2.5 for men. Women with a university degree have a probability of being involuntary part-time of 1.5 percentage points less than women without a high-school degree and for men there is no significant difference for the two groups. Some variables have opposite effects on the probability of involuntary part-time work through the supply and demand components. For example living in high unemployment areas will reduce the probability of joining the queue for full-time jobs and increase the probability of being part-time for those in the queue. In these cases, the overall effect on the total probability of being involuntary part-time is dominated by the effect on the demand-side component.

Women are less likely to be chosen from their queue for full-time jobs than men. The results of the selection model suggest that this is due mainly to the differences in the occupational and industrial distribution of jobs held by women. The importance of service and service-related industries and of clerical, sales and services occupations for women's employment and the importance of these characteristics for the probability of being involuntary part-time means that women who want to work full-time have a higher chance of being constrained to work part-time compared to men. It is interesting that the age effects differ between men and women. For women, age monotonically increases the probability of being chosen for full-time jobs while for men the relationship is concave with a peak in the 35-44 age group.

The existing literature on part-time full-time work does not address why some workers who wish to work full-time are constrained to work part-time. In fact few studies of part-time work have made the distinction between involuntary and voluntary part-time work. Most of the work on this issue has focused on the relationship between the aggregate incidence of involuntary part-time work and the level of economic activity[6] rather than on the structure of wages or the selection of workers into these jobs.[7] Recent work by Stratton (1996) investigates the meaningfulness of the involuntary part-time classification and finds that these workers have preferences similar to full-time workers but are constrained in their hours of work. This supports the usual interpretation of involuntary part-time work.

More generally, there have been few studies of underemployment.[8] Recent work by Kahn and Lang (1991, 1992, 1995, 1996), Lang and Kahn (1997), Doiron (2000), Rebitzer and Taylor (1991), and Landers, Rebitzer and Taylor (1996) constitute an important step in the modelling and empirical analysis of this issue. Kahn and Lang conduct empirical work on Canadian and American data sets containing information on hours constraints. The finding that underemployment is more prevalent among junior workers is interpreted as support for a Mincer-type firm specific human capital investment model rather than a Lazear-type incentive model with deferred compensation. Doiron's work is based on Canadian panel data. She shows that the patterns relating the movements into and out of underemployment and the correlations with changes in wages vary considerably by industry. She constructs a matching model which explains underemployment in growing industries and which agrees with her empirical findings. Rebitzer and

Taylor (1991) and Landers, Rebitzer and Taylor (1996) present an adverse selection model with heterogeneous workers in which hours, employment and wages are endogenous. Firms will offer contracts involving different hours of work in order to induce junior workers to self-select into those having a relative preference for work and those with stronger preferences for short hours of work. In the latter paper, data on two law firms are used to support the predictions of this type of approach. Note that the main prediction of this model is that junior workers are more likely to be overemployed and that although it does find support in the law firm data, it contradicts the findings by Kahn and Lang and Doiron for the general population of workers.

Our results agree with those found in the literature on underemployment in that younger, less-educated workers are more likely to be involuntary part-timers. Our results also suggest that models used to explain the presence of involuntary part-time workers will have to recognise the industrial and occupational distinction of workers, as well as their human capital characteristics.

In the second part of the analysis, we study the wage differentials between the three groups of workers. Specifically, wage equations are estimated for the three groups of workers, initially treating the selection as exogenous and later allowing for the joint determination of wages and the selection of workers. Using the results of wage regressions we decompose the mean wage differential between groups and investigate the extent to which the wage gaps can be explained by differences in personal and job-related characteristics.

Conditional on the selection of workers, we explain between 50 to 75 per cent of the wage gaps between the three groups of workers based on the differences in their personal, regional and job characteristics. When considering the large wage gaps involving the involuntary part-time workers, life-cycle variables (age and education) are as important as industry and occupation in explaining the differences in wages. This is perhaps surprising given the selection results and it is due to the heavy weighting (through the large regression coefficients) of the modest differences in the mean characteristics. For women, it is striking how similar the voluntary part-time workers are to the full-timers. The mean wage gap is 6 per cent only and half of it is due to industry and occupational differences. In fact, based on age and education, the voluntary part-time women should earn more on average than the full-time workers. This is not true for males where the voluntary part-time workers are still younger and have less education on average than the full-time workers.

Models which explain both wages and selection are problematical due to the difficulty of separately identifying the employer's selection of workers from the queue and the wage.[9] In general, the differences in characteristics explain less of the wage gap once these variables are also allowed to determine the selection of workers. The qualitative results mentioned above still hold given the weaker overall explanatory power. That is, together age and education are as equally important as job characteristics in explaining the wage gap, and for women the similarity between voluntary part-time and full-time workers remain.

The paper is organized as follows. The following section contains a description of the data and section 3 provides a discussion of the selection model and the results from its estimation. Section 4 is devoted to wage decompositions and includes results from the estimation of a joint model of wages and selection. The last section offers concluding comments.

2. Description of the Data

Our analysis is based on the 1989 LMAS which was a supplement to the Labour Force Survey conducted by Statistics Canada in January and February of 1990. This survey contains data on the work history of the individuals over the previous year, including information on up to five jobs. We select the last job held during the year for our analysis.[10] Note that our "cross-section" sample of jobs will include individuals who worked at any point in time during the year and conversely, an unemployed individual will have been unemployed for the whole year. Full-time students are excluded from our sample to avoid analyzing educational choices. In addition, jobs are excluded if they are less than 4 weeks long,[11] in the agricultural sector, or if they are not paid jobs (such as self employment and work of unpaid family members). Finally, when constructing the sample of non-participants used in labour supply estimation we consider those who did not work at all during the year and exclude individuals who declared themselves unemployed during every month of the year.[12,13]

Part-time work is defined as working less than 120 usual hours per month which translates to 28 hours per week. This is the standard definition used by Statistics Canada, and by previous researchers in the area.[14] We classify part-time workers as involuntary part-time based on the answer to the following question: *"Approximately how many additional hours per month would ..... have preferred to work at this job?"* These additional desired hours are added to the usual hours worked per month to obtain total desired hours of work. If total desired hours are greater than 120, we consider this part-time worker as desiring full-time work and therefore classify the individual as involuntary part-time.[15] In the LMAS a job is defined by usual duties and usual wages and does not depend solely on the identity of the employer; hence, the question on the desired additional hours of work is conditional on usual duties and wages. Generally, the concept of labour supply is formulated and interpreted in terms of hours conditional on wages and other job characteristics. Hence, the question on additional desired hours is formulated appropriately for a study of labour supply choices.[16]

Table 1 presents a list of the variables used in this study along with weighted sample means.[17] While women form slightly less than half (47 per cent) of our total sample of workers, they comprise 82 per cent of part-time workers. Among part-time workers, women are more likely to be voluntarily working part-time than men (83 per cent of voluntary part-timers are female compared to 74 per cent of involuntary part-timers). Restricting the sample to those who want to work full-time, we find that men are more likely to be chosen for the full-time jobs than women (98.7 per cent of men who want to work full-time are given full-time jobs while the corresponding proportion for women is 94.7 per cent). These raw sample proportions suggest that the process which determines the three groups of workers is different for men and women, which is consistent with results from the labour supply literature. In the remainder of the paper, the analysis will be conducted separately for the male and female samples. Of the sample of males, 95 per cent worked full-time and of the remaining 5 per cent, three quarters were voluntary part-timers. There is a larger proportion of part-time workers among females (27 per cent) of which a larger proportion are voluntary part-time workers (85 per cent).

The most striking difference between involuntary and voluntary part-time workers is in their respective hourly earnings. While the difference in hourly earnings between full-time workers and voluntary part-time workers is less than 1 dollar (36 cents for females and 92 cents for males), the difference between voluntary and involuntary part-time workers is around 3 dollars ($2.55 for females and $3.19 for males). Therefore the distinction between involuntary and voluntary part-time work is central to understanding the full-time/part-time wage differential and differences in the nature of jobs offered to part-time workers.[18]

Table 1 shows that involuntary part-timers work more hours per week on average than the voluntary part-time workers. The lower wages of the involuntary part-time workers therefore cannot be explained as a compensating differential for fewer hours of work. Turning to personal and other job characteristics we see that, on average, part-time workers have less education, they are less likely to be in the middle-age groups, and they are more likely to work in services or in education and health care industries. For females, the presence of children is associated with a greater incidence of working part-time. As for involuntary part-time workers compared to other part-timers, they are not less educated but they tend to be younger and are also more likely to reside in the regions with high unemployment.[19]

The raw data revealed important differences among part-time workers as well as between part-time and full-time workers. The distinction between involuntary and voluntary part-time has yielded large differences in wages and worker characteristics. Voluntary part-time workers are perhaps compensated for their lower wage relative to full-timers by the increase in their leisure hours, but this argument cannot explain the large differential between the wages of voluntary and involuntary part-time workers.

3. Selection into full-time, voluntary and involuntary part-time jobs

In this section, we present a model of selection into our three groups of workers. Inspection of the raw data suggests that there are systematic differences in personal and job-related characteristics across the worker categories. Results from the estimation of the selection process reveal the extent to which these factors determine the selection of workers into the three groups and add to our understanding of the role of part-time work.

Our selection model incorporates both the supply-side and the demand-side components of part-time work through a queuing model. This model can be thought of as a two-stage process and is illustrated in Figure 1. The left most node represents the individual's choice between three alternative: not participating (NP), working part-time (VPT), or joining a queue for full-time jobs (DFT). The middle node represents the employers choice of workers from the queue to fill the full-time jobs.

— INSERT FIGURE 1 HERE —

The individual's initial choice among the three alternatives can be interpreted as a labour supply decision regarding hours of work in which the desired hours are grouped into three intervals: negative or zero hours (nonparticipants), hours greater than zero but less that 120 per month (voluntary part-time), and hours greater than or equal to 120 per month (desiring full-time). Following standard labour supply models, differences in desired hours are generated from differences in the offered wage, the shadow wage in home production, family income, and life-cycle considerations. Our reduced form specification includes personal and family characteristics which control for variation in these factors.

It is important to point out the assumptions underlying the structure of the model represented in Figure 1. It is assumed that all full-time workers desire full-time jobs. As mentioned above, in the LMAS we cannot identify full-time workers who would rather work part-time. Individuals who join the queue for full-time jobs and do not receive an offer of full-time employment are assumed to work part-time; they cannot at that stage decide to exit the labour market. This assumption is also made because of data limitations; we cannot identify those nonparticipants who exited the market because they could not obtain full-time jobs from those who did not want to enter the labour market. Furthermore, implicit in the model is the assumption that anyone desiring work can obtain part-time employment.[20]

We model the labour supply choice as an ordered probit in which the ordering is over the desired hours of work. Formally, the ordered probit can be written as:

$$z_i^* = Z_i\gamma + e_{1i} \qquad \text{and} \qquad z_i = \begin{cases} \text{NP}, & \text{if } z_i^* \leq \mu_1; \\ \text{VPT}, & \text{if } \mu_1 < z_i^* \leq \mu_2; \\ \text{DFT}, & \text{if } \mu_2 < z_i^*. \end{cases} \tag{3.1}$$

where i indexes the individual, z^* denotes a latent variable measuring the net utility of working, z is the observed choice, Z is a vector of personal and family related characteristics and does not include a constant term, γ is a vector of coefficients, e_1 has standard normal distribution, and μ_1 and μ_2 are arbitrary constants with $\mu_1 < \mu_2$.[21]

We now turn to the selection of the workers into full-time and involuntary part-time jobs. This selection is made from a pool of workers desiring to work full-time. The pool of workers desiring full-time jobs can be thought of as a queue for full-time work with the employers choosing those workers who will fill the full-time jobs from the queue. Characteristics of individuals and the jobs in which they work are used to explain the employer's selection from the queue for full-time jobs. These explanatory variables reflect variations in the qualifications and abilities of the worker and in the type of jobs available. For example, the industry in which a particular job is available will influence the expected probability of that job being full-time. Similarly, the education level of a worker will determine the expected probability of that worker being hired in a full-time job.

