HOW INSTITUTIONS AFFECT WORKERS' WELL-BEING: AN INTERNATIONAL STUDY OF DIFFERENCES IN THE GENDER PAY GAP, RATES OF RETURN TO EDUCATION, AND WORKERS' INCOMPLETE INFORMATION ON WAGES

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ABSTRACT

This dissertation attempts to examine cross-country variations in three labor market outcomes- the gender pay gap, rates of return to education, and the incomplete information for workers. Two steps are taken in investigating each of these topics: First, the value of labor market outcome is calculated for each country-year. Second, country characteristics and labor market institutions are employed to explain the emerging cross-country patterns.

The gender pay gap chapter complements the current cross-country studies using the human capital approach. Theory predicts that higher incentives for lifetime labor force participation causes women to invest more in human capital so that the gender pay gap will decrease. The fertility rate, the age gap between husband and wife at the first marriage, the top marginal income tax rate, and the female relative educational attainment are employed to measure women's incentive. The results show that higher incentives of female labor force participation represented by lower values in the first three variables and higher value in the last variable lead to smaller gender pay gaps.

The chapter on returns to education focuses on trade and skill-biased technical change to explain cross-country differences in the returns. It finds that increased imports of labor-intensive (skill intensive) goods reduce relative payoff to domestic unskilled workers (skilled workers) and

raise (reduce) returns to education. Meanwhile, larger values of the use of computer and the extent of high technology exports raise the returns as a result of greater demands for high skills.

The last chapter gathers cross-country evidence supporting the effects of search behavior on employee incomplete information on maximum wage offers. Workers in countries that strongly support unemployment insurance receive wages closer to their potential. A more dense population reduces search costs, thereby leading to less incomplete information. A more industrial economy disseminates wage information better, so that workers exhibit less incomplete information and higher wages. Finally, foreign worker inflows increase incomplete information, and at the same time reduce average wage levels.

This dissertation is dedicated to my wife Xiaohong Xu

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INTRODUCTION

The past two decades have witnessed a flourish of cross-country study in labor economics. This activity is a result of at least two concurrent events: First, economic development progressed quickly in the 1980s and 1990s, causing a vast of differences in labor market performance across countries including within the group of developed countries. For instance, among OECD countries, the stark contrast takes place between the strong job creation and relatively low unemployment rate of the US and the slow job growth and persistently high unemployment rate of many European countries (OECD, 1994). Second, microdata sets became increasingly available for the large sample of countries and time periods, which enabled researchers to conduct large-scale comparisons with control for individual characteristics.

A lot of studies began to examine cross-country differences in labor market institutions in an attempt to learn what causes the heterogeneous labor market performance. This approach has the advantage of using usually exogenous explanatory variables to identify the causal effects. Furthermore, cross-country comparisons offer more variations in explanatory variables, overcoming the deficiency in variation when examined over time within a particular country. Such large variations improve the opportunity to detect the effects of these explanatory variables.

This dissertation follows such an approach, using country characteristics as well as labor market institutions to examine cross-country variations in three labor market outcomes: the gender pay gap, rates of return to education, and the incomplete information for employees. These are

independent but related topics, tied to workers' wages from three different perspectives.[1] The gender pay gap and returns to education both look at between-group wage differences - gender groups and education groups respectively, whereas the last topic examines how incomplete labor market information affects workers' accepted wages. The three chapters all take two steps. First they calculate values of these labor market outcomes for each country-year and then they explain the patterns employing country-level variables.

The first chapter deals with the gender pay gap. This is an old subject, with its evidence traced to the Old Testament. Notwithstanding, recent studies on cross-country comparison revive this topic. It is widely found that the gender pay gap varies a great deal across countries. In the 1990s, for example, countries like Belgium, France, Italy, New Zealand, and Sweden have female-male pay ratios more than 80 percent among full-time workers, whereas nations like Austria, Canada, and Japan have the ratio under 70 percent (Blau and Kahn, 2002, p228). Labor market institutions and wage structures are applied to explain these cross-country variations. For example, studies find collective bargaining coverage and minimum wage laws are negatively correlated with the gender pay gap, while male wage structure and female net supply (supply minus demand) are positively associated with the gap (Blau and Kahn, 2003).

Current cross-country comparisons only examine how exogenous factors affect women's relative earnings position. By and large they neglect endogenous factors that might indeed play a more crucial role. When examined over time, one important finding is that the gender pay gap is narrowing in spite of the growing overall wage inequality. These two trends would obviously contradict each other if there are no other forces taking effect. One argument based on endogenous

[1] In fact, these topics correspond to three basic facts Borjas (2000) summarized from the literature of changes in the wage structure. For details, see Borjas (2000, p278-282).

explanations is the human capital theory, which proposes the diminishing gender pay gap is a result of women's increased incentive to participate in the labor market during the past decades. This argument offers an answer for the above puzzle. The first chapter aims to complement the current gender literature on cross-country comparison using the human capital approach.

This study evaluates a few frequently used gender pay gap measures, including the gender dummy from the Mincer earnings function, the computed gender pay gap using the decomposition technique, and the unadjusted gender pay gap from raw data. On the one hand, the first two measures are likely to overestimate the gender pay gap when there are unobserved human capital variables correlated with wages. On the other hand, these two measures tend to underestimate the gap if the "discrimination" against women affects their acquired skills as well (Polachek, 1975; Borjas, 2000, p365). This study sticks to the more conservative way of using the unadjusted gender pay gap from raw data by employing aggregate wage data from 21 OECD countries over the 1970 to 2000 time period.

Four major explanatory variables are employed to approximate women's incentive for labor force participation: the fertility rate, the age gap between husband and wife at the first marriage, the top marginal income tax rate, and the female relative educational attainment. Lower values of the first three variables imply higher incentives to invest in human capital. They suggest smaller gender pay gaps. The last variable is positively associated with human capital investment. It is negatively related to the pay gap. The empirical results generally support these predictions in various regression models with and without accounting for other labor market institutions. The results of this group of variables highly suggest that the human capital theory is powerful in explaining the cross-country and time-series variations in the gender pay gap. This is the main

conclusion and contribution of the first chapter.

The second chapter deals with rates of return to education. Returns to education are directly related to the literature that addresses rising wage inequalities among OECD countries. A large body of studies documented that the rise in wage premiums to skilled workers in OECD countries occurred since the early 1980s (e.g. Katz and Murphy, 1992; Gottschalk and Smeeding, 1997; OECD, 1997). However, very little work systematically looks at returns to education on a cross-country basis. In a globalized world such a comparative study is increasingly important because countries are largely interconnected now and the returns in one country can easily be affected by behavior of other countries. This is well exemplified by one explanation of this study which clearly links domestic returns to education to international trade with other countries. This chapter intends to fill the current gap by providing a more thorough examination of variations in returns to education.

Specifically, this research begins by estimating rates of return to education based on the Mincer earnings function, using the International Social Survey Programme (ISSP) data and the Luxembourg Income Study (LIS) data covering the years from 1985 to 2002. The bivariate comparisons first support several widely examined patterns concerning the supply side of skills. The refined regressions - after accounting for the country effect – show mean schooling and expenditure on education do not necessarily reduce the returns. The multivariate comparisons incorporate international trade and skill-biased technical change as two explanations on the demand side for skills, complemented by the early supply factors. Two trade variables suggest that increased imports of labor-intensive (skill intensive) goods reduce relative payoff to domestic unskilled workers (skilled workers) and raise (reduce) returns to education. While the use of

computer and the extent of high technology exports tend to support the skill-biased technical change argument that returns rise as a result of larger demands for high skills, though the results are sensitive to specific regression specifications. Finally, the tests to discern a time trend generally fail to show significant patterns. This second chapter makes two contributions to the literature: First, it clarifies mixed empirical results regarding trade by using better trade measures. Second, it introduces skill-biased technical change into the systemic study of returns to education.

The third chapter addresses incomplete employee wage information. Incomplete information leads workers to accept wages below what they could have attained had they full information about each potential employer's pay. In the literature, while a lot of research focuses on the search duration or how to set the reservation wage (e.g. Nelson, 1970; Mortonsen, 1970; McCall, 1970), a group of studies try to directly measure the incomplete information using the stochastic frontier technique (e.g. Hofler-Polachek, 1985; Polachek-Yoon, 1987; Hofler and Murphy, 1992; Daneshvary et al., 1992; Groot and Oosterbeek, 1994). This research conducts a cross-country comparison of computed incomplete information in an attempt to corroborate the findings from past specific country cases.

The study first defines incomplete information measured as the gap between the accepted wage and the maximum potential wage. The accepted wage is observed in data while the maximum potential wage is given by the Mincer earnings function (like a production function). The stochastic frontier regression used here is the Mincer earnings regression with a second residual component. This additional residual term measures skewness of earnings distribution and it is interpreted as the incomplete information in this context. The incomplete information is estimated for eleven countries and various years using the LIS data.

