Estimating Worker Information Gaps From A Stochastic Wage Frontier: A Study Of Canadian Labour Markets

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ABSTRACT

In the presence of imperfect information in labour markets, optimal job search entails accepting a wage offer if it exceeds a worker's reservation wage. However, this generally means that a worker with a given skill, will not earn the maximum wage on offer, and the gap between the maximum wager and the wage earned could be viewed as an indicator of labour market inefficiency arising from worker information gaps. The inefficiency arises because information is costly, so workers do not search long enough to discover the maximum wage, which would otherwise be sought and earned if information were costless. The aim of this paper is to empirically investigate the extent of labour market inefficiency within and across a number of population strata in Canada. These strata include individuals grouped according to various socio-economic and demographic characteristics such as gender, geographical location, education, and immigration status. The econometric model adopted is the stochastic frontier function used initially extensively in studies of production and cost efficiency of firms, and subsequently employed in studies of worker information gaps. The data we use are drawn from the 2001 Census of Canada.

INTRODUCTION

The one aspect of imperfect information in labour markets that has traditionally attracted a great deal of attention, at the theoretical and empirical level, is the efficiency of job search, with the common analytical approach being to model and explain search duration endogenously [see, for instance, Lancaster (1990) and Mortensen (1986)]. Another interesting direction that the empirical literature has taken is that, in the presence of imperfect information and the associated costs of search, workers will earn less than the maximum they could otherwise earn. As a result, there is a wage gap, the size of which reflects the extent of worker ignorance. This latter approach has sought to assess how wage gaps vary across various labour markets and population groups, as well as within a given labour market or population group. Two interesting aspects of imperfect information are that, although workers might adopt optimal search strategies, in that they cease search when the offer wage is greater then the reservation wage, market inefficiency results since workers would not generally search till they found the best wage on offer and, secondly, labour markets reward like individuals differently, so that systematic gaps in individual earnings can arise even among relatively homogenous individuals.

The primary objective of this paper is to empirically investigate the extent of labour market efficiency within and across a number of population strata in Canada, based on the notion that such inefficiency arises from worker information gaps. We study several populations strata, grouped according to various socio-economic and demographic characteristics including, amongst other things, gender, geographical location, education, and immigration status. The study of wage gaps of new immigrant workers seems to be especially relevant, since they likely face relatively greater information acquisition costs, at the margin, arising due to a lack of familiarity with labour markets in the host country. However, if immigrants were successful in adjusting to the host country, one would expect that the extent of labour market inefficiency, as measured by wage gaps, would diminish over time as search costs decline with greater experience.

Labour market inefficiency arising out of imperfect information on the part of workers is modelled within the framework of the stochastic frontier model, initially developed by Aigner, Lovell and Schmidt (1977) and used extensively in the empirical study of productive and/or allocative efficiency - e.g. Kalirajan and Shand (1999), and Battese and Coelli (1995) – as well in the study of labour markets [Polachek and Xiang (2005), Lang (2004), Slottje, Hirschberg, Hayes and Scully (1994), Daneshvary, Herzog, Hofler and Schlottmann (1992), and Hofler and Polachek (1982)]. The stochastic wage frontier is estimated using data from the 2001 Canadian census, and used to compute the proposed measures of labour market inefficiency.

In what follows, we present the principles underlying the stochastic frontier model and how it can be used to measure labour market efficiency. Following that we discuss the data, the variables used, as well as our findings. We conclude with a summary and point to some of the drawbacks of the study.

AN EMPIRICAL MODEL OF LABOUR MARKET EFFICIENCY

The fundamental premise on which the empirical model used in this paper is based is that workers do not possess full information on employer wage offers for a given skill, and since acquiring information is costly, workers generally accept wages that fall short of the maximum they could earn. This follows from search theory, which predicts that workers would carry search up to the point where a wage offer exceeds the worker's reservation wage. The accepted wage would in general be less than the maximum on offer. That is, even as workers pursue optimal search strategies, there is labour market inefficiency in that the maximum attainable wage is not earned. In addition, the labour market will not reward identical individuals identically because the wage shortfall varies across like individuals. This labour market inefficiency would not exist if information acquisition were costless, since then workers would search till they found the maximum wage on offer.