The employer's choice is represented by a binomial probit which can be written as:

$$y_i^* = Y_i\alpha + e_{2i} \qquad \text{and} \qquad y_i = \begin{cases} \text{IPT}, & \text{if } y_i^* \leq 0; \\ \text{FT}, & \text{if } y_i^* > 0. \end{cases} \tag{3.2}$$

where i indexes the individuals, y^* is a latent variable representing the net benefit (to the employer) of hiring the worker in a full-time job, Y is a vector of personal and job related characteristics and includes a constant term, α is a vector of coefficients, e_2 has a standard normal distribution, and y is the observed status of the worker as either full-time (FT) or involuntary part-time (IPT).

In deriving the likelihood function for this model the two selection processes can be treated as either joint or sequential. In the case of sequential selection, the employer's preferences for choosing an individual for a full-time job (summarised by the y^* index function of 3.2) is only defined over the set of individuals who have joined the queue. With joint selection, the employer's preferences are defined over all individuals; although, it is only observed for those who join the queue for full-time jobs.[22] Despite the joint model being more general, the sequential model is usually estimated since it is much simpler to implement and does not entail the estimation of the covariance between the two processes.[23] Conceptually the joint model is preferable as it allows unobserved variables (such as ability or motivation) to affect both the labour supply decision and the employer's choice. Further, the results from the employer's selection in the joint model has a straightforward interpretation since this selection represents a job offer to a random individual rather than an offer conditional on joining the queue. Given these considerations the selection models are estimated assuming joint processes.[24]

The likelihood function for the joint selection model is derived assuming that the error terms e_1 and e_2 are distributed as a bivariate standard normal with correlation ρ_{12}.[25] Results for the second choice (the selection from the queue for full-time jobs) are presented in Table 2. For purposes of interpretation the marginal effect of each variable on the probability of being chosen from the queue are shown in Table 2.[26]

The region in which individuals live, and the industry and occupation of the job they hold are more important determinants of working full-time than the individuals' education and, for men, their age. For example, the probability of working full-time among women falls by 5 percentage points when the job is in education and health compared to a manufacturing job. The probability of working full-time is 4 percentage points higher in a professional job than in services. In contrast if you compare an individual with a university degree to somebody who has not finished high-school, the probability of working full-time increases by 1.6 percentage points for females but is virtually unchanged for men. Individuals living in the relatively low unemployment area (Ontario) have the largest probability of obtaining full-time jobs. This probability gradually decreases as we consider people living in progressively higher unemployment areas (Québec, B.C., Prairies, and the Atlantic provinces).[27] An individual moving from the Atlantic provinces to Ontario would be more likely to work full-time by just over 1 per cent for males and 2.6 per cent for females.

As mentioned earlier, men are more likely to be chosen than women from their respective queues for the full-time jobs. By looking at the estimates in Table 2 and the distribution of characteristics in Table 1, it is clear that the main reason lies in the gender differences in the occupational and industrial distributions. Women are more likely to work in the service and services-related industries (public administration, education and health, transportation and communication, and trade) and in the clerical, sales and services occupations. These are the jobs with the highest probabilities of being constrained to work part-time. It is interesting to compare the age effects between men and women. For women there is a monotonic and positive relationship between age and the probability of being chosen for the full-time jobs. For men the relationship is concave with the highest probability of full-time work occuring in the 35-44 age group.

Are these results consistent with models of hours constraints? The theoretical literature to date suggests a variety of reasons may be at work in explaining the cross-section variations in underemployment when dealing with a large and varied population of workers and jobs. For example, risk-sharing contracts could explain the incidence of involuntary part-time work among firms in high unemployment areas since they are more likely to have experienced negative shocks in their product market and hence use work-sharing to reduce or delay laying-off employees. The industries with the highest use of involuntary part-time work are also the industries which experienced the highest rates of employment growth over the 5 year period prior to the survey date.[28] This result is also found in Doiron's (2000) study of underemployment and is consistent with her matching model. A similar reason could be used to explain the importance of services, clerical and sales occupations among the involuntary part-timers. Alternatively, these differences could be caused by the technological structure underlying the jobs in the various industries and occupations. The positive relationship between age and the probability of being constrained in hours of work can be explained by the matching model. A closely related model, that of firm specific human capital investment is also consistent with this finding (see Kahn and Lang (1996) for more details). Are men less likely to invest in firm specific human capital in the older age-groups compared to women? Or do men have other types of incentives built in their contracts? These are questions left for future work. Data sets containing information on contracts or on the technology of the firm would be of great use in discriminating between these theories.

For males, the estimated correlation between the errors of the two selection processes is very small (0.008) and insignificant. Thus, the results imply that the errors in the two selections for males are not strongly correlated and can be treated as independent. For females, the estimated correlation between the error terms in the two selection processes is negative and significant. The negative sign is perhaps surprising since it suggests that a positive deviation in the unobserved component which makes an individual more likely to be chosen from the queue also makes the individual less likely to join the queue. We estimated several different specifications of this model in order to investigate the sensitivity of this result to various exclusion restrictions on the explanatory variables. In all cases, the estimated correlation was negative and significant. The fact that the result is found among women and not men suggests that it could be related to the secondary worker role of many women. Some of those women who are more likely to be chosen from the queue for full-time jobs because of training, experience, or other characteristics not measured completely with our set of explanatory variables, may be in a position where they do not have to work or can afford to work part-time by choice.[29] To resolve these issues we require more detailed information on household income and joint labour supply behaviour. This is left for future research.

The results from the ordered probits representing the labour supply decision are presented in Tables 3 and 4. The tables also report the estimated marginal effect of the variables on the probability for each alternative.[30]

Focusing first on participation, the estimation results from the ordered probit are consistent with those usually found with binomial probit models for participation. Education is positively related to participation while the effect of age is concave. The presence of an additional worker in the family also has a strong positive impact on participation while the presence of children (under 16 years of age) reduces the desire to participate. Regions with high unemployment also have the highest probabilities of non-participants. These effects are similar in sign for men and women but the effects are stronger for women. Gender differences in the direction of effects can be found in marriage which increases non-participation for women and not for men and the presence of a spouse (in households without children) which has the opposite effect to marriage. Also, Anglophone women are more likely to be non-participants while the opposite is true for Anglophone males.

Turning now to the type of work desired by individuals (full-time or part-time) we see that for both men and women, the results indicate that wanting to work part-time is more similar to a desire not to participate rather than to desire full-time employment. Characteristics associated with a greater desire for part-time work are also associated with a greater likelihood of choosing not to participate in the labour market. Having less education, having children or other workers in the household increases the likelihood of choosing part-time work. An exception to this is that among age groups, women over 55 have the lowest probability of wanting part-time work and the highest probability of being non-participants. This is not so for older men where the desire for part-time work is aligned with the desire for non-participation. For men, the effects of the explanatory variables on the probability of wanting part-time work are small although generally significantly different from zero. This is not surprising given that the two threshold variables μ_1 and μ_2 are located close to each other. This reflects the relatively small sample size of the voluntary part-time group of workers.

To investigate the effects of the restrictions implicit in the ordered probit model we also estimate a more general version of the labour supply decision. This model is described in Pradhan and van Soest (1995) and consists of the ordered probit described above with the lower threshold μ_1 set equal to the upper threshold μ_2 minus an exponential function of all the explanatory variables. This more flexible likelihood function was difficult to estimate especially for men where we could not get it to converge presumably because of the relatively small group involved coupled with the fact that the additional parameters are identified from the nonlinearity of the exponential function.[31] The model did converge for women and we briefly discuss the differences with the results presented above.[32] The results from the employer's selection from the queue are not seriously affected by this change and will not be discussed further.[33] Overall, the changes in the labour supply estimates are not very large quantitatively however since the marginal effects on the probability of desiring part-time work are small, they are the most affected by the new specification. With few exceptions, the signs and the general magnitude of the marginal effects on the probabilities of desiring full-time and not participating are unchanged. With respect to the probability of being in the voluntary part-time group, the main difference is that the effects of some variables (age, region, presence of children) are no longer of the same sign as their effects on non-participation. Specifically, age has a negative effect on the probability of VPT for those over 25, individuals living in high unemployment regions are less likely to be in the VPT group, and with one exception the presence of children under

15 reduces the desire to work part-time.[34] Thus the estimates from the more general model suggest that the desire to work part-time is more complex than is apparent from the standard ordered probit results and that in some respects it does resemble the desire to work full-time.[35]

In concluding this section of the paper, we examine the selection of involuntary part-time workers based on the joint supply and demand selection process. That is, we consider the probability of a random individual becoming an involuntary part-timer due to both a desire for full-time work and the employer's choice from the queue. The effects on the marginal probabilities of being chosen from the queue for full-time jobs has suggested that certain factors are especially important: occupation, industry, region, and for women, age. The effects of personal characteristics and region on the overall probability (i.e. among our total sample which includes non-participants and voluntary part-timers) of being in the involuntary part-time group are more complicated since these factors also affect the probability of joining the queue for full-time jobs. For example, those individuals living in high unemployment areas are less likely to be chosen from the queue but they are also less likely to join the queue.[36] Table 5 presents changes in the overall probability of being an involuntary part-timer for variations in selected characteristics. Using the same notation as above, the joint probability of being IPT is written as: $\Phi(-Y\alpha) - \Phi_{BIV}(-Y\alpha, \mu_2 - Z\gamma, \rho)$ where Φ_{BIV} denotes the bivariate normal distribution and ρ is the correlation between the two error terms. Since we are considering effects of dummy variables, the changes in the probabilities are computed by differencing the distributions evaluated with the dummy set at one and zero. To simplify, we consider changes from a base case of an individual 16-19 years old, Anglophone, living in Ontario, with no training and no high school degree, single, with no spouse and no children, living in a household with no other workers and facing an employer in manufacturing offering a non-union job in a primary occupation. We also present the changes in the marginal probability (these are conceptually comparable to the previous results) which show that the effects on the overall probability are similar (but usually less in magnitude) to the changes presented above for the marginal probabilities, including those factors which have opposing effects on the desire to join the queue and the likelihood of being chosen from the queue.

4. Wage Decompositions

In this section we investigate the extent to which the wage differentials observed in the raw data can be explained by differences in the characteristics of the workers and the jobs. Various regressions are estimated using the *ln* wage as the dependent variable. Independent variables include human capital measures (education, training, age, language[37]), a local labour market variable (region), and job characteristics (union coverage, industry, and occupation).