The effects of several worker characteristics on the incomplete information are assessed through the regressions. Generally married men and women suffer less from incomplete information than the widowed or divorced; and singles suffer the most. Women suffer more from incomplete information than men. Both schooling and labor market experience reduce these losses. The results of cross-country comparisons are largely consistent with the search theory. Workers in countries that strongly support unemployment insurance receive wages closer to their potential. A more dense population reduces search costs leading to less incomplete information. A more industrial economy disseminates wage information better, so that workers exhibit less incomplete information and higher wages. Finally, foreign worker inflows increase incomplete information, and at the same time reduce average wage levels, at least in the short-run. In sum, this chapter has gathered cross-country evidence supporting the effects of search behaviors on the incomplete information.

As a conclusion, this dissertation adds to the growing body of studies on cross-country comparison of labor market performance. It reexamines three important labor market outcomes - the gender pay gap, rates of return to education, and the incomplete employee wage information- on the cross-country basis. The results from these three chapters strengthen the findings from pervious case studies and offer new insights to understanding these labor market outcomes.

CHAPTER I

WOMEN'S INCENTIVE FOR LABOR FORCE PARTICIPATION AND THE GENDER PAY GAP: A COMPARATIVE STUDY OF TWENTY-ONE OECD COUNTRIES

I. Introduction

The phenomenon that women earn less than men is consistently and widely observed.[1] Even after economists try to account for possible differentials of worker characteristics, the observed gender pay gaps largely persist, strongly suggesting that men have a wage premium than comparable women. The explanation of this gender pay gap has attracted enormous attention in the literature; it has been studied using many datasets, various methods of estimation, and numerous subgroups of workers throughout the last several decades.[2]

Despite the abundance of this gender pay gap literature, little attention has been paid to a comparative study across countries.[3] Meanwhile, striking variations in the gender pay gap exist across countries.[4] In one of the data samples considered in this study, twenty-one countries of the Organization for Economic Co-operation and Development (OECD) over the period of 1970-2000, the gender gap in log earnings varies a great deal.[5] Countries like Australia, Belgium, Czech Republic, Hungary, Italy, Poland and Sweden have relatively small gender pay gaps, which are

[1] The evidence of the gender pay gap dates back to the Old Testament, in which women earn sixty percent of men's wage. "A male between twenty and fifty years old shall be valued at fifty silver shekels, that is shekels by the sacred standard. If it is a female, she shall be valued at thirty shekels" (Leviticus, 27: 1-4).
[2] For more details, see Weichselbaumer & Winter-Ebmer (2003).
[3] Among the very few researchers studying international differences of the gender pay gap, Blau & Kahn have conducted most of the study on this subject.
[4] For a description, see Blau and Kahn (2002, 2003).
[5] The gender pay gap is measured at the 50th percentile of wage distribution, using raw wage data for the sample of full-time workers. Also, see appendix 1 for details on country names and available years for each country.

around twenty percent over the time. Whereas other countries such as Austria, Canada, South Korea, and Japan maintain gender pay gaps as large as forty to fifty percent. When examined across time, the gender pay gap declines significantly in the United Kingdom, the United States, and France; it starts at around fifty percent and ends at about twenty-five percent for the former two countries and it declines from about thirty-five percent to ten percent in France over the covered period. On the other hand, the gap is rather constant for many of the other countries in the sample.[6]

This paper aims to explain the patterns of gender pay gap emerging from the above data sample. However, unlike previous comparative studies that would mostly focus on wage setting institutions (Blau and Kahn, 2003; Weichselbaumer and Winter-Ebmer, 2002), this study argues that differentials in women's incentive for labor force participation account for variations in the gender pay gap across country and over time. More specifically, because women compete with men who historically have comparative advantage in labor market, women and married women in particular are likely to be discouraged from the labor market and turn to specialize in household in which they have been shown to have comparative advantage. Even though they do not totally withdraw from the labor market, women are likely to exert less effort when they are affiliated with household work and children raising. Therefore, women's incentive for labor force participation realized both in terms of working time and working effort has become very important in determining their relative wage. I expect women with higher incentive in the labor market to have higher female-male wage ratio, and vice versa for women with lower incentive. Fertility rate, age gap between husband and wife at the first marriage, top marginal income tax rate, and female relative educational attainment are employed to measure women's incentive for labor force participation. The first three variables are expected to be positively related to the gender pay gap, whereas the last one to be negatively associated with the gap.

However, this study does not totally depart from the track of previous studies; it eventually connects to previous findings by adding several widely used wage-setting variables into regression. This paper proceeds in the following way: section two is devoted to review of literature on the gender pay gap, with a focus on comparative studies. The importance of examining women's

[6] The result of my raw observation is likely to be affected by different lengths of time period covered for different countries. As a result, regressions are employed later on as a more formal examination.

incentives for labor force participation is argued in section three. Various gender pay gap measures are compared in section four. Section five provides descriptions of a few competing wage datasets. Research designs and empirical results appear in the next section. The final section contains concluding remarks and indicates possible directions for future research.

II. Literature Background

The study focusing on international comparison comprises only a small part of the gender pay gap literature. Emerging after the vast number of single-country case studies, this comparative study has borrowed a lot of theoretical arguments from earlier studies. In the literature, two well-known theories are represented by the human capital theory and the segregation theory. The human capital theory seeks to explain the male–female wage difference in terms of male-female human capital heterogeneity. Female workers accumulate less human capital over their life time than their male counterparts, and this human capital stock deficiency determines that they earn less in labor market. The observed gender pay gap generally reduces a significant proportion after accounting for male-female human capital differentials, and it shrinks to almost zero in Mincer and Polachek (1974).[7] This human capital argument provides a powerful economic foundation for understanding men's wage premium that is originally assumed as a result of pure discrimination against women. First developed by Blinder (1973) and Oaxaca (1973), a group of studies began to decompose the observed gender pay gap into two parts, one part explained by human capital differentials and another left un-explained part.

Starting with Bergmann (1974), feminist economists tried to offer the alternative proposition that women have been consistently and largely placed into "bad" segments of the labor market with less well paying jobs, which as argued is responsible for the gender wage differential. This segregation theory amounts to an argument that women are discriminated by corporations and eventually they are prevented from getting "good" jobs. Despite the debate on whether women endogenously choose or are exogenously assigned their occupations, this theory does not appear as

[7] Their study has taken effort to account for women's actual working experience rather than potential experience that is usually measured as age minus schooling years minus six. This latter way of computation is widely used in the literature because it is convenient and requires much less data information.

powerful as the human capital theory in its economic explanation of the gender pay gap.[8]

The ensuing international comparisons draw a great deal on arguments from the above theories. Blau and Kahn (1992, 1995, 1996b) first examine international differences in the gender pay gap, focusing on cross-country variations in market returns to skills and sectoral wage differentials. Inferring from the human capital theory that on average women have less skills and the segregation theory that they are placed in unfavorable sectors, these studies have empirically shown that gender pay gaps are likely to be exaggerated in countries with higher rewards to skills and larger sectoral wage differentials, *ceteris paribus*.

Blau and Kahn (1996a) investigate the impact of dispersions of overall wage structure on gender pay gap differences. They find that the gender pay gap tends to be higher in countries with larger wage inequalities because generally female workers are more likely to be located at the bottom of wage distributions. In a more recent paper, Blau and Kahn (2003) offer an international comparison of gender pay gaps for twenty-two countries, employing female net supply (supply minus demand) and male wage structure as wage structure measurements. The findings strengthen their previous conclusions; countries with more compressed male wage structures and lower female net supplies are likely to have smaller gender pay gaps. In addition, collective bargaining coverage, a labor market institution measuring wage structure, is found to be negatively associated with the gender pay gap.

Weichselbaumer and Winter-Ebmer (2002) propose equal treatment legislation and economic competition as potential determinants of gender pay gaps. Through their comparative study, they find that ratification of international conventions supporting equal treatment of male and female workers has a negative and significant effect on the gender pay gap. At the same time, countries with higher economic competitions measured by the Economic Freedom Index tend to display lower gender pay gaps. The second finding is predicted by Becker (1957)'s argument that in the long run, competitive markets eliminate gender discrimination when firms try to minimize their costs.

As shown in the above review, current cross-country comparisons only examine how exogenous factors affect women's relative earnings position. By and large they neglect endogenous

[8] See Polachek (2004) for a survey of explanation powers of the segregation theory.

factors that might indeed play a more crucial role. When examined over time, one important finding is that the gender pay gap is narrowing in spite of the growing overall wage inequality. These two trends would obviously contradict each other if there are no other forces taking effect. One argument based on endogenous explanations is the human capital theory, which proposes the diminishing gender pay gap is a result of women's increased incentive to participate in the labor market during the past decades. This argument offers an answer for the above puzzle. The study aims to complement the current gender literature on cross-country comparison using the human capital approach.