Labour market inefficiency resulting from imperfect worker information can be modelled empirically by using a stochastic wage frontier function. Specifically, assuming that w_i* stand for the log wage an individual worker would earn with full information, we can write the stochastic wage frontier as:

$$w_i^* = \boldsymbol{\beta}'\boldsymbol{x}_\mathbf{i} + u_i \qquad (1)$$

where $\boldsymbol{x}$ is a vector of observed individual worker characteristics that cause the full-information wage w* to differ across workers, while u is the usual random disturbance term, assumed to follow a normal distribution with zero mean and constant variance σ^2. The frontier (1) shows the maximum wage that could be earned by all workers with a given bundle of characteristics. It also shows that random factors ensure that this maximum wage would vary across like individual. However, when worker information gaps exist, actual wages $w \leq w^*$. The wage gap is, thus, $(w - w^*) \leq 0$. Denoting this wage gap by v, we can write represent the actual log wage w by the following equation:

$$w_i = w_i^* + v_i = \beta'\boldsymbol{x}_\mathbf{i} + u_i + v_i \qquad (2)$$

This is the generic stochastic frontier function model used by most studies in studying worker information gaps. We can re-write (2) in natural units as:

$$W_i = \exp(\boldsymbol{\beta}'\boldsymbol{x}_\mathbf{i} + u_i + v_i) \qquad (3)$$

From this, it follows that labour market efficiency can be measured by the ratio of actual to full-information wage, which is:

$$(W_i/W_i^*) = \exp(v_i) \qquad (4)$$

In order to estimate the labour marker efficiency index given by (4) at the level of the individual worker, we need to be able to estimate v_i. As Jondrow, Lovell, Materov and Schmidt (1982) have shown, it is possible to do so by estimating the mean of u condition on (v+u). But estimation of (2) and hence (4) requires some assumption about the probability distribution of v. That is, we need an assumption of how worker ignorance is distributed. A common assumption in the literature is that it follows an exponential distribution:

$$f(v) = (1/\theta)\exp(v/\theta)\ ,\ \theta > 0 \text{ and } v \leq 0 \tag{5}$$

It is easy to verify that $E(v) = -\theta$, $var(v) = \theta^2$, where $-\theta$ is the mean of worker ignorance.

Under the assumptions about u and v, it is possible to estimate all the relevant parameters so that equation (4) can then be used to estimate individual specific labour market efficiency (that is, v_i) from the conditional mean of u given (v+u), which can be shown to be equal to:

$$E(v_i|\ \varepsilon_i)= -\sigma\{f(A_i)/[1-F(A_i)] - A_i\} \tag{6}$$

where $\varepsilon_i= (v_i + u_i)$, $A_i = (\varepsilon_i/\sigma) + (\sigma/\theta)$, and F(.) is the cumulative normal density function.

Once we have estimated the labour market efficiency index in terms of wage gaps as given by (4), we can also study the distribution of efficiency within each of the population groups examined.

In order to estimate the labour market efficiency index, the stochastic wage frontier can be estimated by the maximum likelihood method. As shown by Aigner et al (1997), the log-likelihood function for this model is as follows:

$$\log L = -n\log\theta + (n/2)\sigma^2\ \theta^{-2} + \theta^{-1}\ \Sigma\varepsilon_i + \Sigma\log F(\varepsilon_i\ \sigma^{-1}+ \sigma\theta^{-1})] \tag{7}$$

The maximization of (7) yields the maximum likelihood estimates of the vector of regression coefficients $\boldsymbol{\beta}$, as well as the scalar parameters σ and θ. Once the stochastic wage frontier has been estimated, the labour market efficiency index can be computed as described above.