Using the estimation results we decompose differences in ln hourly wages as follows. Let i and j denote two different groups of workers chosen from the three groups: full-time, involuntary part-time, and voluntary part-time. Also, let $\overline{W}$ represent weighted average ln wages, then

$$\overline{W}_i - \overline{W}_j \quad = \quad (\overline{X}_i - \overline{X}_j)\beta^* \quad + \quad (\beta_i - \beta^*)\overline{X}_i \quad + \quad (\beta^* - \beta_j)\overline{X}_j \qquad (4.1)$$

where $\overline{X}_i$ is the vector of weighted average characteristics for group i, and β_i is the vector of regression coefficients for the same group. β^* is usually interpreted as the equilibrium vector of coefficients which would hold in the absence of discrimination. Unfortunately, there is no consensus in the literature regarding the appropriate definition of β^* and various approaches are used. The most common method is the Oaxaca decomposition in which one group's coefficients are chosen to evaluate the differences in the characteristics.[38] We use the arithmetic average of the two groups coefficients to perform the decomposition.[39]

The first term on the right-hand side of equation (4.1) measures the contribution of differences in the characteristics, the second and third terms represent the contribution of differences in the returns to these characteristics. The last two terms are often interpreted as labour market discrimination. The interpretation is not straightforward in this framework. In particular, discrimination against part-time workers cannot explain the differential between voluntary and involuntary part-time workers, while discrimination against those who want to work part-time cannot explain the difference between the full-time and involuntary part-time workers. In theory, one can still interpret the fraction of the wage gaps due to differences in returns as discrimination, but the basis of this discrimination is not observed in the data when dealing with involuntary part-time workers. Alternatively, this component of the wage differentials may be attributed to differences in productivity or local labour market effects not captured by the observed characteristics. For example, if employers are using hours constraints to facilitate the promotion of junior workers to senior (more productive) jobs as in Doiron (2000) or to encourage the investment in firm specific human capital as in Kahn and Lang (1992), the component of the wage differentials due to differences in returns will reflect differences in productivity and job market alternatives which are not fully measured by our explanatory variables.

In the first set of wage regressions we treat the selection of the workers into part-time and full-time work as exogenous. Since it is likely that the two processes are jointly determined, we interpret the first set of results as conditional on the selection. The second part of this section estimates wage models in which the selection is endogenous.

4.1. Exogenous Selection

Table 6 summarises the results of the decompositions of the wage differentials conditional on the selection. We present a breakdown of the contributions by various groups of characteristics as well as the total over all the characteristics. To simplify, the effects of differences in returns are presented as one term only (the sum of the last two terms of equation (4.1)).[40] Standard errors are computed based on the variance-covariance matrix of the estimated coefficients. We also present results of F-tests on the hypotheses of joint equality of the coefficients.

Beginning with women, Table 6 shows that around one half of the very large wage gaps involving involuntary part-time workers can be explained by differences in personal and job-related characteristics. The explanatory power of endowments is about evenly divided between personal (education, age) and job (occupation, industry) characterictics It is interesting that variations in personal characteristics play a larger role in explaining the involuntary part-time wage differentials than what may have been expected from the selection results presented above. The selection model estimates revealed that variations in job attributes such as region, industry and occupation were more important than variations in personal characteristics such as age and education in explaining the allocation of workers into involuntary part-time and full-time jobs. Even though the differences in the distribution of personal characteristics across the three groups of workers are not very large, these characteristics are important in generating wages and the differences weighted by the coefficients become large.

For males, differences in the endowments explain even more (60 to 75 per cent) of the differentials involving involuntary part-timers. As for women, personal characteristics (especially age) are more important than the selection results would suggest. For men however, differences in the occupation and industry distributions are relatively more important determinants compared to education and age.

The results in Table 6 also show how similar the female voluntary part-time workers are to women working full-time. The wage gap is very small at only 6 per cent and half of this gap is explained by differences in job characteristics. Indeed, if only personal characteristics are included in the regressions (results not shown) we would predict a larger voluntary part-time wage relative to the full-time wage based on differences in the endowments. This is not true for men. The age distribution of women workers generates a larger mean wage for voluntary part-time workers than for full-time workers while for males, the age distribution of workers contributes to the higher mean wage for full-time workers. This difference by gender is due to both a flatter age-earnings profile for females and a larger proportion of female voluntary part-time workers in the middle-age groups compared to males.

Finally, we mention briefly the results of the wage decompositions conditional on selection when alternating between the groups' coefficients in evaluating the effect of differences in characteristics.[41] As mentioned earlier, the range of values gives an indication of the importance of the differences in the groups' coefficients. In the context of full-time part-time wage differentials, they also provide a check on the possibility of bias caused by measurement error in the wage.[42] For women, alternating between the groups' coefficients does not alter the results. For comparisons involving the involuntary part-timers, differences in endowments explain between 40 and 60 per cent of the total wage gap and the importance of the various groups of characteristics remain generally the same. The comparison of full-time and voluntary part-time female workers shows that not only are their characteristics similar but so are the coefficients of the wage equations and consequently the range of values for the contribution of differences in each set of characteristics to the wage gap is very small. (The total differential explained by differences in characteristics varies between 46 to 52 per cent for these two groups of workers.) For men, similar overall results also hold but the flat age-earnings and education-earnings profiles for involuntary part-time workers provides larger ranges for these characteristics. The same holds for occupation but for opposite reason: occupational status is more important in generating wage variation for the involuntary part-time workers than the two other groups.

4.2. Endogenous Selection

When the selection of workers is treated as jointly determined with wages the issue of identification arises. In our model, the labour supply decision is identified by the inclusion of household characteristics which do not enter in the employer's decisions. However it is not clear which characteristics, if any, would affect the employer's choice of workers from the queue but not the wage offered to them. We proceed by excluding the different job characteristics in turn and look for robust results from the decomposition of the wage differentials.[43] In what follows we present only the set of estimates for the models with the occupational dummies excluded from the wage equations. However, in the discussion of the results we outline the consequences of excluding alternative sets of variables. (Detailed results are presented in Appendix Table 4.)

Referring to Figure 1, the full model contains five error terms which are jointly distributed with a variance-covariance matrix whose elements we denote by σ_{kl} . It is not possible to estimate either σ_{2V} or any of the covariances between the errors on the wage equations. This leaves the possible estimation of σ_{12}, σ_{1V}, σ_{1I}, σ_{1F}, σ_{2I}, and σ_{2F}. We estimate a FIML model which provides efficient estimates of these variance-covariance terms. However, the relatively small number of involuntary part-time workers especially in the male sample leads to problems in estimating the full likelihood function.[44] For this reason, we present the FIML results for females only. The data on women produced a better behaved likelihood function and a well-defined maximum. The derivation of the likelihood function is presented in the Appendix). Given the complexity of the likelihood and the problems of identification for males, we also present the 2-stage corrected estimates which are consistent but inefficient.[45]

Table 7 presents wage decompositions for the FIML and the 2-stage selection correction models based on the identifying exclusion of occupational dummies from the wage equation. The results of the FIML estimation are very close to the 2-stage estimates despite the independence assumption used in the latter.[46] The estimates of the selection coefficients in the FIML model (not shown) are also very close to the ones presented in the previous section of the paper. Incorporating the information on wages does not alter our previous results concerning the selection of workers.[47]

Allowing for the endogenous selection of workers leads to a substantial reduction in the portion of the differentials attributable to differences in endowments.[48] Nevertheless, most of the overall qualitative results described above for the wage decomposition conditional on selection still hold although the effects are smaller in magnitude. For women, the portion of the wage gaps between involuntary part-timers and other workers explained by differences in characteristics are still generated mainly by differences in education and age, although the effect of age is relatively lower when its effect on selection is taken into account. When comparing voluntary and full-time female workers, education still explains a positive portion of the small gap in wages but age causes the predicted wage for the part-timers to be greater. These results also hold when other job characteristics (union and industry) are omitted to provide identification. When comparing results across specifications, the components of the wage gaps attributable to job characteristics are the most variable especially for the full-time involuntary part-time wage gaps, which is unsurprising given it is the exclusion of job characterisitics from the wage equations which provides identification of the employer selection.

For men, there is more variation in the results across the specifications. Differences in education still contribute a positive portion to the wage gaps involving the involuntary part-timers but the effects are smaller than for women and in particular they are smaller than the effects of age. One interesting change from the exogenous selection wage decompositions is that the effect of age on the voluntary part-time full-time wage differential is now negative, similar to the finding for women.

The models allowing for the endogeneity of work status provide estimates of the covariances between the errors in the two selections and the error terms in the wage determination process.[49] The largest and most significant covariance terms are those involving unobserved factors influencing selection from the queue for full-time jobs. For both men and women, the coefficients suggest positive selection for the involuntary part-time workers and negative selection for the full-time workers. In other words, an unobservable component in the selection of workers from the queue, which increases the likelihood a person gets a full-time job, reduces the full-time wage and increases the involuntary part-time wage compared to an average person in the population.

The covariances involving the labour supply process are generally insignificant for women. For males, the covariances are stronger and suggest positive selection for voluntary part-timers and negative selection effects for the other two groups of workers. The usual interpretation of unobservables capturing ability or motivation and hence generating positive selection effects doesn't apply for all groups of workers. For example, these estimates suggest that unobservables which make a male more likely to join the queue for full-time jobs also reduce their full-time and involuntary part-time wage relative to the average. Negative selection effects are not uncommon in the literature; it seems that unobservables include several conflicting wage and selection components.

The empirical results regarding wage differentials can be reconciled with the theories of underemployment. According to the models of firm specific human capital, the involuntary part-time have relatively low levels of observed and unobserved human capital and hence they receive a lower wage reflecting their lower productivity. According to the matching model, there is relatively little labour market information available on the group of involuntary part-timers and they receive a lower wage as employers learn individual worker quality. It is more difficult to explain the pattern of wage differentials with models of risk sharing contracts as these models suggest that involuntary part-time workers should receive a compensating wage rather than the observed wage penalty.

5. Conclusion

The use of information on desired hours of work among part-time workers has resulted in the identification of two quite different groups of part-time workers: those who choose to work part-time and those who are constrained in their hours of work in their current job. The involuntary part-time workers earn a wage which is around 18 per cent lower than other part-time workers despite working slightly longer hours. A selection model is developed in order to explain how workers are chosen for these poorly paid jobs. The empirical findings suggest that occupation and industry of employment and regional location are more important factors in that selection than are human capital characteristics.

Conditional on selection, personal characteristics such as age and education were found to be important in explaining the wage differential. For example, approximately one quarter of wage gaps involving involuntary part-time workers can be explained by the lower age and educational attainment, and another quarter by their occupation and industry of employment. Our results also suggest that unobserved selection effects may be an important component of the observed wage gap facing involuntary part-time workers. We found important similarities in the selection of involuntary part-time workers for men and women, however a number of interesting differences were noted. There was a higher incidence of involuntary part-time work among women due to their greater concentration in service and service-related jobs. A striking finding for women was the similarity in worker characteristics and wage structure of full-time and voluntary part-time jobs. Further empirical work examining wage dynamics or firm specific factors will help clarify the role of part-time jobs and the structure of compensation.

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Endnotes

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1. Recent studies include Averett and Hotchkiss (1996), Blank (1990), Hotchkiss (1991), and Ehrenberg and Li (1988) which analyze U.S. data; and Ermisch and Wright (1992) and Rice (1990) which are based on British data. The most recent studies based on Canadian data are Simpson (1986) who analyzes data from the 1981 Survey of Work History and Nakamura and Nakamura (1983) who use the 1971 Census data.

2. See for example, Averett and Hotchkiss (1996), Blank (1990), Ermisch and Wright (1992), Nakamura and Nakamura (1983), and Simpson (1986).

3. See the data description below for fuller details on the definition of involuntary part-time workers.

4. Involuntary part-time workers are a relatively small fraction of total part-time workers in these data: 15 per cent for women and 23 per cent for men. Note however that the data pertain to a year at the peak of the business cycle and we would expect a larger fraction of involuntary part-time workers at other times.