III. Women's Incentive for Labor Force Participation

A distinct feature of women's labor force participation is their discontinuous attachment to the labor market (Mincer and Polachek, 1974). Concurrently, the human capital theory predicts that one invests till the present value of income stream from an additional unit of human capital equals to its costs. Because this total income stream positively depends upon one's working horizon, women's intermittent labor force participation determines that they would acquire less human capital in school and on the job. This labor force participation pattern also makes women accumulate less market experience. These two reasons largely explain the existing gender pay gap.

What accounts for women's different labor force participation behavior is probably the division of labor within household. Throughout history, women have displayed a comparative advantage in the household, whereas men have enjoyed a comparative advantage in the labor market. These comparative advantages are first derived from intrinsic differences between the sexes. Men contribute to the production of children only at the very early stage, after which women take over and go through the long reproductive process. Because of the biological amenity between mothers and children, women usually take responsibility for rearing children, which is another very long process. When the number of children is big in a family, a woman can spend most of her prime adult lives with children. On the contrary, men are less biologically committed to the care of children, and they would spend most of their time in labor market in order to support the family (Becker, 1991, p. 37-39). These initial biological differences between the sexes further

encourage sexual division of labor because specializations in different sectors produce gains for the family (Becker, 1991, p. 57-61). Due to this sexual division of labor, women have less incentive to participate in the labor market, and they are likely to invest less amounts of human capital relating to market work.

Table 1-1 and Table 1-2 document labor force participation rates for women and men in the United States for each decade over the last century, which provide some evidence of male-female labor force participation differences. For all decades, the column of All Men in Table 1-1 uniformly displays greater rates than the corresponding ones in the column of All Women in Table 1-2, strongly suggesting that women on average have lower labor force participation rates. Additionally, the column of Married Women obviously contains smaller rates than the column of Single Women for every corresponding decade, further supporting the division of labor argument that married women have to spend a lot of time taking care of their children and household work. Furthermore, for those women who work, they are more likely to work in part-time jobs than men. The 1997 U.S. data indicate that 16.4 percentage of women work in part-time jobs, whereas only 4.1 percentage of men fall into that category.[9] Combining all the evidence, women generally work less time in the labor market and input more time in household work.

Over the past several decades, women's incentive for labor force participation has greatly increased, accompanied by a decrease in the fertility rate and a diminishing in the sharp division of labor in families. Arguably, this increase could be a result of decreases in the latter two. Women can and are willing to devote more time to the labor market when they face raising a smaller number of children.[10] It is also true in the situation when they no longer have strong comparative advantage in household work.[11] One direct result of their increased incentive is an increasing trend of women's labor force participation. Table 1-1 and Table 1-2 provide an apparent example here. As opposed to a slight decline of labor force participation rates for men, women display a steady

[9] The data are from Current Population Survey in March based on population aged between 25 and 64. Part-time workers are defined as those who work less than 30 hours per week.

[10] This argument is subject to the endogeneity problem prevalent in labor economics. It is also argued that the fertility rate reduces because women's relative earning position improves over time and they have a higher opportunity cost to have a large number of children.

[11] This diminishing in comparative advantages between sexes could partly be due to the technological progress. On the one hand, a lot of previous household-made goods and services now can be purchased outside in markets, such as packaged foods and ready-made clothes. On the other hand, monetary cost as well as time cost to maintain a household have been greatly reduced because of new capital goods, ranging from washing machines to microwave (Greenwood and Guner, 2004, p.4).

increase in the rates. These two sequences tend to converge over time, suggesting the division of labor in families is diminishing. Table 1-3 provides labor force participation rates of women for eight OECD countries over the last four decades. The rate increases uniformly over the decades within any country, despite any cross-country variations.

A caveat should be made here of the index of women's labor force participation rates: it is not a satisfied predictor of the gender pay gap, not even of the amount of actual working time.[12] As previously argued, the amount of actual working time largely determines benefits from human capital investment, thereby affecting the gender pay gap. However, there remains some part of the gender pay gap that cannot be explained by observed human capital, which is labeled as "discrimination" against women. The concept of incentive for labor force participation, on the other hand, can render some possible economic explanation here: for persons of opposite sex who work a similar amount of time, women are more likely to exercise less effort in work given they are continuing their responsibility for housework. Ofer and Vinokur (1981) conclude this after they study earnings of married women in former Soviet Union. Becker writes in his book "the earnings of women are adversely affected by household responsibilities even when they want to participate in the labor force as many hours as men, because they become tired, must stay home to tend to sick children or other emergencies, and are less able to work odd hours or take jobs requiring much travel" (1991, p.64). Because incentive captures both concepts of working time and working effort that correspond to observed human capital and unobserved human capital, it is better than the labor force participation rates to predict the gender pay gap.[13]

IV. Measures of the Gender Pay Gap

In the literature, how to estimate the gender pay gap is an important topic by its self. Weichselbaumer and Winter-Ebmer (2003) conduct a search of all empirical papers on gender pay gap measurements through EconLit in 2000 and find 263 articles that meet their criteria. In Table

[12] In case that labor force participation rates are close in both sexes, women's working horizon is still less than men's if women are likely to get employed in part-time jobs, which usually turns out to be true.

[13] Another problem with the index of labor force participation rates is that it casts mixed effects on the gender pay gap; on the one hand, it predicts a smaller gender pay gap inferred from the human capital theory. On the other hand, it can induce a larger gender pay gap because the entrance of many women with little market experience would make them worse off in the short run.

2C, they group these articles by method of estimation and find a total number of nine methods used in the study to measure the gender pay gap. Among these methods, the dummy variable from Mincer earnings equation and the Blinder-Oaxaca decomposition appear to be most common in the literature.[14] In this section, I will examine these two methods as well as the measure by raw wage data to determine the most appropriate measure for this study.

The Mincer earnings equation is probably the most widely used equation to estimate the age-earnings profile, largely because of its estimation convenience and its explanatory power.[15] The dependent variable in this equation is the natural logarithm of earnings, and the most common independent variables include number of years of schooling, number of years of labor market experience, and a quadratic term of experience. This earnings equation could be easily extended to include more demographic variables, and a female (male) dummy on the right hand side measures a percentage of wage deficiency (premium) of female (male), holding other characteristics constant. This dummy variable measures a female wage deficiency unexplained by the human capital, assuming male and female have same returns to skills (e.g. schooling, experience).

This gender pay gap measure is subject to debate on its assumption that men and women have the same returns to skills. It is widely argued that employers value similar skills at different prices for men and women. Based on this argument, Blinder (1973) and Oaxaca (1973) first propose a decomposition technique to decompose the observed gender pay gap into two parts: differential due to "discrimination" and differential due to difference in skills. More specifically, in the Oaxaca decomposition, the unadjusted wage differential

$$\Delta \overline{w} = \overline{w}_M - \overline{w}_F = \overline{x}_M \beta_M - \overline{x}_F \beta_F ,$$

where $\overline{x}_M$ and $\overline{x}_F$ represent mean values of vectors of characteristics of men and women respectively, β_M and β_F are coefficients from male and female separated earnings regressions. After a harmless trick,

$$\Delta \overline{w} = \overline{x}_F (\beta_M - \beta_F) + (\overline{x}_M - \overline{x}_F)\beta_M ,$$

where the first part on the right hand side is wage differential due to price "discrimination" and the

[14] Other than these two ways, there are another four decomposition techniques as well as methods by IV, panel data, and Heckman's selectivity correction. See Table 2C in Weichselbaumer and Winter-Ebmer (2003) for details.
[15] See Mincer (1974) for details on the derivation of this earnings equation. Also, see Heckman and Polachek (1974) for an empirical test of the functional form of the earnings-schooling relationship.

second part is wage differential due to difference in skills.

However, this decomposed gender pay gap invites some criticism. The validity of the "discrimination" part is dependent upon whether differentials of all relevant characteristics are controlled for. If any human capital measurements affecting earnings are left out, the measured "discrimination" part would be a mixed result together with unmeasured human capital, thereby failing to capture the real meaning of discrimination. In fact, this hypothesis turns out to be true, because usually we cannot put in regressions all observed human capital variables that account for male-female wage differentials, not to mention other unobserved variables like ability, effort, and motivation (Borjas, 2000, p.365). As a result, the decomposed gender pay gap usually overestimates the discrimination against women. This criticism also applies to the dummy variable measure, in which not all male-female human capital differentials are netted out.

In their 2003 paper, Blau and Kahn propose "a predicted gender pay gap on the assumption that the men and women in each country-year microdata file have the same average levels of measured characteristics as U.S. men and women for that year" (p. 117). This gender pay gap measure mirrors the above decomposition technique: it attempts to eliminate cross-country differentials in male-female relative human capital stocks so as to sort out the price effect on the gender wage differential. Inevitably, this predicted gender pay gap suffers the same criticism that so called "net" price effect actually mixes with the effect of unmeasured human capital.[16]

On the other hand, were there any discrimination against women in the labor market, this discrimination could happen in the first place to influence women's accumulation of human capital. Under this argument, the two adjusted gender pay gaps will underestimate the discrimination. As concluded in Borjas (2000), "a more complete accounting of the economic impact of discrimination, therefore, should not net out the differences in skills among groups, and would therefore focus much more on the raw wage differentials"(p.365).