Before we proceed with a discussion of our findings, a couple of issues are worth noting. First, a priori, we cannot predict how worker employer information gaps might vary across different population groups (after controlling for various factors), since the outcome would depend upon offsetting influences on the costs of information acquisition. Thus, for example, in large areas and/or large populations groups, the volume of information is large, which would widen information gaps. On the other hand, if population density is higher in such areas, this could lower the cost of acquiring information and work to reduce information gaps. On balance, how these two opposing tendencies will play out is uncertain a priori, and is an empirical question. In general, one would expect that the amount of information and/or the costs of acquiring would differ from one population group to another, causing information gaps to vary across these groups. Of course, individual heterogeneity would also cause intra-group variability in wages among like individual workers. Second, it needs emphasizing that the labour market efficiency index should not be taken to be an indicator of the absolute level of efficiency. This is because, given the nature of the indices, they are likely to be reflect unobserved heterogeneity across individuals [see, for instance, Polachek and Yoon (1987)]. For these reasons, it is the *relative* magnitude of labour market efficiency across population groups that matter since unobserved heterogeneity is less likely to be a problem across groups than within them.

THE DATA, VARIABLES AND FINDINGS

The data for the variables used in this study are taken (or constructed) from the public-use 2001 micro-data census file for individuals. The samples used are restricted to individuals aged 25-64 years, who were working full-time, full-year. Full-time, full-year employment requires that an individual work at least 30 hours a week for 49 weeks or more.

The variables appearing in our stochastic wage frontier given by (2) are as follows. The dependent variable is the log of the weekly wage, while in choosing the explanatory variables, we adopt the standard human capital variables - schooling (in years) and labour market experience, estimated as (age-schooling –6), which is specified as a quadratic. We also introduce a number of additional control variables. Gender is likely to be an important determinant of earnings, as is occupation. Gender is introduced as a dummy variable equal to one for females. To control for the impact of occupation, we classify individuals into four occupational classes: a) Managers b) Professionals c) Supervisors and (d) all other occupations. These are also dummy variables (with the last category being the reference group). Three dummy variables are used to capture the occupational impact on wages, with category (d) being the reference category.

Full-information wages can vary across workers also because of location, which reflects the particular characteristics of regional labour markets. Regional impacts are measured by introducing dummy variables for the following regions/provinces of Canada: Atlantic Canada, Quebec, Ontario, the Prairies (comprised of the provinces of Manitoba, Saskatchewan and Alberta), and British Columbia and the Yukon. There are no observations from Atlantic Canada (the provinces of Nova Scotia, Newfoundland, Prince Edward Island and New Brunswick) in our immigrant sample because the immigrant group detail we use is not available for that region. However, we do include an Atlantic Canada category when we look at non-immigrant population groups. Finally, in most of the regressions we also incorporate the impact of an individual worker's immigrant status by distinguishing between immigrants and the native-born. For immigrants, we also distinguish between three groups: a) new immigrants b) recent immigrants and c) established immigrants. All immigrant variables are dummy variables, with the established immigrants being the reference group. New immigrants are defined as those who came into Canada during 1995-1999, recent immigrants are those who came during 1990-1994, and established immigrants are those who came prior to 1990. Note that we do not include those who came in 2001 and 2000 in the category of new immigrants because the vast majority of this cohort could not possibly meet the full-time, full-year requirement.

We estimate our frontiers for each of the following population strata:

1. The total sample of all Canadian full-time, full-year workers aged 25-64 years.
2. Males
3. Females
4. Primarily urban residents (those living in census metropolitan areas - CMAS)
5. Rural residents (non-CMA residents)
6. Individuals with a high school education or less
7. Individuals with an university education
8. Employment insurance (EI) recipients
9. Non-employment insurance recipients
10. Individuals living in households with only 1 primary maintainer
11. Individuals living in households with 2 or more maintainers
12. Native-born Canadians
13. Second-generation Canadians (that is, native-born with at least one parent born outside Canada)
14. All immigrants, as well as three sub-immigrant groups as defined above.