5. The econometric model allows for correlation between unobservables in these two selection processes.

6. See Blank (1990) and Mayer (1993) for research linking involuntary part-time work and unemployment.

7. Blank (1990) includes a dummy variable for involuntary part-time workers in a several wage regressions. However, these workers are not analyzed separately in her selection model and more general differences in the wages (i.e. other than through a constant term) are not modelled.

8. Workers are underemployed when they report working fewer hours than they would like given their wage or their job. In general underemployment can occur at any level of actual hours of work and is not restricted to part-time workers.

9. The labour supply component of the selection process is identified separately from the wage equation due to the household characteristics included in labour supply. It is more difficult to come up with convincing exclusion restrictions which identify the wage from the demand-side choice for the full-time workers. Different specifications are estimated to ensure the robustness of the main results regarding the selection bias in the estimated wage differentials.

10. We do not use the main job as this is usually defined based on time spent at work which is endogenous in this study. The last job is also nearest to the time of the survey which should minimize recall error and correspond more closely to the personal and household information also collected at the time of the survey. We do not use multiple jobs for the same individuals to avoid problems of dependence in the error terms.

11. As discussed below, our definition of involuntary part-time is based on information concerning desired hours of work per month. For those with jobs of less than one month, we cannot accurately classify them as voluntary or involuntary part-time.

12. As shown in Jones and Riddell (1995), there are problems in measuring the length of unemployment spells with the LMAS. We define individuals as unemployed during a month if they searched for work at least one week during the month. This means that we overestimate the number who were unemployed for the entire year. We discuss the issue of unemployment further when presenting the labour supply model.

13. From an initial sample of 63660, we exclude the self-employed, unpaid family workers, jobs less than 4 weeks, and jobs in agriculture (7120), full-time students at any point in the year (7494), full-year unemployed (389), and observations with missing values (mostly in language) and with occupation classified as other (1811). This leaves a sample of 46846.

14. It is also the definition used for distinguishing between full-time and part-time workers in employment contracts and labour regulations.

15. Individuals were also asked reasons why they did not work these additional hours. There were quite a few missing values in this information (15 per cent of our involuntary part-time group). However, among the involuntary part-time workers who answered this question, virtually all (over 99 per cent) gave demand side constraints as the main reason rather than say family responsibility. This is consistent with the findings of Stratton (1996).

16. The LMAS does not collect information on overemployment - cases where the workers work more than they desire. Evidence from other sources suggest that the problem of overemployment is generally not as prevalent among workers at least in North America. See Lang and Kahn (1997) for more details.

17. The weights are provided by Statistics Canada and are based on the sample design. All analysis and results are computed using the weights.

18. We find a smaller differential between full-time and part-time workers than was found by Simpson (1986) using 1981 Canadian data. This is due to a greater wage for part-time workers in our data rather than a smaller wage for full-time workers. His wage differential is closer to our measure of the wage gap between full-time and involuntary part-time workers. Additionally, we have a smaller proportion of part-time workers in our sample. These differences can be explained by the timing of the two samples: our data represent conditions at the peak of the business cycle while his sample was collected at a time when a severe recession was under way. Hence, one would expect a greater number of involuntary part-time workers in his data and a larger full-time part-time wage differential.

19. There is a surprisingly high incidence of union coverage among involuntary part-time workers, which is due to the substantial difference between union membership versus coverage. For full-time and voluntary part-time workers, coverage is 12 to 15 per cent greater than membership. For involuntary part-time workers, the figure is 25 per cent for males and 21 per cent for females. Union membership among involuntary part-time workers is lower than for full-time workers, and is either the same (for males) or slightly higher (for females) than union membership among voluntary part-time workers.

20. We do not incorporate unemployment in our selection model for several reasons. First, we cannot distinguish among the unemployed those who desire full-time work from those who desire part-time work; hence, these individuals cannot be incorporated in a queuing framework such as the one described above. Secondly, using the LMAS to study unemployment is problematical since the duration of unemployment spells cannot be measured correctly in this data set. Finally, our aim is to study part-time work and incorporating unemployment in the analysis in a non-trivial fashion would change the direction and focus of the paper. The implication of excluding the unemployed from the sample is that our results should be interpreted as conditional on this selection. In practise, since unemployment is defined as being unemployed for a year, the excluded group is small (389) and this initial selection is unlikely to alter the main results concerning the determinants of part-time versus full-time work.

21. The choice of an ordered probit as written in equation (3.1) imposes fairly stringent restrictions on the form of the effects of the explanatory variables on the probabilities. Specifically, two continuous variables will have the same marginal effect on the probability of queuing relative to their marginal effect on the overall probability of working. An alternative model consists of two binary choices, one for the decision to participate and one representing the decision to join the queue. See Nakamura and Nakamura (1983) for an example of this approach. We do not adopt this method here because we also estimate a full model in which the wages and the two selections are determined jointly. For computational reasons, we want to restrict ourselves to selection models with (no more than) two jointly-determined choices. In order to investigate the effects of the restrictions imposed by the ordered probit, we re-estimate the selection model using a generalization described later in this section.

22. For a more detailed discussion of these issues, see Maddala (1983: 278-289).

23. One of the earliest examples is Abowd and Farber (1982).

24. The identification of the individuals in the queue (including those who do not get chosen) is important information which is generally not available in studies of queuing models such as

the union-nonunion selection model. It is this information that enables us to identify all the parameters of the joint model.

25. We chose to estimate the selection as a bivariate probit rather than a nested logit because this model is also used in the joint estimation of selection and wages in the next section of the paper.

26. For a continuous variable, Y_m, the effect of a unit change equals $\phi(Y\alpha)\alpha_m$ where $\phi(.)$ denotes the standard normal pdf. For a dummy variable, Y_k, the change in the probability equals $\Phi_1(Y\alpha) - \Phi_0(Y\alpha)$ where $\Phi_1(.)$ is the standard normal cdf evaluated with Y_k set at 1 and $\Phi_0(.)$ is the standard normal cdf evaluated with Y_k set at 0. These effects are evaluated at each data point and the weighted average over the sample is calculated. Since the model involves two jointly distributed random variables, the effects of the variables on the probability shown in Table 2 should be interpreted as the effects on the marginal probability function. There is more discussion of this issue later.

27. The models were re-estimated with the set of regional dummy variables replaced by the regional unemployment rate. The coefficient estimates (and standard errors) were -3.069 (1.694) and -4.467 (1.236) for the male and female samples, respectively. This more restrictive model was rejected in favor of the specification which includes the regional dummies.

28. The average annual growth rate of employment was calculated for each industry. The primary and manufacturing industries experienced employment growth below the aggregate average annual growth rate. An indicator variable representing these "low growth" industries was constructed and included in the employer probits in place of the separate industry dummies. The coefficient estimates for this variable were 0.355 (0.090) and 0.438 (0.096) for the male and female sample, respectively. Again, this more restrictive approach was rejected in favour of the model discussed in the text.

29. This conclusion is consistent with evidence of assortative mating in the marriage market.

30. The calculation of the marginal effects is a straightforward extension of the methods outlined for the binomial probit and is presented in Greene (1997:927-929).

31. For these reasons we used the usual ordered probit in the selection corrected wage equations presented in the following section of the paper.

32. The results from the generalized ordered probit are presented in Appendix Table 3.

33. The estimated correlation between the errors in the two processes is slightly stronger at -0.426 (0.131) compared to -0.390 (0.108).

34. The exception is that of own children aged 6-15 in households with a spouse present.

35. This issue obviously requires further investigation. A data set with a larger group of part-time workers, as well as information on overemployment, would be useful.

36. For those variables which enter one component of the selection process only, the effects on the overall probability of being in a group will be of the same sign (but of smaller magnitude) as the effects on the marginal probability.

37. Language may capture human capital effects through variations in mobility across labour markets but it may also measure variations in local markets or even discrimination.

38. See Oaxaca and Ransom (1994) for a good presentation and discussion of these various methods.

39. We also perform the wage decompositions treating each group, in turn, as the reference group. These results are presented in Appendix Table 5 and are briefly discussed later.

40. It has been shown in Jones (1983) that a breakdown of the effects of differences in coefficients is arbitrary and depends on the particular reference group chosen for the dummy variables, and on the units of measure of the continuous variables. The sum of the contributions of differences in returns does not suffer from this problem and nor does the breakdown of the effects of differences in characteristics. Note that information on the importance of the differences in the two groups' coefficients can be retrieved from the range of values for the contribution of the characteristics obtained when alternating between the groups' coefficients.

41. The tables of results are presented in Appendix Table 5.

42. We expect more part-time workers to be paid by the hour, therefore the calculation of hourly earnings for full-time workers may be more prone to measurement error as their hours of work

along with their total earnings are used to compute their hourly wage. Note that hours are not included in the right hand side of the wage regressions so that the problem of a spurious negative correlation with the dependent variable will not be severe. Nevertheless, if measurement error causes an incorrect classification of workers into the three groups, a spurious correlation between wages and group affiliation will emerge. Since this is likely to be more important for full-time workers, it will induce a downward bias in the expected full-time wage relative to the predicted part-time wage. Using the part-time wage coefficients to measure the effects of differences in characteristics should alleviate any such bias. Since none of the overall results are changed when alternating between part-time and full-time coefficients, we conclude that measurement error is not a serious concern here.

43. The alternative to exclusion restrictions is to rely upon functional form restrictions based on the nonlinearity of the selection model. We do not rely on this because of the small size of the involuntary part-time group. Since the predicted probabilities of being an involuntary part-time worker are small, they are located in the tail of the distribution where the function is close to linear and hence, identification is weak and the resulting estimates are imprecise.

44. Specifically, the likelihood function exhibits flat segments and the data do not allow an easy identification of the optimum among various combinations of the parameters.

45. In constructing the inverse Mill's ratios we assume independence between the errors of the two decisions in the selection process. For males, the results of the selection model presented earlier imply that this assumption is reasonable. For women, the error terms are significantly correlated across the two selection processes; nevertheless we maintain the independence assumption to simplify the estimation. Note that the FIML estimates presented for women do allow for general interdependence between the random terms. Under the assumption of independence between the selection processes, correction for selectivity bias in the wage regressions is a straightforward extension of the usual correction for a selection process consisting of a single choice. Specifically, in the full-time wage regression we include two terms measuring: $\mathrm{E}(e_{FT}|e_1 > \mu_2 - Z\gamma)$ and $\mathrm{E}(e_{FT}|e_2 > -Y\alpha)$. In the involuntary part-time wage regression, two terms are also included: $\mathrm{E}(e_{IPT}|e_1 > \mu_2 - Z\gamma)$ and $\mathrm{E}(e_{IPT}|e_2 \leq -Y\alpha)$. For voluntary part-time wages, only one correction term is needed: $\mathrm{E}(e_{VPT}|\mu_1 - Z\gamma < e_1 \leq \mu_2 - Z\gamma)$.

46. To find the maximum in the FIML model, we began by estimating a reduced version of the model with few variables included in the wage equations and in the selection from the queue. Gradually, additional variables were added as each version converged. This implies that the similarity of the results with the 2-stage estimates is not an artifact of a flat likelihood and a starting point at the previous parameter estimates.

47. The labour supply estimates are virtually unchanged in magnitude. In the selection from the queue for full-time jobs, the industrial distribution is somewhat reduced in importance but the group of variables consisting of region, industry, and occupation are still more important than personal attributes.

48. This is caused by the usual problem when dealing with a small group in the selection process: the linearity of predicted probabilities at the tail of the distribution and the lack of variation in the selection terms across individuals produces identification problems between the coefficient on the selection terms and the other coefficients, particularly the constant term.