The danger of overestimation and underestimation leaves the unadjusted gender pay gap from raw wage data a more appropriate measure. Furthermore, women's incentive for labor force participation is expected to influence their accumulation of both observed and unobserved human capital. This constitutes another important reason for this study to employ the unadjusted gender

[16] It is particularly true here because only schooling and market experience are accounted for in their earnings equation.

pay gap as the dependent variable.[17]

V. Data

One critical issue in a comparative study is the choice of data sample. A representative sample can avoid biased conclusions induced by non-random sample, thereby rendering general statistical inference. On the other hand, limited availability of empirical data is a common problem for researchers; it is often difficult to have a comprehensive sample covering detailed and consistent information. This situation applies to the study of international differences of gender pay gap; sources of aggregate data as well as microdata are both limited with regard to information on separated male-female wages. In current literature, the study sample is mostly comprised of developed countries, because statistics are more frequently collected for this group of countries. Consequently, inferences from the findings of the comparative study of gender pay gaps can be drawn for the developed countries, but little inference can be drawn from such findings for developing countries.

Following the previous argument that the unadjusted gender pay gap measure is preferred here, this study is open to both aggregate data and microdata.[18] One candidate from micro datasets is International Social Survey Programme (ISSP), which is used by Blau and Kahn (2003).[19] The ISSP, which began in 1985, is an ongoing survey conducted annually for a sample within thirty-nine countries. The emphasis for the survey varies each year, as do the participating countries.[20] In each survey, standardized questions are asked about social atitudes as well as respondents' age, sex, schooling years, earnings, and weekly working hours.

Appendix 1 contains detailed data information regarding sample countries, their available

[17] Blau and Kahn (1992, 1995, 1996b) also use a gender pay gap measure from raw wage data.
[18] A lot of gender pay gap studies adopt microdata because information regarding individual workers is crucial when worker characteristics are to be adjusted.
[19] Their sample only covers the time periods of 1985-1994, with 100 observations in total. This study extends their sample to the year 2002.
[20] The ISSP surveys topics on Role of Government in 1985, 1990, and 1996, Social Networks in 1986, Social Inequality in 1987, 1992, and 1999, Family and Changing Gender Roles in 1988, 1994, and 2002, Work Orientations in 1989, 1997, and 2005, Religion in 1991, and 1998, Environment in 1993, and 2000, National Identity in 1995, and 2003, Citizenship in 2004, and Social Relations and Support Systems in 2001. Data are downloadable from Inter-University Consortium for Political and Social Research (ICPSR), except for years of 1999, 2001 and years after 2002.

years, and earnings definitions. After excluding a few outlier country-years, there are a total number of 250 observations.[21] As can be seen from the appendix, most of these sample countries are OECD countries that have relatively high development level. It is also obvious that the number of available years varies a great deal across sample countries: it ranges from one year on one extreme to sixteen years on the other extreme.

The last column in Appendix 1 shows the earnings definition for each country. Dependent upon whether earnings are calculated before or after taxes, they are grouped into two categories: gross earnings and net earnings.[22] As argued by Blau and Kahn (2003), this difference does not have significant effect on computed gender pay gaps, indicated by the insignificant coefficient of a dummy for the group of net earnings countries (p.115). A second potential problem with this earnings variable is that, in a significant proportion of the sample, earnings are reported by midpoints of categories. This particular way of reporting would smooth population earnings, which could either narrow the gender difference or exaggerate it, depending on how wages of the two sexes are fitted into categories: for comparable men and women, if women are likely to have earnings in low percentiles of a category while men in high percentiles of that same category, the measured gender pay gap would be smaller. On the contrary, if these men and women were in two adjacent categories, say women in high percentiles of the low category while men in low percentiles of the high category, the gender pay gap would be exaggerated. This problem could be more serious than the first one, because compared to taxes this earnings smoothing is more likely to have asymmetric effect on two sexes.

Another issue related to this earnings variable is that it is not calculated as hourly earnings. If working hours are ignored when comparing male-female wages, it is likely to have a larger gender pay gap, because women are more inclined to work part-time and their total earnings would inevitably be less as a result of fewer working hours. The ISSP data have information on weekly working hours, but do not collect data on weeks worked. A part-time dummy and two interaction terms - one between weekly working hours and the part-time dummy and the other between weekly working hours and a full-time dummy - are employed in the regressions to correct for the

[21] See footnote b in Appendix 1 for excluded country-years. Also, some country-years are omitted because of lack of crucial information (either earnings or weekly working hours).
[22] A few countries lack information on earnings definition, and they are labeled without gross or net.

above heterogeneity of working time in Blau and Kahn (2003).[23] In order to maintain consistency with the two following datasets used in this study, I take another strategy by focusing on the sample of full-time workers, defined as working at least 30 hours per week.[24] The computed gender pay gaps (at both mean and median values) indeed are very close from these two methods.[25]

Along with this ISSP dataset, another frequently used international micro dataset is Luxembourg Income Study (LIS). LIS is a collection of household data compiled from ongoing statistical surveys in twenty-nine countries widely spread across Europe, America, Asia and Oceania. The LIS began in 1983 and is now jointly sponsored by the Luxembourg government and the Centre for Population, Poverty and Policy Studies (CEPS), the Centre Universitaire (CU) de Luxembourg. The data are standardized in order to facilitate comparative research. Data include country-specific labor force surveys over various labor market structures. These data provide demographic, income and expenditure information on three different levels: household, person and child. I concentrate on extracting sex, earnings, and weekly working hours data from the LIS person files.[26]

Because weekly working hours data are often missing in LIS, Appendix 2 only lists those country-years provided with this information. Appendix 2 contains a column of survey names in addition to the three usual columns that appeared in Appendix 1. As may be seen from the appendix, average available years are much less in LIS than in ISSP, so is the country sample. A total number of 71 observations are obtained from the LIS data. As usual, OECD countries comprise most of the sample countries. Except that it is always defined in terms of annual earnings, the earnings variable in LIS has similar definition here: it is also comprised of gross and net earnings. The same treatment applies to solve the problem of working time heterogeneity: the sample is restricted to full-time workers who work at least 30 hours a week.

A final dataset examined in this study is an aggregate wage dataset from OECD labor market

[23] For details see Blau and Kahn (2003, p.115-117).
[24] This 30 hours threshold for full-time work is set by OECD in 1997.
[25] Correlation coefficients are as high as .9 and regression coefficients are close to 1 when one measure is regressed on the other one.
[26] The data information on weeks worked is available for a proportion of the sample in LIS. Again, this information is omitted here to keep consistence with the other two datasets examined in this study. Later on, computed gender pay gaps based on hourly earnings produce very similar regression results for the LIS data sample.

statistics. This dataset provides calculated wage information on three levels: male, female and both sexes. At each level, values of eleven percentiles as well as mean of the wage distribution are usually available. These percentiles range from the 10^{th} to the 90^{th}, plus the 25^{th} and the 75^{th}. As indicated in Appendix 3, this OECD wage dataset collects sample information on full-time workers of gross earnings through surveys conducted by individual national labor institutes.[27] Twenty-one countries are in the sample with varying lengths of years. The earliest available year starts in 1950 for France, but most countries begin to have data in the 1970s and the 1980s. There are 292 observations at the 50^{th} percentile measure and 322 observations at the mean value measure.

In the literature, two common ways to obtain the gender pay gap are through values of mean and the 50^{th} percentile measures. The gender pay gap is computed as a difference between males' log of wages and females' log of wages. For the above three datasets, I first compute the gender pay gap at mean wage values, which is the difference between log of males' mean wages and log of females' mean wages based on the full-time sample. Next, I do the same thing to compute the gender pay gap at the 50^{th} percentile. Because three datasets have overlapping country-years, I compute correlation matrixes between datasets based on the 50^{th} percentile and mean, which are displayed in Table 1-4 and Table 1-4A respectively. As may be seen from the correlation coefficients, the computed gender pay gaps between the LIS and ISSP data have the least linear relationship.[28] On the other hand, the results from OECD data seem to correlate very well with those from the other two datasets, especially with the results from the LIS data.

Besides examining the gender pay gap of common country-years, I also check calculated gender pay gaps by the time series of every country for each dataset. This is to investigate the consistence of data for the same country over years. The findings show that the ISSP data are not consistent across years; results jump and fall rapidly within a country time series.[29] This situation is unlikely to occur in reality because the gender pay gap cannot change significantly in two succeeding years. What possibly account for this result are the consistently changing survey topics

[27] The exception on the definition of full-time workers is Austria which uses information of both full-time and part-time employees. Also, the exception on the definition of gross earnings is France which uses net earnings instead.

[28] This observation is strengthened by the P value; it is not significant at 1 percent level between the LIS and ISSP data.