Table 1 presents the estimates of the stochastic wage frontier (3). For brevity, we report the results for only selected population groups. Looking at the earnings functions of the population groups presented in Table 1, it can be seen that the coefficient estimates conform in sign to those one would expect on prior grounds in all equations. Furthermore, all coefficients are highly significant at the one- percent level or less, a result that is not altogether surprising given the large samples we are working with. It can be seen that schooling has a positive impact on earnings, while labour market experience has a positive but diminishing impact, which one would expect on prior grounds. The estimates also indicate that females earn less than equivalent males (the reference group), that all immigrant cohorts earn less than the native-born (the reference group), other things being equal. In addition, this adverse impact of immigrant status is weakest for established immigrants, but clearly larger for recent and new immigrants. As far as the impact of occupation is concerned, on average, managers, professionals and supervisors earn more than the reference group, which is made up of various levels of clerical and sales personnel and manual workers. This wage differential is greatest for managers and smallest for supervisors. Finally, the evidence points to substantial inter-regional variation in wages, on average, for identical individuals, with Ontario residents showing the greatest wage premium relative to equivalent individuals living in the reference region (Atlantic Canada). It might be noted that by there are no Atlantic Canadians in the immigrant samples. Hence, in the immigrant regression in Table 1, the reference group comprises residents of British Columbia and the Yukon.

Table 1: Estimates of the Stochastic Wage Frontier*

Variables	Population Groups					
	Total sample	**CMA residents**	**Females**	**University educated**	**EI recipients****	**Immigrants**
Intercept	5.822 (647.5)	5.857 (420.0)	5.480 (416.1)	5.872 (254.5)	5.965 (110.3)	6.296 (314.1)
Schooling	0.0516 (117.9)	0.0509 (95.9)	0.0555 (87.1)	0.0412 (32.7)	0.0389 (13.4)	0.0385 (42.0)
Experience	0.0276 (67.5)	0.0288 (59.5)	0.0258 (44.4)	0.0405 (52.2)	0.0160 (6.62)	0.0136 (13.4)
Experience squared	-0.0004 (-46.2)	-0.0004 (-40.7)	-0.0004 (-32.3)	-0.0007 (-40.2)	-0.0002 (-4.80)	-0.0002 (-8.09)
Ontario	0.2330 (48.4)	0.1998 (19.0)	0.2342 (35.2)	0.2581 (30.1)	0.2550 (10.6)	0.0607 (8.25)
Quebec	0.0752 (15.1)	0.0367 (3.45)	0.0901 (13.1)	0.1148 (12.8)	0.0711 (3.02)	-0.1238 (-12.7)
Prairie provinces	0.1411 (27.5)	0.0937 (8.69)	0.1141 (15.9)	0.1460 (15.9)	0.1235 (4.53)	-0.0394 (-4.11)
British Columbia &Yukon	0.1986 (36.0)	0.1495 (13.5)	0.2168 (28.2)	0.1697 (17.7)	0.1941 (6.42)	*
Females	-0.3212 (-141.9)	-0.2947 (-106.9)	*	-0.2616 (-65.7)	-0.3528 (-24.4)	-0.2995 (-56.1)
Managers	0.3680 (121.8)	0.4036 (11.7)	0.3710 (78.4)	0.4308 (84.4)	0.1891 (7.83)	0.4230 (59.2)
Professionals	0.2369 (80.3)	0.2494 (72.0)	0.2525 (61.5)	0.2443 (54.4)	0.2287 (11.9)	0.3282 (47.5)
Supervisors	0.1231 (23.7)	0.1481 (20.9)	0.0904 (10.8)	0.1072 (9.47)	0.0933 (2.57)	0.1724 (12.1)
Immigrants	-0.0543 (-17.3)	-0.0830 (-24.0)	-0.0326 (-7.33)	-0.0724 (-14.3)	-0.0134 (-0.592)	*
New immigrants	-0.0543 (-28.3)	-0.1951 (-27.1)	-0.1865 (-18.9)	-0.1995 (-20.9)	-0.1666 (-3.99)	-0.2241 (-27.8)
Recent immigrants	-0.1631 (-25.9)	-0.1662 (-25.5)	-0.1506 (-17.4)	-0.1690 (-17.8)	-0.1284 (-2.82)	-0.1778 (-24.5)
Σ	0.3116 (352.9)	0.3155 (295.6)	0.2823 (229.3)	0.3220 (203.2)	0.3082 (53.5)	0.3222 (156.1)
λ^{-1}	1.950 (455.1)	2.015 (374.2)	1.987 (302.7)	2.235 (240.3)	1.609 (70.9)	1.743 (206.7)
N	192,667	130,139	82,274	64,673	5,693	39,180
Log likelihood	-157,650	-104,771	-63,087	-49,020	-5,289	-35,194

*Numbers is parentheses are t ratios. ** EI = employment insurance.