49. See Appendix Table 6 for the estimates.

TABLE 1

Variable Definitions and Weighted Sample Means[(1)]

Variable	Females Full-Time	Females Part-Time Total	Females Part-Time Invol.	Females Part-Time Vol.	Males Full-Time	Males Part-Time Total	Males Part-Time Invol.	Males Part-Time Vol.
Hourly Earnings[(2)]	11.70	11.02	8.79	11.34	15.35	13.76	11.24	14.43
Weekly Hours	38.28	16.99	19.03	16.62	41.59	15.86	17.38	15.39
Education Distribution:								
Some High Sch.*	0.192	0.232	0.296	0.223	0.274	0.327	0.337	0.324
High School	0.275	0.262	0.271	0.260	0.234	0.249	0.266	0.244
Some Post Sec.	0.106	0.103	0.113	0.102	0.101	0.100	0.114	0.097
Certificate	0.262	0.252	0.252	0.252	0.222	0.189	0.182	0.191
University	0.165	0.150	0.067	0.162	0.169	0.135	0.101	0.144
Training[(3)]	0.081	0.050	0.068	0.047	0.084	0.062	0.047	0.066
Age Distribution:								
16-19	0.013	0.021	0.040	0.018	0.014	0.028	0.039	0.025
20-24	0.119	0.060	0.146	0.048	0.099	0.163	0.304	0.126
25-34*	0.347	0.296	0.336	0.290	0.326	0.274	0.320	0.262
35-44	0.287	0.298	0.278	0.301	0.278	0.210	0.131	0.231
45-54	0.163	0.194	0.159	0.199	0.176	0.118	0.107	0.121
55-69	0.070	0.131	0.042	0.144	0.106	0.206	0.099	0.235
Language Distribution:[(4)]								
English*	0.591	0.640	0.576	0.650	0.588	0.584	0.527	0.600
French	0.260	0.254	0.355	0.239	0.254	0.297	0.319	0.291
Other	0.150	0.106	0.070	0.111	0.157	0.119	0.154	0.109
Union Coverage	0.386	0.340	0.405	0.330	0.458	0.382	0.404	0.376
Industrial Distribution:[(5)]								
Primary					0.044	0.024	0.014	0.026
Construction					0.099	0.086	0.105	0.082
Manufacturing*	0.169	0.065	0.055	0.067	0.278	0.085	0.103	0.080
Transp. Comm.	0.057	0.037	0.020	0.039	0.112	0.173	0.182	0.170
Trade	0.153	0.215	0.284	0.205	0.157	0.141	0.154	0.137
Finance	0.096	0.057	0.052	0.058				
Educ. Health	0.254	0.370	0.324	0.376	0.085	0.173	0.149	0.179
Public Adm.	0.086	0.040	0.061	0.037	0.087	0.069	0.031	0.079
Services	0.185	0.217	0.205	0.218	0.137	0.250	0.261	0.247
Occupational Distribution:[(6)]								
Professional*	0.354	0.311	0.220	0.325	0.290	0.247	0.123	0.280
Clerical	0.329	0.308	0.306	0.309	0.064	0.073	0.105	0.064
Sales	0.074	0.126	0.143	0.123	0.059	0.065	0.056	0.068
Services	0.131	0.209	0.278	0.199	0.084	0.214	0.303	0.190
Primary	0.086	0.025	0.036	0.023	0.030	0.029	0.026	0.030
Processing					0.349	0.179	0.202	0.173
Transportation	0.026	0.021	0.016	0.022	0.065	0.139	0.109	0.147
Mater. Handl.					0.058	0.054	0.076	0.048

TABLE 1 - Continued

Variable	Females Full-Time	Females Part-Time Total	Females Part-Time Invol.	Females Part-Time Vol.	Males Full-Time	Males Part-Time Total	Males Part-Time Invol.	Males Part-Time Vol.
Regional Distribution:								
Atlantic	0.081	0.082	0.143	0.073	0.085	0.090	0.124	0.081
Québec	0.259	0.246	0.320	0.236	0.266	0.304	0.297	0.306
Ontario*	0.396	0.354	0.227	0.373	0.383	0.281	0.197	0.304
Prairies	0.157	0.192	0.183	0.194	0.154	0.178	0.223	0.166
B.C.	0.106	0.125	0.127	0.125	0.113	0.146	0.159	0.142
Family Structure:(7)								
Not Head	0.687	0.800	0.717	0.812	0.196	0.258	0.318	0.242
Married	0.658	0.817	0.683	0.836	0.718	0.571	0.484	0.594
Num. of Family Wkrs. - Tot	0.887	0.992	0.905	1.004	0.839	0.831	0.938	0.802
" " " - Fy-Ft	0.678	0.723	0.563	0.745	0.503	0.501	0.513	0.497
No Children ws	0.261	0.199	0.193	0.200	0.243	0.266	0.194	0.285
Children:								
With Children ns					0.033	0.053	0.048	0.054
- Own Children:								
Aged 0-5					0.204	0.144	0.187	0.133
Aged 0-5 ws	0.153	0.230	0.159	0.241				
Aged 0-5 ns	0.015	0.012	0.031	0.009				
Aged 6-15					0.283	0.190	0.196	0.188
Aged 6-15 ws	0.221	0.356	0.310	0.362				
Aged 6-15 ns	0.043	0.036	0.087	0.028				
- Other Children:								
Aged 0-15					0.011	0.008	0.006	0.009
Aged 0-15 ws	0.011	0.009	0.011	0.009				
Aged 0-15 ns	0.007	0.004	0.005	0.004				
- Children at School:								
Aged 16-24					0.177	0.147	0.130	0.151
Aged 16-24 ws	0.142	0.201	0.179	0.204				
Aged 16-24 ns	0.025	0.022	0.023	0.021				
Sample Size	11858	4344	666	3678	17187	976	229	747

Notes:(1) The variables denoted as distributions sum to one down the column for each sub-group. An * denotes the omitted category in regressions. All variables except hourly earnings, hours, and the two variables measuring the number of working family members are dummy variables. (2) Hourly earnings include tips, bonuses, overtime, and commisions. For those individuals not paid by the hour, Statistics Canada computes an hourly earnings value by using usual hours worked for the job in question. (3) Training includes public and private training programs. (4) Language denotes the first language spoken. (5) Due to small numbers, finance is grouped with services for males while primary and construction are grouped with manufacturing for females. (6) For females, processing is grouped with primary and material and handling is grouped with transportation due to small cells. (7) The family structure variables allow for the separate treatment of individuals depending on whether they are heads of household, married, and living in households with other workers. The presence of a spouse is controlled for as well as the presence of children along with their ages. For women, each child-age category is interacted with the presence of a spouse dummy while for men, only the presence of children is interacted due to small sample sizes for households without spouses. The omitted group in the family structure variables is head of household, single, no spouse, and no children. The variables measuring the number of workers in the family do not include the individual in our sample. ws denotes that a spouse is present. ns denotes that there is no spouse present.

TABLE 2

Employer Selection - Marginal Effects on the Probability of Full-time[1]

Variable	Females: Marginal Effects	Females: Standard Errors	Males: Marginal Effects	Males: Standard Errors
Education:				
High School	0.0037	(0.004)	0.0011	(0.004)
Some Post Sec.	0.0004	(0.005)	0.0007	(0.005)
Certificate	0.0029	(0.005)	0.0003	(0.004)
University	0.0156	(0.006)	-0.0009	(0.006)
Training	-0.0050	(0.007)	0.0050	(0.006)
Age:				
16-19	-0.0256	(0.016)	-0.0124	(0.016)
20-24	-0.0056	(0.005)	-0.0150	(0.010)
35-44	0.0011	(0.004)	0.0056	(0.005)
45-54	0.0061	(0.004)	0.0045	(0.004)
55-69	0.0219	(0.006)	0.0006	(0.009)
Language:				
French	-0.0096	(0.008)	-0.0074	(0.008)
Other	0.0130	(0.005)	-0.0014	(0.005)
Region:				
Atlantic	-0.0263	(0.012)	-0.0134	(0.013)
Québec	-0.0069	(0.007)	-0.0019	(0.006)
Prairies	-0.0174	(0.008)	-0.0123	(0.010)
B.C.	-0.0177	(0.008)	-0.0131	(0.011)
Union Coverage	-0.0069	(0.004)	0.0012	(0.003)
Industry:				
Primary			0.0061	(0.010)
Construction			-0.0103	(0.011)
Finance	-0.0158	(0.013)		
Transp. Comm.	0.0017	(0.011)	-0.0175	(0.017)
Trade	-0.0558	(0.019)	-0.0059	(0.009)
Educ. Health	-0.0487	(0.018)	-0.0243	(0.022)
Public Adm.	-0.0173	(0.013)	0.0042	(0.007)
Services	-0.0222	(0.013)	-0.0108	(0.013)
Occupation:				
Clerical	-0.0117	(0.006)	-0.0230	(0.020)
Sales	-0.0297	(0.012)	-0.0092	(0.014)
Services	-0.0391	(0.011)	-0.0387	(0.024)
Primary	-0.0047	(0.012)	-0.0222	(0.027)
Processing			-0.0048	(0.010)
Transportation	-0.0034	(0.014)	-0.0149	(0.017)
Mater. Handl.			-0.0154	(0.017)
Constant[2]	2.674	(0.130)	3.089	(0.229)
Corr(e_1,e_2)[3]	-0.390	(0.108)	0.008	(0.341)
Log Lklhd. Value	-22002.2		-10349.2	
Sample Size:	IPT=666	FT=11858	IPT=229	FT=17187

Notes: (1) Marginal effects are computed for each observation and a weighted average is taken. Please see the text for more details. The standard errors are computed from asymptotic variances which are approximated for each observation using the delta method and then averaged over the sample. (2) The constant is the coefficient rather than a marginal effect. (3) Corr(e_1,e_2) is the estimated correlation between the error term on the labour supply (e_1) and the error on the employer selection (e_2).