[29] I include the estimated gender pay gap for each country-year from the ISSP data in Appendix 4 and 4A. Appendix 4 contains the measure based on mean and Appendix 4A is based on median. The erratic pattern can be clearly seen from these two appendixes.

in ISSP; the selection of sample can be biased toward particular survey topics.[30] In fact, this inconsistence in ISSP has been reflected in the above correlation matrixes: the results of the ISSP data have the least linear relationship with the result of the other two datasets.

All the above results lead to a conclusion that the best candidate for the calculation of gender pay gaps is the OECD dataset. Compared to the ISSP dataset, it is much more consistent over time; whereas compared to the LIS dataset, it has many more observations. This paper will adopt the OECD dataset as its primary dataset, and use the ISSP and LIS datasets to corroborate the main findings.

VI. How Women's Incentive for Labor Force Participation Affect the Gender Pay Gap

Measures of Women's Incentive for Labor Force Participation

It has been previously argued that women's incentive for labor force participation can affect their human capital accumulation and working effort, thereby largely determining the gender pay gap. The division of labor in families and women's responsibility for taking care of children and housework are underlying reasons for their low incentive. Because incentive is unobservable and it cannot be well approximated by any other means (like an IQ test score for one's ability), one conceivable way to capture it is through observable factors that can directly influence incentive. In the following, I employ a few variables that are expected to decide women's incentive for labor force participation to study cross-country differences in the gender pay gap.

Arguably the most apparent variable available to indicate women's incentive is fertility rate. When women have a large number of children, the division of labor in families is expected to be sharper and they would have lower incentive to participate in the labor market. Two observable consequences appear from this high fertility rate: First, women are expected to drop out of labor force more frequently, which suggests less market experience and less schooling of women. Second, they are likely to exert less effort on market work in case they work a similar amount of

[30] Another possible reason is the categorical reporting of earnings data in ISSP.

time as men. Both of these two consequences eventually lead to a larger gender pay gap.

This inverse relationship between fertility rate and female labor force participation (and earnings) receives wide empirical evidence in the literature. Eckstein and Wolpin (1989) use the National Longitudinal Surveys mature women's cohort to estimate a dynamic model of married women's labor-force participations and fertility, and their findings conclude that an increase in young children aged under six substantially reduces women's labor force participation. Using the 1980 Population Census of Japan, Yamada and Yamada (1984) find a negative labor supply elasticity for married women with respect to their fertility rates, after estimating a 2SLS model of married women's labor force participation and fertility in urban Japan. Based on a cohort of more than 2,000 women in the Cebu Longitudinal Health and Nutrition Survey, Adair, Guilkey, Bisgrove, and Gultiano (2002) conclude that an additional child aged under two would reduce women's working hours and that women's earnings are substantially decreased if they have two or more additional children born in the eight years as surveyed. In another recent study regarding the impact of fertility on female labor force participation, the results after accounting for endogeneity of fertility suggest that in urban Morocco, women's participation in all types of wage work (e.g. public and private wage work) is significantly decreased by the presence of school-age children (Assaad and Zouari, 2003). There are many other case studies suggesting this inverse relationship (e.g. Psacharopoulos and Tzannatos, 1992).

A second variable that conveys information on women's incentive to participate in the labor market is age gap between husband and wife. It is hypothesized that men intend to have younger wives and women like to marry wealthier husbands. Generally older males are likely to accumulate more wealth and have higher wages, so the equilibrium exists in which husbands are older than their wives.[31] This proposition of match between older husbands and younger wives receives universal empirical supports.[32] This age gap between husbands and wives also suggests the extent to which the labor is divided in families; the larger the age gap is, the more men and

[31] Under the assumption that economic roles of males are more varied than the roles of females, Bergstrom and Bagnoli (1993) find in the model equilibrium "males with poor prospects marry at an early age, whereas those who expect success will marry later in life. All females marry relatively early in life. The more desirable females marry successful older males and the less desirable females marry the young males who do not expect to prosper" (p. 186).

[32] In some United Nations data surveyed on age gap at the first marriage, all countries except for San Marino show the above pattern. In San Marino, husbands are only .2 year younger than their wives.

women are expected to specialize in their individual fields with comparative advantages.[33] As a result, women in countries with larger age gap between husband and wife are likely to have lower incentive in the labor market. Unfortunately, little empirical evidence exists in the literature relating this age gap to the gender pay gap. From the above argument, it is expected that the gender pay gap is likely to be smaller in countries with lower marriage age gaps, holding all other factors at the constant.

Due to the fact that married women are the second earners in families, fiscal policies such as income tax rates are expected to influence their incentive for labor force participation. This works because women's labor supply is more elastic, and therefore more sensitive to income tax rates. Married women would rather choose to take care of household when a large proportion of their income has to go into paying taxes. At the same time, their attitude can change very quickly if a tax cut is implemented. In case the tax cut policy steadily exists, this low income tax regime is likely to exert a positive effect on women's incentive to consistently participate in the labor market. As a result, the gender pay gap can diminish in the long run.

The effect of tax rates on women's labor force participation has been studied in a number of studies. Baffoe-Bonnie (1995) investigates the effect of Negative Income Tax on the labor supply of different family members and finds that females are likely to reduce their labor supply at all levels of tax rates, whereas males can increase the labor supply at certain program parameter levels. Another study based on a sample of married women in the Antwerp district in Belgium finds that women's labor supply would decrease over 20 percent if they receive an individual transfer of 15,000 Belgium Francs a month as the basic income and simultaneously face an increase in the income tax rate (Kesenne, 1990). Additionally, based on the four countries of Britain, Denmark, Ireland, and East and West Germany, Smith, Dex, Dirk Vlasblom and Callan (2003) find that women's incentive and their labor force participation are highly influenced by the design of tax schemes (e.g. joint taxation and separate taxation).

A final variable found in this study to indicate women's incentive is female educational attainment. In a traditional intermittent labor force participation pattern, married women have little incentive to invest in education because the investment would depreciate quickly during the time

[33] The equilibrium situation in Bergstrom and Bagnoli (1993) also implies this.

they are out of the labor force (Mincer and Polachek, 1974).[34] There are two implications regarding the gender pay gap after women obtain more schooling. First, the pay gap is expected to decrease as a direct result of a larger human capital stock. Second, women are expected to join the labor force more continuously.[35] The second implication provides the evidence relating to women's incentive to join the labor force. Combining these two effects, women begin to have more human capital in terms of experience and education, which would strongly predict a diminishing gender pay gap.

One frequently observed empirical pattern is that labor force participation rates usually increase as education levels rise. If the whole population is divided into groups with less than upper secondary education, with upper secondary education, and with tertiary education, we usually notice that the first group has the lowest labor force participation rates while the last one has the highest (e.g. Table D in OECE Employment Outlook, 2002). Chaykowski and Powell (1999) examine the progress of Canadian women in the labor market during the period from 1978 to 1998, and find women's educational attainment to be one of the major factors contributing to the increase of women's labor force participation. Eckstein and Wolpin (1989) also find "increase in the level of schooling has the largest (positive) impact on participation" (p.389).

Based upon the above design of empirical test, I collect relevant variables and show their summary statistics in Table 1-5.[36] The top two variables in the table are measures of the dependent variable discussed in the Data section. From the summary statistics, the dependent variable varies from some country-years with high equal pay to others with huge wage differentials, with the average over 30 percent. These results indicate women are consistently in a disadvantaged wage position, but their situation varies a lot across countries and years. The median measure of the gender pay gap seems to be smaller than the mean measure, suggesting female wage distribution tends to be more left skewed when compared to male wage distribution.

Seven independent variables occupy the second part of Table 1-5. Fertility rate defined as births per women is used to capture the effect of children on married women. As can be seen from

[34] Also, they are unlikely to invest in human capital with high "atrophy" rates. See Polachek (1981) for more details.
[35] This is under the assumption that women only invest in a large amount of human capital if they plan to stay in the labor force.
[36] The summary is based on the OECD data sample that has been proposed to be the primary dataset used in this study.

the range of this variable, women in some country-years have the total fertility rate three times as high as that of women in other country-years, although most country-years are observed at relatively low fertility rates. There also are a lot of variations in mean age gap between husband and wife at the first marriage, but this variable is more symmetrically distributed than the fertility rate. Top marginal income tax rate is employed to represent the effect of income tax rates under the assumption that it is reflective of other levels of income tax rates in a country as well.[37] Female educational attainment, defined as a ratio of female educational attainment over male educational attainment at the third level, intends to measure women's relative human capital stock.[38] The relative measure is used here because as shown by the definition of gender pay gap, women's schooling and market experience matter in a relative term (relatively to men's in that country). The last two variables also have large heterogeneity among country-years.