Our primary interest, however, is in the implications for labour market efficiency across various population groups. As indicated earlier, we measure this by the efficiency index given by equation (4), which indicates the extent to which the actual wage falls short of the full-information wage, given any specific set of characteristics. Table 2 presents the average level of this index in the second column, and the distribution of individuals about this average for all population groups in the remaining columns. First, a few words on the interpretation of this index using as an example the total sample for Canadians. For this group, the index is 65.8, and this implies that Canadian workers earn on average 65.8 percent of, or 34.2 percent less than what they would earn in the absence of market inefficiency resulting imperfect information. However, as indicated earlier, we are really interested in the relative level of efficiency across population groups as well within each group, rather than in the absolute level of efficiency. The table shows that, relative to the national average, labour market efficiency is highest for those with a university education, second-generation Canadians, and lowest for individuals who were employment insurance recipients, immigrants, especially those that are new or recent, and those who have no more than a high school education. It is interesting to note that although immigrants fare worse than the native-born, their children do better. Thus, even though immigrants do not appear to catch up fully even after living in Canada for an extended period of time, their children do and in fact surpass the native-born.

The table also shows that those who live in households where there is a single household maintainer do relatively worse than those in which there are two or more maintainers, presumably because the latter face lower search costs and can, therefore, can afford to search more. There is also greater labour market inefficiency associated with employment insurance recipients relative to non-recipients. On the one hand, one might expect the opposite if employment insurance is viewed as a search subsidy. However, those on unemployment insurance also include those who are sick, or are on maternity or paternity leave, factors that likely mean that these individuals are less in a position to engage in labour market search. Our results are consistent with this. Note finally that those living in CMAs have less imperfect information (greater market efficiency) than those do not. This is a plausible result because, in large areas such as CMAs, while the volume of information is large and this would tend to widen information gaps, population density is high, which would tend to could lower the cost of acquiring information and narrow information gaps, so that the net impact could go either way. Our results suggest that the latter impact is stronger, a result found in other studies as well (see, for instance, Polachek and Yoon (1987)]. Finally note that labour market efficiency is just slightly higher for females relative to males. This is somewhat counterintuitive in that one would expect the opposite given the greater labour market attachment of males.

In cases where a comparison is possible, these findings match those of other studies. For instance, Hofler and Murphy (1992) find that better educated workers and those living in large urban centres in the US have smaller information gaps, while Daneshvary et al (1992) find that length of residence in the US lowers information gaps of immigrants. However, there are some differences as well. Thus, unlike our study, the Daneshvary et al. study as well as the study on German immigrants by Lang (2004) finds that native-born and overall immigrant wage gaps are very similar. In addition, unlike the finding in this paper, Hofler and Murphy (1992) find that females have larger gaps than males in the US, which is more in line with expectations.

Apart from a comparison of relative average efficiency across population groups, one can look at the way efficiency varies within each population group. It is evident from Table 2 that the efficiency distribution is highly skewed to the left, so that only a relatively small fraction of individuals has an efficiency index below 50 percent. within each population group. But the pattern of skewness shows some distinct patterns. Thus, relative to the Canadian efficiency distribution, the distributions for those with a university education, second-generation Canadians, those living in CMAs and the native-born have ticker right tails, while the distributions for immigrants, EI recipients, and those with no more than a high school education have perceptibly thicker left tails. In general, there is also greater variability in efficiency for the latter groups, pointing to greater variability in information gaps.