TABLE 3

Female Labour Supply - Marginal Effects on the Probabilities[1]

Variable	Non-Participant Marginal Effects	Non-Participant Standard Errors	Voluntary Part-Time Marginal Effects	Voluntary Part-Time Standard Errors	Desiring Full-Time Marginal Effects	Desiring Full-Time Standard Errors
Education:						
High School	-0.1219	(0.005)	-0.0141	(0.002)	0.1360	(0.005)
Some Post Sec.	-0.1162	(0.006)	-0.0166	(0.002)	0.1328	(0.007)
Certificate	-0.1591	(0.005)	-0.0218	(0.002)	0.1808	(0.006)
University	-0.1918	(0.006)	-0.0330	(0.003)	0.2248	(0.007)
Training	-0.1570	(0.009)	-0.0281	(0.004)	0.1852	(0.011)
Age:						
16-19	0.0506	(0.020)	0.0037	(0.005)	-0.0542	(0.021)
20-24	-0.0306	(0.008)	-0.0034	(0.002)	0.0340	(0.008)
35-44	0.0536	(0.005)	0.0046	(0.002)	-0.0582	(0.006)
45-54	0.1735	(0.007)	0.0097	(0.003)	-0.1831	(0.007)
55-69	0.5380	(0.008)	-0.0318	(0.005)	-0.5062	(0.008)
Language:						
French	-0.0172	(0.006)	-0.0017	(0.002)	0.0189	(0.006)
Other	-0.0107	(0.004)	-0.0011	(0.001)	0.0118	(0.005)
Region:						
Atlantic	0.0239	(0.012)	0.0021	(0.003)	-0.0259	(0.013)
Québec	0.0556	(0.006)	0.0047	(0.002)	-0.0603	(0.006)
Prairies	0.0156	(0.007)	0.0014	(0.002)	-0.0170	(0.008)
B.C.	0.0546	(0.005)	0.0042	(0.002)	-0.0587	(0.005)
Family Structure:						
Family Wkrs.	-0.0212	(0.007)	-0.0021	(0.001)	0.0233	(0.004)
Fam. Wkrs. Fy-Ft	-0.0437	(0.007)	-0.0042	(0.001)	0.0479	(0.004)
Not Head	0.0844	(0.005)	0.0103	(0.002)	-0.0947	(0.005)
Married	0.0730	(0.005)	0.0088	(0.002)	-0.0818	(0.006)
No Kids ws	-0.0439	(0.005)	-0.0050	(0.002)	0.0489	(0.005)
Children:						
- Own Children:						
Aged 0-5 ws	0.1612	(0.007)	0.0101	(0.003)	-0.1713	(0.007)
Aged 0-5 ns	0.3194	(0.013)	-0.0128	(0.005)	-0.3066	(0.012)
Aged 6-15 ws	0.0511	(0.005)	0.0046	(0.002)	-0.0557	(0.005)
Aged 6-15 ns	0.0556	(0.010)	0.0040	(0.003)	-0.0596	(0.011)
- Other Children:						
Aged 0-15 ws	0.0071	(0.018)	0.0007	(0.005)	-0.0077	(0.019)
Aged 0-15 ns	0.1467	(0.019)	0.0043	(0.005)	-0.1510	(0.019)
- Children at School:						
Aged 16-24 ws	-0.0016	(0.006)	-0.0002	(0.002)	0.0017	(0.006)
Aged 16-24 ns	0.0109	(0.012)	0.0010	(0.003)	-0.0119	(0.013)
$\mu 1^{(2)}$	-1.038	(0.035)				
$\mu 2$	-0.582	(0.034)				
Corr(e_1,e_2)	-0.390	(0.108)				
Log Lklhd. Value	-22002.16					
Sample Size:	8963		3678		12524	

Notes: (1) Please see the notes to Table 2. (2) $\mu 1$ and $\mu 2$ are the two (constant) threshold coefficients.

TABLE 4

Male Labour Supply - Marginal Effects on the Probabilities(1)

Variable	Non-Participant Marginal Effects	Non-Participant Standard Errors	Voluntary Part-Time Marginal Effects	Voluntary Part-Time Standard Errors	Desiring Full-Time Marginal Effects	Desiring Full-Time Standard Errors
Education:						
High School	-0.0417	(0.004)	-0.0056	(0.001)	0.0473	(0.005)
Some Post Sec.	-0.0455	(0.006)	-0.0063	(0.001)	0.0518	(0.006)
Certificate	-0.0717	(0.005)	-0.0102	(0.001)	0.0819	(0.006)
University	-0.0910	(0.006)	-0.0135	(0.001)	0.1045	(0.006)
Training	-0.0426	(0.007)	-0.0060	(0.001)	0.0486	(0.008)
Age:						
16-19	0.0384	(0.016)	0.0047	(0.002)	-0.0431	(0.017)
20-24	-0.0042	(0.007)	-0.0006	(0.001)	0.0048	(0.008)
35-44	0.0356	(0.005)	0.0044	(0.001)	-0.0399	(0.006)
45-54	0.0873	(0.007)	0.0101	(0.001)	-0.0974	(0.007)
55-69	0.4575	(0.013)	0.0384	(0.002)	-0.4959	(0.012)
Language:						
French	0.0036	(0.005)	0.0005	(0.001)	-0.0040	(0.005)
Other	0.0006	(0.004)	0.0001	(0.001)	-0.0007	(0.004)
Region:						
Atlantic	0.0315	(0.012)	0.0039	(0.002)	-0.0354	(0.013)
Québec	0.0361	(0.005)	0.0046	(0.001)	-0.0406	(0.005)
Prairies	0.0339	(0.006)	0.0042	(0.001)	-0.0382	(0.007)
B.C.	0.0271	(0.005)	0.0034	(0.001)	-0.0305	(0.006)
Family Structure:						
Family Wkrs.	-0.0179	(0.008)	-0.0023	(0.001)	0.0202	(0.003)
Fam. Wkrs. Fy-Ft	-0.0214	(0.008)	-0.0028	(0.001)	0.0242	(0.004)
Not Head	0.0590	(0.005)	0.0073	(0.001)	-0.0663	(0.005)
Married	-0.0918	(0.007)	-0.0115	(0.001)	0.1033	(0.007)
No Kids ws	0.0252	(0.005)	0.0033	(0.001)	-0.0284	(0.006)
Children:						
With Kids ns	-0.0305	(0.008)	-0.0042	(0.001)	0.0347	(0.009)
- Own Children:						
Aged 0-5	0.0161	(0.007)	0.0020	(0.001)	-0.0182	(0.007)
Aged 6-15	0.0030	(0.006)	0.0004	(0.001)	-0.0033	(0.006)
- Other Children:						
Aged 0-15	0.0722	(0.015)	0.0084	(0.002)	-0.0806	(0.016)
- Children at School:						
Aged 16-24	-0.0397	(0.006)	-0.0055	(0.001)	0.0452	(0.006)
$\mu1^{(2)}$	-1.153	(0.027)				
$\mu2$	-0.979	(0.027)				
Corr(e_1,e_2)	0.008	(0.341)				
Log Lklhd. Value	-10349.17					
Sample Size:	3518		747		17416	

Notes: (1) Please see the notes to Table 2. (2) $\mu1$ and $\mu2$ are the two (constant) threshold coefficients.

TABLE 5

Changes in the Probability of Being Involuntary Part-Time(1)

Changes in Characteristics	Females: Changes in the Marginal Probability	Females: Changes in the Total Probability	Males: Changes in the Marginal Probability	Males: Changes in the Total Probability
Increasing age to 55-64	−0.011	−0.011	−0.008	−0.007
Increasing Education to a University Degree	−0.007	−0.006	+0.001	+0.004
Living in a high unemployment area (Atlantic)	+0.016	+0.014	+0.020	+0.014
Having Children 0-5 yrs, married & spouse present	0	−0.002	0	+0.001
Changing Industry to Education and Health	+0.037	+0.033	+0.037	+0.029
Changing Occupation to Services	+0.021	+0.019	+0.013	+0.010

Notes: (1) All changes are from a base case of an individual 16-19 years old, Anglophone, living in Ontario, with no training and no high school degree, single, with no spouse and no children, living in a household with no other workers and facing an employer in manufacturing offering a non-union job in a primary occupation.

TABLE 6

Ln Wage Decompositions - Exogenous Selection[1]

(Standard Errors in Parentheses)

	FT-IPT		**VPT-IPT**		**FT-VPT**	
			Females			
Total Differential	0.244	(0.012)	0.184	(0.013)	0.060	(0.008)
Characteristics:[2]						
Education[3]	0.041	(0.003)	0.037	(0.003)	0.005	(0.001)
Age	0.010	(0.001)	0.016	(0.004)	-0.016	(0.002)
Language	-0.005	(0.003)	0.002	(0.003)	-0.002	(0.001)
Region	0.016	(0.003)	0.011	(0.004)	0.001	(0.001)
Union	-0.004	(0.000)	-0.017	(0.001)	0.011	(0.001)
Industry	0.033	(0.005)	0.011	(0.002)	0.020	(0.002)
Occupation	0.030	(0.004)	0.024	(0.002)	0.010	(0.002)
Total Charact.	0.121	(0.006)	0.084	(0.006)	0.029	(0.003)
(percent)	(50%)		(46%)		(48%)	
Returns	0.123	(0.013)	0.100	(0.014)	0.031	(0.009)
(percent)	(50%)		(54%)		(52%)	
F-test 1 (d. of f.)[4]	2.714*	(29,12466)	1.560*	(29,4286)	5.775*	(29,15478)
F-test 2 (d. of f.)	1.772*	(28,12466)	0.952	(28,4286)	5.530*	(28,15478)
			Males			
Total Differential	0.357	(0.026)	0.169	(0.032)	0.187	(0.020)
Characteristics:[2]						
Education[3]	0.013	(0.005)	0.004	(0.004)	0.017	(0.002)
Age	0.066	(0.009)	0.046	(0.012)	0.007	(0.004)
Language	-0.005	(0.004)	0.004	(0.004)	0.002	(0.002)
Region	0.020	(0.007)	0.014	(0.006)	0.004	(0.002)
Union	0.010	(0.002)	-0.007	(0.001)	0.017	(0.002)
Industry	0.030	(0.014)	0.003	(0.006)	0.039	(0.009)
Occupation	0.084	(0.013)	0.062	(0.010)	0.020	(0.007)
Total Char.	0.218	(0.018)	0.127	(0.016)	0.106	(0.010)
(percent)	(61%)		(75%)		(57%)	
Returns	0.139	(0.032)	0.042	(0.036)	0.081	(0.022)
(percent)	(39%)		(25%)		(43%)	
F-test 1 (d. of f.)[4]	3.018*	(32,17352)	1.628*	(32,912)	5.952*	(32,17870)
F-test 2 (d. of f.)	2.614*	(31,17352)	1.649*	(31,912)	4.849*	(31,17870)

Notes:(1) FT-IPT denotes the wage differential between full-time and involuntary part-time workers. Similarly, VPT stands for voluntary part-time. The form of the decomposition is explained in the text. (2) For a list of the variables included in each group of characteristics, please see Table 1. (3) Education includes the effects of training. (4) F-test 1 is an F-test of the null hypothesis: all coefficients are jointly equal in the two groups. F-test 2 is a test of the null hypothesis: all coefficients except the constant term are jointly equal in the two groups. A * on the F-statistic denotes rejection of the null at a 5% level of significance. Finally, (d. of f.) stands for degrees of freedom.