Finally, three country characteristics variables from the current gender literature on cross-country comparison are included. They are bargaining centralization, economic competition, and public employment ratio. Bargaining centralization is argued to facilitate the reduction of wage differentials among different firms and sectors by including more firms and sectors into a common wage settlement (Blau and Kahn, 2003; Iversen, 1999; Wallerstein, 1999). This is relevant to the gender pay gap because in the real world we observe that female workers are placed more in "unfavored" sectors and that sectoral wage differentials account for part of wage inequality. It is expected that the gender pay gap is negatively associated with this bargaining centralization variable. Economic competition is supposed to negatively affect the gender pay gap because firms would eliminate the discrimination against women to minimize costs in a highly competitive market (Becker, 1957; Weichselbaumer and Winter-Ebmer, 2002). Public employment is another indicator of compression of wages because public sectors are more inclined to equalize wages for their employees than private sectors. Some studies find that public employment benefits women's relative earnings (e.g. Kolberg 1991). As shown in Table 1-5, these three variables vary a great deal.

[37] This assumption is subject to some debate. However, this top marginal tax rate variable captures the tax impact on women who earn at high wage percentiles. If this group of women is discouraged by income taxes and have more incentive in housework, men are likely to occupy more positions at high wage percentiles. As a result, the gender pay gap becomes bigger.

[38] The primary and secondary educational attainments are close in this group of OECD countries. On the other hand, a lot of variations display at the third level.

Results of the Comparative Study

I run a fixed effects model to empirically test the effect of women's incentive for labor force participation on the gender pay gap, assuming there are unobserved time-invariant effects with each sample country (e.g. culture, labor market tradition).[39] As previously mentioned, the OECD wage data are the primary data source for my dependent variable, with which I run regressions and display the results in Table 1-6. Next, I incorporate gender pay gap data from the LIS and ISSP datasets into the OECD data.[40] With such a bigger sample, I can complement my main regression results in Table 1-6. These results are shown in Table 1-7. Each of Table 1-6 and Table 1-7 is comprised of two parts of results that rest on two measures of the gender pay gap, the median measure and the mean measure. Under each measure, there are a few regression models designed to test robustness.

(Insert of Table 1-6 and Table 1-7 here)

As shown in Table 1-6, there are three models under each gender pay gap measure. The first models, namely Model 1 and Model 4, examine the effects of fertility rate, age gap at the first marriage, and top marginal income tax rate. Female educational attainment is not included in the first models because its effect on the gender pay gap is two fold: First, a higher educational level increases women's wage directly. Second, it works to raise women's incentive for labor force participation which increases their wage indirectly. By excluding the direct effect of the educational attainment variable, the first models show how incentive of female labor force participation solely affects the gender pay gap. The important role of education is captured in the second models, namely Model 2 and Model 5, in which all four independent variables are put together to test their effects. Finally, Model 3 and Model 6 are provided to accommodate effects of other institutional variables from current literature. As a conclusion, by using two measures of the gender pay gap and various regression models, I can render more empirical evidence to test my

[39] This fixed effects model is equivalent to Ordinary Least Squares dummy variable estimation in which each country is assigned for a country dummy variable.

[40] Separate regression results for ISSP data and LIS data are omitted here mainly because of the previously mentioned reason: the former data are not consistent over time and the latter data have much less observations, which induced erratic results from separate estimations.

theoretical argument.

The regression results in Table 1-6 generally support my argument that the gender pay gap is negatively related to the extent of women's incentive for labor force participation. First, all three independent variables have positive and statistically significant coefficients in both Model 1 and Model 4, suggesting that low incentive measured by large values of these variables induces a bigger gender pay gap. The result of fertility rate has two implications here: it extends the findings in many case studies that fertility rate exerts a negative impact on female labor force participation to an OECD sample; also, it directly relates fertility rate to the gender pay gap. The finding on age gap at the first marriage is new in the literature. This variable suggests that one fundamental determinant of the gender pay gap can be traced to specializations between family members happened in the first place. As predicted, top marginal income tax rate affects the gender pay gap in a positive way through its asymmetric impact on men and women. The above results largely hold in Model 2 and Model 5 with the additional educational attainment variable.[41] The coefficients of female educational attainment appear to support the theoretical argument that more schooling for the women group reduces the gender pay gap. As a group, these four variables lend strong empirical evidence to support my argument that women's low (high) incentive for labor force participation increases (decreases) the gender pay gap.[42]

A final corroboration is shown in Model 3 and Model 6, in which bargaining centralization, economic competition, and public employment ratio are added to the regression models.[43] As can be seen, only the public employment variable shows its predicted effect in both models among the three variables.[44] On the other hand, most of the results of the four independent variables hold after accommodating these three new variables. As a conclusion, the incentive of female labor force participation has shown its very important role in deciding the gender pay gap in various

[41] Age gap at the first marriage turns out to be insignificant under the mean measure, which is probably a result of its correlation with female educational attainment.
[42] Some simple bivariate regression results are shown in Appendix 6. Four independent variables all act in their predicted directions after controlling for the country effect. As shown, the coefficient magnitude shrinks in the multivariate regressions except for top marginal income tax rate.
[43] Minimum wage law is another alternative, but it would be dropped in regressions with country dummies because it is also measured in terms of dummy variable.
[44] Bargaining centralization and economic competition fail to show their predicted effects on the gender pay gap. In fact, these three variables all show negative and statistically significant coefficients in the same regressions without other four independent variables.

model specifications.[45]

As a final note from Table 1-6, top marginal income tax rate demonstrates the strongest effect on the gender pay gap as shown by its straight statistical significance in all models. Because this variable specifically refers to the tax rate at top wage percentiles, a further test is to examine its effect on the gender pay gap measured at different wage percentiles. It is predicted top marginal income tax rate has the stronger effect on the gender pay gap measured at higher wage percentiles. The regression results obtained at eleven wage percentiles generally support this prediction as shown in appendix 7. The coefficient of this tax variable is much more likely to be statistically significant in cases beyond the 50^{th} wage percentile. Furthermore, the coefficient magnitude increases in those high wage percentiles.

Table 1-7 is intended to complement the results in Table 1-6 and to show differences between three datasets as well. The main structure of Table 1-7 is similar to Table 1-6, except that the full models (Model 3 and Model 6 in Table 1-6) are omitted here.[46] Two dummy variables are added to control for the individual dataset effect on estimated gender pay gaps. The results on LIS dummy and ISSP dummy provide the information that the OECD dataset tends to estimate the gender pay gap smaller, although the gap between datasets is very small.[47] After accounting for these dataset differences, results of the four independent variables reveal they are less statistically significant compared to results in Table 1-6.[48] However, as a group, they have continuously demonstrated to be very important in explaining differences in the gender pay gap.

VII. Conclusion

This paper proposes and empirically tests the argument that women's incentive for labor force participation is an important determinant of the gender pay gap. Using a data sample of twenty-one OECD countries covering the 1970-2000 period, I find that fertility rate, age gap between husband

[45] The effect of time is not controlled for in Table 1-6 mainly because it is not assumed to affect the gender pay gap by any theory. Also, it has strong correlations with a few independent variables and could induce a serious multicollinearity problem.
[46] The full models are not the main interest in Table 1-7 and they are omitted.
[47] It is not fully understood why estimation gaps exist between datasets. Possible conjectures are that the way of sampling is different in each datasets or/and that it is a result of missing data information.
[48] One important reason is that neither the LIS dataset nor the ISSP dataset has uniformly larger gender pay gaps than the OECD dataset. Therefore, the two dummies cannot account for all the heterogeneities between datasets.

and wife at the first marriage, and top marginal income tax rate are all positively associated with the gender pay gap while female educational attainment is negatively related to the gap. These results are tested to be robust against various model specifications and different data samples. Because current comparative studies on the gender pay gap focus on factors affecting wage structures and societal discrimination against women in a country, my study adds new findings to the literature.

At the same time, this paper is only an attempt to incorporate these variables into the comparative study, so future research is needed to refine some research designs. For example, many case studies have addressed the endogeneity between fertility rate and female labor force participation (and the gender pay gap) using either instrumental variables or simultaneous equations.[49] Another issue relates to measurements of income tax rate. This study assumes second-earners face the same tax rate as single individuals, which is an assumption subject to debate.[50] When data permit, both of these improvements could be done in the comparative study.

[49] Additionally, age gap between husband and wife at the first marriage and female educational attainment are subject to being endogenous. However, the endogeneity problem is less severe here because these two variables are defined in relative terms and there is no clear theory that predicts the relative values to change as a result of the narrowing gender pay gap. For example, not only women but also men postponed their marriage age as the gender pay gap was declining. Therefore, the age difference must be determined by something more than the gender pay gap to explain why men postponed their marriage age as well.

[50] The tax ratio of second earners over singles is not necessarily similar across countries. See Jaumotte (2003, p.58).