Table 2: Percentage Distribution of Individuals by Efficiency by Population Group

Population groups	Mean efficiency (%)	Efficiency Interval					
		Under 50	50-60	60-70	70-80	80-90	90-100
Total sample	65.8	17.1	11.5	19.6	29.4	20.8	1.6
High school or less	63.4	21.4	12.6	19.5	26.7	18.3	1.1
University educated	68.5	12.8	9.4	19.1	33.4	23.3	2.0
Males	65.5	16.7	12.0	21.2	29.3	19.5	1.4
Females	66.5	17.4	10.6	17.5	29.1	23.2	2.2
CMA residents	66.6	15.7	11.2	19.7	30.4	21.3	1.7
Non-CMA residents	64.8	19.6	11.6	18.9	27.0	21.4	1.6
Native-born	66.6	16.1	11.0	19.3	29.7	22.1	1.8
All immigrants	63.4	20.8	13.0	20.0	27.5	17.4	1.2
New immigrants	62.2	22.1	14.2	21.3	25.4	16.2	0.85
Recent immigrants	62.1	22.3	13.6	21.4	26.8	15.0	1.0
Established Immigrants	64.0	20.3	12.4	19.5	28.2	18.4	1.2
Second-generation Canadians	67.3	14.8	10.5	19.5	30.6	22.8	1.8
EI recipients*	61.2	26.5	12.3	18.5	23.4	18.5	0.84
Non-EI recipients	66.2	16.6	11.4	19.5	29.7	21.2	1.7
One maintainer households	64.0	20.0	12.5	19.9	28.0	18.3	1.2
Multiple maintainer households	65.9	17.9	11.2	18.2	28.5	22.8	1.5

* EI = employment insurance.

CONCLUSIONS

In this paper, we empirically investigated the extent of labour market efficiency within and across a number of population strata in Canada, based on the notion that such inefficiency arises from imperfect information in labour markets. We modelled labour market inefficiency as arising from imperfect information on the part of workers with the help of a stochastic wage frontier. Specifically, labour market efficiency was measured as the ratio of the actual wage to the full-information wage (in percentage terms). Within this framework it is possible to get individual-specific measures of worker information gaps, and hence individual-specific estimates of labour market efficiency. Of course, our interest was not in the absolute measures of labour market efficiency, since these are contaminated by unobserved individual heterogeneity; rather, we wished to look at relative labour market efficiency – that is, how different population groups rank. A relative analysis is far less likely to suffer from the problem posed by unobserved individual heterogeneity.

Our results indicated that, on average, individuals with a university education, second-generation Canadians, and the native-born ranked highest in terms of labour market efficiency, while employment insurance recipients, immigrants, especially those that are new or recent, and those with an education no higher than high school were at the bottom end of the efficiency spectrum. An interesting feature of our results was that although immigrants rank lower than the native-born in terms of labour market efficiency, their children do better than the latter. This implies that even though immigrants might not catch up fully to the native-born even after living in Canada for a period of time, their children do and in fact surpass them. Our findings also indicted that those who live in households where there is a single household maintainer do relatively worse than those with two or more maintainers, likely because the latter face lower search costs and can, therefore, search more. There is also greater labour market inefficiency associated with employment insurance recipients relative to non-recipients, and with those that do not live in CMAs relative to those that do, and female labour market efficiency is slightly higher than that for males. We also examined the efficiency distributions within each population group. In all cases, only a relatively small proportion of individuals have show labour market efficiency of less than 50 percent, with a majority lying in the 70-90 percent interval. In conjunction with this, we found that, relative to the Canadian efficiency distribution, the distributions for those with a university education, second-generation Canadians, those living in CMAs and the native-born have thicker right tails, while the distributions for immigrants, EI recipients, and those with no more than a high school education have perceptibly thicker left tails.

Our overall findings thus suggest that better educated individuals living in large urban centres are most likely to have the smallest information gaps and hence display the greatest labour market efficiency. Immigrants as a whole fare relatively worse, although established immigrants seem to do somewhat better than newer ones. But second-generation Canadians rank relatively higher than the native-born, indicating that although immigrants do not necessarily catch up to native born Canadians, their children seem to surpass them

In concluding, we note that the robustness of the findings would require further testing. In this regard, specification tests would be especially important because in the frontier approach, incomplete information is measured from residuals, and is likely be sensitive to model specification. It is also important to keep in mind that the model of the labour market used here ignores other likely motives underlying labour market behaviour. For example, employers may pay higher than the minimum wage for efficiency-wage reasons, not because they lack information. Similarly, workers may accept low wages not so much because they lack information about offers, but rather because the non-recognition of foreign-acquired credentials, which has become a serious issue in Canada in recent times, effectively blocks of certain jobs to immigrants, especially those of the non-traditional kind

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