TABLE 7

Ln Wage Decompositions - 2 Stage Selection Correction and Joint Wage-Selection Model(1)

(Standard Errors in Parenthesis)

	FT-IPT		**VPT-IPT**		**FT-VPT**	
	Females - Joint FIML Wage-Selection Estimation					
Total Differential	0.244	(0.012)	0.184	(0.013)	0.060	(0.008)
Characteristics:						
Education	0.043	(0.004)	0.038	(0.004)	0.008	(0.001)
Age	0.007	(0.002)	0.008	(0.007)	-0.013	(0.002)
Language	-0.013	(0.004)	-0.002	(0.004)	-0.003	(0.001)
Region	0.013	(0.004)	0.010	(0.004)	0.001	(0.001)
Union	-0.004	(0.000)	-0.019	(0.001)	0.012	(0.000)
Industry	0.009	(0.007)	0.013	(0.002)	0.013	(0.002)
Total Charact.	0.055	(0.011)	0.048	(0.009)	0.018	(0.003)
(percent)	(7%)		(6%)		(31%)	
Returns	0.755	(0.130)	0.705	(0.129)	0.041	(0.015)
(percent)	(93%)		(94%)		(69%)	
Selection(2)	-0.566	(0.124)	-0.569	(0.124)	0.001	(0.016)
	Females - 2-Stage Correction					
Total Differential	0.244	(0.012)	0.184	(0.013)	0.060	(0.008)
Characteristics:						
Education	0.035	(0.005)	0.038	(0.005)	0.007	(0.001)
Age	0.006	(0.002)	0.011	(0.007)	-0.011	(0.003)
Language	-0.014	(0.004)	-0.002	(0.004)	-0.003	(0.001)
Region	0.006	(0.004)	0.008	(0.005)	0.000	(0.001)
Union	-0.004	(0.000)	-0.019	(0.002)	0.012	(0.001)
Industry	-0.006	(0.008)	0.013	(0.002)	0.002	(0.003)
Total Charact.	0.023	(0.015)	0.049	(0.011)	0.007	(0.005)
(percent)	(2%)		(7%)		(4%)	
Returns	0.901	(0.215)	0.695	(0.209)	0.173	(0.033)
(percent)	(98%)		(93%)		(96%)	
Selection(2)	-0.680	(0.203)	-0.560	(0.202)	-0.120	(0.031)
	Males - 2-Stage Correction					
Total Differential	0.357	(0.026)	0.169	(0.032)	0.187	(0.020)
Characteristics:						
Education	0.007	(0.005)	0.004	(0.004)	0.018	(0.003)
Age	0.021	(0.020)	0.050	(0.022)	-0.022	(0.010)
Language	-0.009	(0.004)	0.005	(0.004)	-0.001	(0.003)
Region	-0.002	(0.011)	0.004	(0.008)	0.001	(0.004)
Union	0.009	(0.002)	-0.006	(0.001)	0.016	(0.003)
Industry	-0.031	(0.028)	0.008	(0.006)	0.030	(0.011)
Total Charact.	-0.005	(0.060)	0.064	(0.027)	0.042	(0.017)
(percent)	(0%)		(5%)		(9%)	
Returns	1.794	(0.668)	1.257	(0.640)	0.426	(0.111)
(percent)	(100%)		(95%)		(91%)	
Selection(2)	-1.432	(0.611)	-1.152	(0.619)	-0.281	(0.101)

Notes:(1) Please see the notes at the bottom of Table 6. The variance-covariance matrix for the 2-stage selection correction coefficients is computed using White's estimator. (2) Selection represents the average difference in the groups' gap between the observed and the unconditional wage.

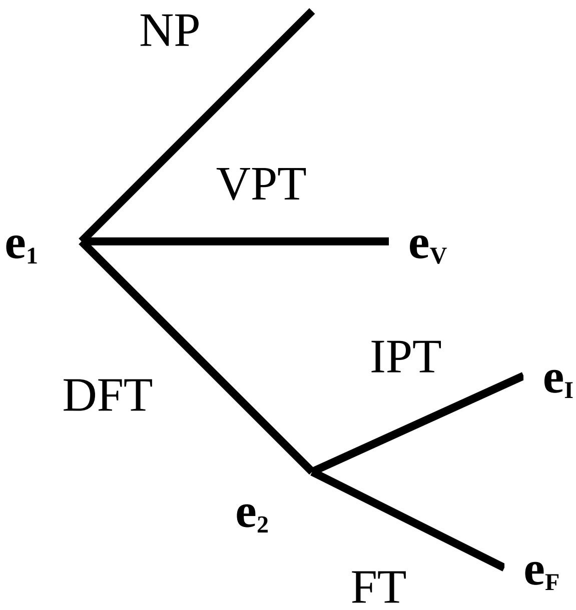

Figure 1

Structure of the Error Terms

Appendix A

In this appendix, we describe the likelihood function for the FIML joint selection model. The notation is defined in the text.

I. Labour Supply Decision

This is modelled with an ordered probit:

$$z_i^* = Z_i\gamma + e_{1i} \tag{A1. 1}$$

where

$$\begin{aligned} \Pr(z_i = \text{NP}) &= \Pr(z_i^* < \mu_1) \\ \Pr(z_i = \text{VPT}) &= \Pr(\mu_1 \leq z_i^* < \mu_2) \\ \text{and } \Pr(z_i = \text{DFT}) &= \Pr(z_i^* \geq \mu_2). \end{aligned} \tag{A1. 2}$$

II. Employer Selection

This is modelled with a binomial probit:

$$y_i^* = Y_i\alpha + e_{2i} \tag{A1. 3}$$

where $\Pr(y_i = 0 = IPT) = \Pr(y_i^* \leq 0)$ and $\Pr(y_i = 1 = FT) = \Pr(y_i^* > 0)$.

III. Wage Equations

Wage equations take the form

$$lnw_{ji} = X_{ji}\beta_j + e_{ji} \tag{A1. 4}$$

where $j = VPT, IPT, FT$.

The error terms are jointly normally distributed as $N(0, \Sigma)$ where

$$\sum = \begin{pmatrix} 1 & \rho_{12} & \sigma_{1V} & \sigma_{1I} & \sigma_{1F} \\ & 1 & \sigma_{2V} & \sigma_{2I} & \sigma_{2F} \\ & & \sigma_V^2 & \sigma_{VI} & \sigma_{VF} \\ & & & \sigma_I^2 & \sigma_{IF} \\ & & & & \sigma_F^2 \end{pmatrix}. \tag{A1. 5}$$

IV. The Likelihood Function

The likelihood function is given by:

$$\prod_{i\in NP}\Phi\left(\mu_1 - Z_i\gamma\right)$$
$$\prod_{i\in VPT}\left(\Phi\left(\frac{\mu_2 - Z_i\gamma - \mathrm{E}\left(e_1|e_V\right)}{\sqrt{\mathrm{Var}\left(e_1|e_V\right)}}\right) - \Phi\left(\frac{\mu_1 - Z_i\gamma - \mathrm{E}\left(e_1|e_V\right)}{\sqrt{\mathrm{Var}\left(e_1|e_V\right)}}\right)\right)\phi\left(\frac{e_V}{\sigma_V}\right)\frac{1}{\sigma_V}$$
$$\prod_{i\in IPT}\left(\Phi\left(\frac{-Y_i\alpha - \mathrm{E}\left(e_2|e_I\right)}{\sqrt{\mathrm{Var}\left(e_2|e_I\right)}}\right) - \right.$$
$$\left.\Phi_{BIV}\left(\frac{\mu_2 - Z_i\gamma - \mathrm{E}\left(e_1|e_I\right)}{\sqrt{\mathrm{Var}\left(e_1|e_I\right)}}, \frac{-Y_i\alpha - \mathrm{E}\left(e_2|e_I\right)}{\sqrt{\mathrm{Var}\left(e_2|e_I\right)}}, \rho_{12.I}\right)\right)\phi\left(\frac{e_I}{\sigma_I}\right)\frac{1}{\sigma_I}$$
$$\prod_{i\in FT}\left(1 - \Phi\left(\frac{\mu_2 - Z_i\gamma - \mathrm{E}\left(e_1|e_F\right)}{\sqrt{\mathrm{Var}\left(e_1|e_F\right)}}\right) - \Phi\left(\frac{-Y_i\alpha - \mathrm{E}\left(e_2|e_F\right)}{\sqrt{\mathrm{Var}\left(e_2|e_F\right)}}\right) + \right.$$
$$\left.\Phi_{BIV}\left(\frac{\mu_2 - Z_i\gamma - \mathrm{E}\left(e_1|e_F\right)}{\sqrt{\mathrm{Var}\left(e_1|e_F\right)}}, \frac{-Y_i\alpha - \mathrm{E}\left(e_2|e_F\right)}{\sqrt{\mathrm{Var}\left(e_2|e_F\right)}}, \rho_{12.F}\right)\right)\phi\left(\frac{e_F}{\sigma_F}\right)\frac{1}{\sigma_F} \tag{A1. 6}$$

where $\mathrm{E}(e_i|e_j) = \frac{\sigma_{ij}}{\sigma_j^2}e_j$, $\mathrm{Var}(e_i|e_j) = 1 - (\frac{\sigma_{ij}}{\sigma_j})^2$, for $i = 1, 2$ and $j = V$ (for VPT), I (for IPT), F (for FT),

$$\rho_{12.k} = \frac{\rho_{12} - \left(\frac{\sigma_{1k}}{\sigma_k}\right)\left(\frac{\sigma_{2k}}{\sigma_k}\right)}{\sqrt{\left(1 - \left(\frac{\sigma_{1k}}{\sigma_k}\right)^2\right)}\sqrt{\left(1 - \left(\frac{\sigma_{2k}}{\sigma_k}\right)^2\right)}} \tag{A1. 7}$$

for $k = I$ (for IPT), F (for FT), $\phi(.)$ is the standard normal density function, $\Phi(.)$ and $\Phi_{BIV}(.,.,.)$ are the standard normal univariate and bivariate distribution functions respectively.

TABLE A1

Employer Selection - Coefficient Estimates

Variable	Females Coefficients	Females Standard Errors	Males Coefficients	Males Standard Errors
Education:				
High School	0.066	(0.066)	0.043	(0.094)
Some Post Sec.	0.007	(0.082)	0.029	(0.122)
Certificate	0.051	(0.072)	0.012	(0.099)
University	0.331	(0.100)	-0.037	(0.151)
Training	-0.080	(0.084)	0.245	(0.164)
Age:				
16-19	-0.331	(0.133)	-0.348	(0.199)
20-24	-0.091	(0.068)	-0.434	(0.083)
35-44	0.020	(0.054)	0.257	(0.106)
45-54	0.112	(0.065)	0.209	(0.126)
55-69	0.606	(0.121)	0.025	(0.230)
Language:				
French	-0.155	(0.079)	-0.257	(0.138)
Other	0.269	(0.078)	-0.055	(0.115)
Region:				
Atlantic	-0.348	(0.074)	-0.381	(0.153)
Québec	-0.114	(0.085)	-0.072	(0.132)
Prairies	-0.255	(0.065)	-0.373	(0.106)
B.C.	-0.252	(0.073)	-0.380	(0.114)
Union Coverage	-0.115	(0.051)	0.047	(0.081)
Industry:				
Primary			0.332	(0.397)
Construction			-0.312	(0.143)
Finance	-0.227	(0.126)		
Transp. Comm.	0.030	(0.155)	-0.474	(0.192)
Trade	-0.644	(0.104)	-0.201	(0.155)
Educ. Health	-0.614	(0.107)	-0.578	(0.207)
Public Adm.	-0.245	(0.125)	0.198	(0.257)
Services	-0.315	(0.108)	-0.336	(0.191)
Occupation:				
Clerical	-0.187	(0.063)	-0.552	(0.169)
Sales	-0.383	(0.090)	-0.281	(0.202)
Services	-0.494	(0.072)	-0.795	(0.120)
Primary	-0.076	(0.132)	-0.522	(0.283)
Processing			-0.173	(0.180)
Transportation	-0.056	(0.168)	-0.410	(0.209)
Mater. Handl.			-0.415	(0.198)
Constant	2.674	(0.130)	3.089	(0.229)
Cov(e_1,e_2)(1)	-0.390	(0.108)	0.008	(0.341)
Log Lklhd. Value	-22002.2		-10349.2	
Sample Size:	IPT=666	FT=11858	IPT=229	FT=17187

Notes:(1) Cov(e_1,e_2) is the estimated covariance between the error term on the labour supply (e_1) and the error on the employer selection (e_2).