Table 1-1: Labor Force Participation Rates of Men in U.S., by Age Groups, 1900-1997 (Borjas, 2000, Table 2-1)

Year	All Men	Men Aged 25-44	Men Aged 45-64	Men Aged over 65
1900	90.9	98.5	94.1	67.5
1920	89.8	99.4	94.5	60.0
1930	87.3	99.6	94.8	58.4
1940	84.3	98.7	92.5	46.2
1950	86.8	97.1	92.0	45.8
1960	84.0	97.7	92.0	33.1
1970	80.6	96.8	89.3	26.8
1980	77.4	95.4	82.8	19.0
1990	76.1	94.3	77.9	16.4
1997	75	92.8	82.4	17.1

Sources: U.S. Bureau of the Census, *Historical Statistics of the United States, Colonial Years to* 1970, Washington, DC: Government Printing Office, 1975; U.S. Bureau of the Census, S*tatistical Abstract of the United States*, Washington, DC: Government Printing Office, various issues.

Table 1-2: Labor Force Participation Rates of Women in U.S., by Marital Status, 1900-1997 (Borjas, 2000, Table 2-2)

Year	All Women	Single Women	Married Women	Windowed, Divorced, or Separated
1900	20.6	45.9	32.5	5.6
1910	25.5	54.0	34.1	10.7
1930	25.3	55.2	34.4	11.7
1940	26.7	53.1	33.7	13.8
1950	29.7	53.6	35.5	21.6
1960	37.7	58.6	31.9	41.6
1970	43.3	56.8	40.5	40.3
1980	51.5	64.4	49.8	43.6
1990	57.5	66.7	58.4	47.2
1997	59.8	67.9	61.6	48.6

Sources: Clarence D. Long, The Labor Force Under Changing Income and Employment. Princeton, NJ: Princeton University Press, 1985, Table A-6. and U.S. Department of Commerce, S*tatistical Abstract of the United States*, 1997. Washington, DC: Government Printing Office, 1998, p. 408.

Table 1-3: Labor Force Participation Rates of Women Aged 25-54, by Country (Borjas, 2000, Table 2-4)

Country	1960	1970	1980	1991
Canada	28.5	39.8	60.1	75.8
France	39.7	50.1	63.0	73.3
Germany	44.5	47.6	53.6	
Italy	25.7	28.3	39.9	49.9
Japan	53.1	55.1	56.7	65.0
Sweden	36.9	64.2	82.9	90.5
United Kingdom		53.2	63.4	72.9
United States	42.8	49.7	63.8	74.0

Source: OECD, *Demographic Trends, 1950-1990*. Paris, 1979; U.S. Bureau of the Census, *Statistical Abstract of the United States*. Washington, DC: Government Printing Office, various issues.

Table 1-4: Correlation Matrix of Gender Pay Gaps based on the 50th Percentile Measure

	ISSP	OECD	LIS
ISSP	1.0000		
	250		
OECD	0.5777	1.0000	
	0.0000		
	103	292	
LIS	0.3633	0.8025	1.0000
	0.0377	0.0000	
	33	41	71

Note: The first number is correlation coefficient, the second one is P value, and the last one is number of observations.

Table 1-4A: Correlation Matrix of Gender Pay Gaps based on the Mean Measure

	ISSP	OECD	LIS
ISSP	1.0000		
	250		
OECD	0.6919	1.0000	
	0.0000		
	97	322	
LIS	0.3138	0.7454	1.0000
	0.0754	0.0000	
	33	39	71

Note: The first number is correlation coefficient, the second one is P value, and the last one is number of observations.

Table 1-5: Variable Summaries based on OECD Statistics

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Gender Pay Gap_50th	292	.306	.127	.099	.731
Gender Pay Gap_Mean	322	.374	.137	.194	.862
Fertility Rate	341	1.77	.338	1.13	3.32
Age Gap at the First Marriage	330	2.62	.469	1.32	3.70
Top Marginal Income Tax Rate	312	58.00	12.259	33	89
Female Educational Attainment	304	.859	.237	.332	1.212
Bargaining Centralization	201	.264	.161	.071	.589
Economic Competition	330	6.8	.858	3.6	8.6
Public Employment Ratio	275	10.98	4.358	5.57	24.97

Note:

a): Variable Definition

Gender Pay Gap_50th: The difference between log of males' median wage and log of females' median wage based on the full-time sample;

Gender Pay Gap_Mean: The difference between log of males' mean wage and log of females' mean wage based on the full-time sample;

Fertility Rate: Births per woman;

Age Gap at the First Marriage: Mean age gap between husband and wife at the first marriage;

Top Marginal Income Tax Rate: Top marginal income tax rate in percentage;

Female Educational Attainment: The ratio of female educational attainment over male educational attainment at the third level (educational attainment is originally defined as third level students per 1000,000 population by sex);

Bargaining Centralization: The Index of Centralization;

Economic Competition: The Economic Freedom Index;

Public Employment Ratio: Civilian government employment as a percentage of the working age population (15-64).

b): Data sources refer to Appendix 3 and Appendix 5.

Table 1-6: Effects of Women's Incentive for Labor Force Participation on the Gender Pay Gap, Based on the OECD data

Explanatory Variables	Gender Pay Gap_50th			Gender Pay Gap_Mean		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Fertility Rate	.073***	.030*	.054*	.128***	.120***	.074**
	(.017)	(.018)	(.032)	(.012)	(.012)	(.030)
Age Gap at the First Marriage	.086***	.081***	.052**	.032**	.013	.003
	(.014)	(.016)	(.021)	(.015)	(.017)	(.019)
Top Marginal Income Tax Rate	.003***	.001***	.003***	.003***	.003***	.003***
	(.0002)	(.0004)	(.001)	(.0002)	(.0004)	(.001)
Female Educational Attainment		-.168***	-.011		-.073*	-.012
		(.042)	(.090)		(.042)	(.086)
Bargaining Centralization			-.053			-.044
			(.032)			(.032)
Economic Competition			.006			.001
			(.019)			(.019)
Public Employment Ratio			-.009**			-.014***
			(.004)			(.003)
Constant	-.197***	.126	.012	-.126***	.027	.208
	(.045)	(.086)	(.142)	(.038)	(.077)	(.129)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	273	252	151	287	266	157
Probability>F	.0000	.0000	.0000	.0000	.0000	.0000

Note:
a): *** denotes P<.01, **denotes P< .05, * denotes P< .10. Standard errors are in parentheses.
b): Robust standard errors are experimented, and the statistical significance of the variables holds in most cases, despite of small fall in the t-values.

Table 1-7: Effects of Women's Incentive for Labor Force Participation on the Gender Pay Gap, Based on the OECD, LIS, and ISSP data

Explanatory Variables	Gender Pay Gap_50th		Gender Pay Gap_Mean	
	Model 1	Model 2	Model 3	Model 4
Fertility Rate	.059	.031	.088***	.073***
	(.042)	(.045)	(.026)	(.027)
Age Gap at the First Marriage	.090***	.076*	.041	.021
	(.033)	(.039)	(.027)	(.031)
Top Marginal Income Tax Rate	.002***	.0004	.003***	.001*
	(.001)	(.001)	(.001)	(.001)
Female Educational Attainment		-.272***		-.191**
		(.105)		(.085)
LIS Dummy	.029**	.028*	.033**	.034**
	(.015)	(.015)	(.013)	(.014)
ISSP Dummy	.062***	.065***	.057***	.060***
	(.011)	(.012)	(.010)	(.010)
Constant	-.171	.280	-.073	.254
	(.106)	(.214)	(.075)	(.160)
Country Dummies	Yes	Yes	Yes	Yes
Number of Observations	528	500	542	514
Probability>F	.0000	.0000	.0000	.0000

Note:

a): *** denotes P<.01, **denotes P< .05, * denotes P< .10. Standard errors are in parentheses.

b): Robust standard errors are experimented, and the statistical significance of the variables holds in most cases, despite of small fall in the t-values.

CHAPTER II

RETURNS TO EDUCATION: AN INTERNATIONAL COMPARISON

I. Introduction

The estimation of profitability of investment in education has captured a great deal of attention since the early 1960s. With parallels to investment in physical capital, investment in education exhibits positive returns to earnings.[1] Rates of return to education have been estimated in many different countries and time periods by individual studies using a variety of econometric methods and datasets.[2] From a policy perspective, such estimates are illuminating because they have implications regarding the optimal allocation of resources between education and other sectors (e.g. Dougherty and Psacharopoulos, 1977). These estimates also influence the behavior of students and their families regarding their investments in education (e.g. Freeman, 1976).

Comparative study of returns to education has become increasingly important in a globalized world, because countries are largely interconnected now and returns to education in one country can easily be affected by behavior of other countries. For example, it is proposed that international trade is one source that causes the rising skill premiums in OECD countries occurred since the 1980s. Under the growing body of trade with developing countries, unskilled workers in the OECD countries become relatively worse off as a result of the increased imports of labor-intensive goods (e.g. Borjas et al.,1991; Borjas and Ramey 1993; Sachs and Shatz, 1994). However, there is

[1] The "screening" hypothesis questions the returns to education by arguing that earnings differences are actually due to superior ability inherited in the more educated rather than to their extra education. But, this "ability bias" is argued to only have a very small effect (Becker, 1964; Griliches, 1977).