TABLE A2

Labour Supply - Coefficient Estimates

Variable	Females		Males	
	Coefficients	Standard Errors	Coefficients	Standard Errors
Education:				
High School	0.455	(0.022)	0.249	(0.019)
Some Post Sec.	0.447	(0.031)	0.282	(0.028)
Certificate	0.602	(0.024)	0.451	(0.022)
University	0.769	(0.029)	0.609	(0.025)
Training	0.633	(0.044)	0.266	(0.038)
Age:				
16-19	-0.178	(0.076)	-0.205	(0.070)
20-24	0.112	(0.036)	0.024	(0.034)
35-44	-0.193	(0.025)	-0.198	(0.024)
45-54	-0.612	(0.029)	-0.454	(0.026)
55-69	-1.667	(0.029)	-1.682	(0.023)
Language:				
French	0.062	(0.030)	-0.020	(0.024)
Other	0.039	(0.024)	-0.003	(0.018)
Region:				
Atlantic	-0.085	(0.032)	-0.171	(0.055)
Québec	-0.197	(0.031)	-0.200	(0.022)
Prairies	-0.056	(0.025)	-0.185	(0.028)
B.C.	-0.192	(0.028)	-0.149	(0.024)
Family Structure:				
Family Wkrs.	0.077	(0.016)	0.102	(0.015)
Fam. Wkrs. Fy-Ft	0.157	(0.017)	0.123	(0.017)
Not Head	-0.312	(0.026)	-0.319	(0.020)
Married	-0.268	(0.031)	0.498	(0.025)
No Kids ws	0.163	(0.029)	-0.139	(0.024)
Children:				
With Kids ns			0.186	(0.041)
- Own Children:				
Aged 0-5			-0.091	(0.030)
Aged 0-5 ws	-0.567	(0.029)		
Aged 0-5 ns	-1.077	(0.062)		
Aged 6-15			-0.017	(0.026)
Aged 6-15 ws	-0.183	(0.025)		
Aged 6-15 ns	-0.196	(0.049)		
- Other Children:				
Aged 0-15			-0.365	(0.060)
Aged 0-15 ws	-0.025	(0.082)		
Aged 0-15 ns	-0.499	(0.096)		
- Children at School:				
Aged 16-24			0.241	(0.029)
Aged 16-24 ws	0.006	(0.029)		
Aged 16-24 ns	-0.039	(0.060)		
$\mu 1$	-1.038	(0.035)	-1.153	(0.027)
$\mu 2$	-0.582	(0.034)	-0.979	(0.027)
Log Lklhd. Value	-22002.2		-10349.2	
Sample Size:	NP=8963 VPT=3678 DFT=12524		NP=3518 VPT=747 DFT=17416	

TABLE A3

Female Labour Supply - Generalized Ordered Probit[1]

Variable	Marginal Effect on Probabilities		
	NP	VPT	DFT
Education:			
High School	-0.1145	-0.0315	0.1459
Some Post Sec.	-0.1195	-0.0144	0.1338
Certificate	-0.1667	-0.0126	0.1793
University	-0.2131	-0.0018	0.2149
Training	-0.1794	-0.0091	0.1885
Age:			
16-19	0.0338	0.0338	-0.0676
20-24	-0.0006	-0.0585	0.0592
35-44	0.0779	-0.0372	-0.0407
45-54	0.2082	-0.0421	-0.1661
55-69	0.5656	-0.0901	-0.4755
Language:			
French	-0.0035	-0.0297	0.0332
Other	0.0196	-0.0671	0.0476
Region:			
Atlantic	0.0535	-0.0563	0.003
Québec	0.0736	-0.0284	-0.0451
Prairies	0.0173	-0.0007	-0.0166
B.C.	0.0655	-0.0141	-0.0514
Family Structure:			
Family Wkrs.	-0.0151	-0.0108	0.0259
Fam. Wkrs. Fy-Ft	-0.0532	0.0096	0.0436
Not Head	0.0974	-0.0101	-0.0873
Married	0.0682	0.0245	-0.0927
No Kids ws	-0.0338	-0.0333	0.0671
Children:			
- Own Children:			
Aged 0-5 ws	0.1873	-0.0269	-0.1604
Aged 0-5 ns	0.3669	-0.1030	-0.2640
Aged 6-15 ws	0.0457	0.0217	-0.0674
Aged 6-15 ns	0.0905	-0.0462	-0.0443
- Other Children:			
Aged 0-15 ws	0.0238	-0.0324	0.0086
Aged 0-15 ns	0.1975	-0.0832	-0.1143
- Children at School:			
Aged 16-24 ws	-0.0164	0.0257	-0.0092
Aged 16-24 ns	0.0013	0.0181	-0.0194
$\mu 1$ (s.e.)	-1.038	(0.035)	
$\mu 2$ (s.e.)	-0.582	(0.034)	
Cov(e_1,e_2) (s.e.)	-0.390	(0.108)	
Log Lklhd. Value			
Sample Size:	8963	3678	12524

Notes: (1) Please see the main text for details and references on this specification. (s.e.) stands for the standard error on the coefficient estimates.

TABLE A4

Ln Wage Decompositions - 2-Stage Selection Correction[1]

	Females			Males		
	FT-IPT	VPT-IPT	FT-VPT	FT-IPT	VPT-IPT	FT-VPT
a) Industry Dummies are Excluded.						
Total Difference	0.244	0.184	0.060	0.357	0.169	0.187
Characteristics:						
Education	0.038	0.037	0.006	0.004	0.000	0.013
Age	0.009	0.015	-0.011	0.059	0.075	-0.025
Language	-0.009	0.001	-0.002	-0.004	0.006	0.001
Region	0.011	0.009	0.000	0.013	0.011	0.002
Union	-0.005	-0.020	0.013	0.011	-0.008	0.020
Occupation	0.030	0.026	0.012	0.065	0.056	0.029
Total Charact.	0.074	0.069	0.018	0.148	0.140	0.040
(percent)	(14%)	(15%)	(18%)	(27%)	(262%)	(8%)
Returns	0.469	0.375	0.080	0.403	-0.086	0.459
(percent)	(86%)	(85%)	(82%)	(73%)	(-162%)	(92%)
Selection	-0.299	-0.260	-0.038	-0.194	0.115	-0.312
b) The Union Dummy is Excluded.						
Total Difference	0.244	0.184	0.060	0.357	0.169	0.187
Characteristics:						
Education	0.093	0.080	0.006	-0.0001	0.000	0.013
Age	0.029	0.054	-0.014	-0.242	-0.165	-0.022
Language	0.032	0.027	-0.001	-0.040	-0.015	0.001
Region	0.064	0.047	0.001	-0.110	-0.077	0.001
Industry	0.160	0.032	0.024	-0.250	-0.032	0.035
Occupation	0.131	0.072	0.017	-0.325	-0.165	0.025
Total Char.	0.509	0.311	0.034	-0.968	-0.453	0.053
(perc.)	(-12%)	(-7%)	(-41%)	(-8%)	(-4%)	(11%)
Returns	-4.770	-4.490	-0.117	12.481	11.503	0.410
(perc.)	(112%)	(107%)	(141%)	(108%)	(104%)	(89%)
Selection	4.505	4.363	0.143	-11.156	-10.881	-0.276

Notes:(1) The table provides wage decompositions under different identifying restrictions. Please see the main text for more information.

TABLE A5

Ln Wage Decompositions(1)

Range of Values when Alternating Between the Groups' Coefficients

	Females						Males					
	FT-IPT		VPT-IPT		FT-VPT		FT-IPT		VPT-IPT		FT-VPT	
a) Exogenous Selection.												
Obs.Gap	0.244		0.184		0.060		0.357		0.169		0.187	
Char.:												
Educ.	0.042	0.039	0.038	0.037	0.007	0.002	0.029	-0.002	0.015	-0.005	0.016	0.019
Age	0.013	0.008	0.021	0.012	-0.019	-0.012	0.098	0.035	0.049	0.044	0.004	0.011
Lang.	-0.003	-0.008	0.009	-0.005	-0.002	-0.002	0.001	-0.010	0.005	0.002	-0.004	0.008
Region	0.024	0.008	0.009	0.013	0.002	0.000	0.015	0.024	0.013	0.015	0.002	0.005
Union	-0.003	-0.004	-0.016	-0.018	0.010	0.013	0.008	0.011	-0.007	-0.006	0.012	0.022
Indus.	0.032	0.034	0.009	0.013	0.025	0.015	0.034	0.026	0.013	-0.007	0.032	0.047
Occup.	0.042	0.018	0.033	0.014	0.008	0.012	0.058	0.109	0.043	0.080	0.024	0.016
Tot.Char.	0.147	0.095	0.103	0.066	0.031	0.028	0.243	0.193	0.131	0.123	0.086	0.128
(percent)	(60)	(39)	(56)	(36)	(52)	(46)	(68)	(54)	(78)	(73)	(46)	(68)
Returns	0.097	0.149	0.081	0.118	0.029	0.032	0.114	0.164	0.038	0.046	0.101	0.059
(percent)	(40)	(61)	(44)	(64)	(48)	(54)	(32)	(46)	(22)	(27)	(54)	(32)
b) FIML Model - Wage equations exclude occupation dummies.												
Obs.Gap	0.244		0.184		0.060							
Char.:												
Educ.	0.057	0.028	0.051	0.026	0.010	0.006						
Age	0.012	0.002	0.017	-0.002	-0.017	-0.009						
Lang.	-0.006	-0.019	0.009	-0.013	-0.004	-0.002						
Region	0.025	0.002	0.013	0.007	0.001	0.000						
Union	-0.003	-0.005	-0.018	-0.020	0.010	0.014						
Indus.	0.019	-0.002	0.015	0.010	0.012	0.014						
Tot.Char.	0.104	0.006	0.087	0.008	0.012	0.023						
(percent)	(13)	(1)	(12)	(1)	(20)	(39)						
Returns	0.706	0.804	0.666	0.745	0.047	0.036						
(percent)	(87)	(99)	(88)	(99)	(80)	(61)						
Selec.	-0.566		-0.569		0.001							
c) 2-Stage Selection Correction - Wage equations exclude occupation dummies.												
Obs.Gap	0.244		0.184		0.060		0.357		0.169		0.187	
Char.:												
Educ.	0.043	0.027	0.051	0.026	0.008	0.006	0.028	-0.013	0.018	-0.010	0.015	0.021
Age	0.008	0.004	0.018	0.005	-0.013	-0.009	0.079	-0.036	0.072	0.028	-0.035	-0.010
Lang.	-0.013	-0.016	0.009	-0.012	-0.005	-0.002	-0.002	-0.017	0.007	0.002	-0.006	0.006
Region	0.015	-0.003	0.012	0.003	-0.001	0.000	0.005	-0.008	0.013	-0.005	-0.001	0.003
Union	-0.004	-0.005	-0.018	-0.020	0.011	0.014	0.007	0.010	-0.008	-0.005	0.011	0.022
Indus.	-0.008	-0.003	0.015	0.010	-0.009	0.014	0.016	-0.078	0.010	0.006	0.016	0.043
Tot.Char.	0.041	0.004	0.087	0.012	-0.009	0.023	0.133	-0.142	0.112	0.016	0.000	0.085
(percent)	(4)	(0)	(12)	(2)	(-5)	(13)	(7)	(-8)	(8)	(1)	(0)	(18)
Returns	0.883	0.920	0.658	0.733	0.189	0.157	1.656	1.931	1.209	1.305	0.468	0.383
(percent)	(96)	(100)	(88)	(98)	(105)	(87)	(93)	(108)	(92)	(99)	(100)	(82)
Selec.	-0.680		-0.560		-0.120		-1.432		-1.152		-0.281	

Notes:(1) FT-IPT denotes the wage differential between full-time and involuntary part-time workers. Similarly, VPT stands for voluntary part-time. For each pair, the first column was calculated using the first group's coefficient and the second column was derived using the second group's coefficients. For example, using the first two columns of panel a, 0.042 is computed with the full-time coefficients while 0.039 uses the involuntary part-time coefficients.