[2] For example, see Card (1999) for a discussion of earnings functional form, measurement of education and measure of earnings. Also see Psacharopoulos (1985, 1994, and 2002) for summaries of estimates of returns from various studies.

a paucity of estimates of rates of return to education from comparable data and subsequent explanations of the variations in returns for large samples of countries and years in the current literature. Trostel et al. (2002) and Denny et al. (2001) are the only two papers I am aware of that contain comparable estimates of returns for a large sample of countries and years based on International Social Survey Programme (ISSP) data and that utilize formal econometric methods to explain the patterns.[3]

This paper intends to extend the above two existing studies in both estimating rates of return and explaining the patterns. It begins with estimating rates of return to education using a more complete sample of data. Trostel et al. (2002) and Denny et al. (2001) use a sub-sample of the ISSP data which covers the time period from 1985 to 1995. This paper extends their sample to include all available years, which is from 1985 to 2002. In addition, it incorporates data from the Luxembourg Income Study (LIS) to augment the ISSP data. As a second step, it explains cross-country variations in returns employing a set of country characteristics variables that add new findings to the current conclusions. Specifically, this study incorporates explanations from international trade and skill-biased technical change. Both of these two describe the demand side for skill; returns to education are larger when demand for skill is higher, after holding supply of skill constant. The results generally support the theoretical predictions. As the imports of labor-intensive (skill-intensive) goods increase, the demand for domestic unskilled (skilled) workers decreases. As a result, domestic unskilled (skilled) employees become worse off and the returns to education rise (reduce). Similarly, the returns to education rise as a result of a progress in skill-biased technologies.

The rest of the paper is organized as follows: Section II reviews literature on the comparative study of returns to education. The estimation of rates of return is implemented in section III, where several methodological issues are discussed as well. Section IV is devoted to bivariate comparisons. A few existent patterns are reexamined using the extended data sample. Multivariate comparisons of cross-country variations in the returns are given out in section V. Two competing explanations of the rising wage premiums for skilled workers in developed countries are

[3] Several works by Psacharopoulos also summary rates of return from individual studies, but these estimates are obtained through quite different datasets and methods. In addition, these papers only explain the patterns in a descriptive way.

introduced and their individual measures are used in the regressions. A conclusion of this paper is provided in section VI.

II. Review of Literature

The literature on cross-country comparisons of rates of return to education is relatively small. Among the very few articles dealing with this topic, Psacharopoulos conducted the earliest systematic studies. In a series of studies, Psacharopoulos (1985, 1994, and 2002) compiled estimated returns to education from various datasets using a multitude of specifications.[4] Because the methodology underling these estimates vary, it is difficult to conduct precise comparisons even though a meta-analysis can serve as a possible approach.[5] Psacharopoulos (1985, 1994, and 2002) instead use descriptive statistics to illustrate several world-wide patterns of the returns. First, he finds rates of return decline by level of education. Primary education is found to be the most profitable investment, followed by secondary education. This finding is explained as "the result of the interaction between the low cost of primary education (relative to other levels) and the substantial productivity differential between primary school graduates and those who are illiterate"(Psacharopoulos, 1985, p585). Second, rates of return are declining by a country's per capita income level. On average, African countries have the highest returns while advanced industrial countries have the lowest. Following the argument of law of diminishing returns, the relative scarcity of human-to-physical capital within each country explains this pattern. Third, women have higher rates of return than men. As a group that has a relatively smaller human capital stock, women have a greater profitability to invest in education. Fourth, competitive sectors have higher rates of returns than noncompetitive public sectors. This is a result of the equalization policy of pay in the public sectors. These patterns are repeatedly shown in several of his works across a large time span.[6]

Based on the ISSP data, Trostel et al. (2002) uses a unified methodology to estimate rates of

[4] See the appendixes of these papers for detailed lists of rates of return and their definitions.
[5] For example, Weichselbaumer and Winter-Ebmer (2003) conducts a meta-analysis of the international gender pay gap using estimates from various sources.
[6] Besides those mentioned patterns, Psacharopoulos (1985, 1994, and 2002) address a few others including higher returns to general secondary education than to vocational education, and higher returns to private returns than to social returns, among others.

return for 28 countries covering the 1985-1995 period. This study contributes to the literature by providing a sample of comparable estimates of returns and subsequent explanations of the patterns which reinforce several patterns mentioned in Psacharopoulos (1985, 1994, and 2002). Rates of return are negatively correlated with a country's per capital income and a country's mean years of schooling, and they are higher for females (it is not statistically significant in the final case).[7] However, the findings in Trostel et al. (2002) are more compelling because they are based on strictly comparable data and are drawn as statistical inference as opposed to the descriptions in Psacharopoulos (1985, 1994, and 2002).

Denny et al. (2001) incorporates a range of general supply and demand factors, trade variables and indicators of education quality and quantity as country-specific characteristics to further explain cross-country variations in the returns to education. This study is based on estimated returns from Trostel et al. (2002), but its multivariate regression analysis lends more power to explain patterns of the returns. As shown in the study, the rates of return are declining in both labor force participation and GDP per capita, and are increasing with the proportion of people with third-level education. The more interesting findings are for the trade measures: trade openness measured as trade as a proportion of GDP and trade protection in terms of import duty as a proportion of imports are both found to increase a country's returns to education, whereas net foreign direct investment (FDI) inflows as a proportion of GDP are negatively associated with the returns. Although the last result contradicts the argument that capital complements high skilled labor, the overall findings relating trade to returns to education add insights to understanding cross-country variations in the returns and provide some direction for future work.

In addition to the comparative international analyses, interregional studies within a given country can also shed light on explaining rates of return. One example is about the impact of school quality on returns to education. Using 1980 US census data, Card and Krueger (1992a) find that those educated in states with higher school qualities (qualities measured in terms of student-teacher ratio, the average term length, and the relative pay of teachers) have higher returns to education. Card and Krueger (1992b) conclude that school quality of black people accounts for a significant part of black-white earnings gap in the United States during 1960-1980.

[7] There are a number of idiosyncratic results of the data, as shown in Table 3 in the paper.

III. The Estimation of Rates of Return to Education

Methodological Issues

In the literature, rates of return to education are computed using two different methods: the "elaborate" method and the "earnings function" method. The elaborate method directly follows the definition of rates of return, "working with detailed age-earnings profiles by level of education and finding the discount rate that equates a stream of education benefits to a stream of educational costs at a given point in time" (Psacharopoulos, 1994, p1325). The stream of education benefits is measured by the annual extra earnings associated with another year of schooling or a higher level of education, and the stream of costs consists of the direct schooling costs and the foregone earnings while the individual is still in school. The earnings function method is largely based on Mincer earnings equation (1974). In a semi-log regression with the dependent variable as the natural logarithm of earnings and the independent variables as years of schooling, years of potential working experience and its squared term, the coefficient of years of schooling is interpreted as the average rate of return to one additional year of schooling.[8] The second method is widely used in the literature because of its estimation convenience and less demand for data.[9]

A few issues have been raised concerning the Mincer earnings function. First, many studies have examined its functional form. As an approximation to a more general functional form $\ln y = F(S, t) + e$,[10] the Mincer earnings equation has been relaxed its functional specification. The age-earnings profile from the non-parametric method makes a much better fit of the data.[11] An alternative improvement is to add higher-order terms in both schooling and potential experience. Murphy and Welch (1990) concludes that a third or possibly forth polynomial of the potential

[8] The above two definitions are based on private rates of return. The computation of social rates of return needs to include additional social resource costs. Trostel et al. (2002) and Denny et al. (2001) estimate the private rates of return based on the Mincer earnings equation and this study follows their way.

[9] There are some debates on the validity of the earnings function method, for example see Heckman et al. (2003) and Psacharopoulos (1994).

[10] Where y, S, and t are measures for earnings, schooling, and potential working experience respectively, F is a general functional form, and e is a disturbance term.

[11] For example, see Zheng (1996) and Heckman et al. (2003) for kernel density estimation of rates of return to education.

experience measure makes the Mincer earnings function a much better fit of the age-earnings profiles. However, there exists little evidence to suggest that estimated rates of return to education will change significantly after the Mincer earnings functional form is modified (e.g. Harmon, Oosterbeek and Walker, 2000).

Second, some researchers have questioned the functional imposition that log earnings are a linear function of years of schooling completed. This imposition implies that each additional year of schooling affects earnings in the same proportion, *ceteris paribus*. The "sheepskin effect" hypothesis argues that wage premiums come from fulfilling the final years of primary school, high school, or college/university rather than years of schooling per se. Hungerford and Solon (1987) and Belman and Heywood (1991) find some evidence of the sheepskin effect, especially from wage premiums of college/university graduates. On the other hand, Park (1994) shows that the linear functional form fits very well the 1979-1991 Current Population Survey (CPS) data, except for some non-linearity at 16 years of schooling. Card (1999) also finds years of schooling completed to be a good fit in the 1994-1996 CPS data.[12]

The Data

The estimation of rates of return to education in this study is based on the ISSP data, complemented by the LIS data. The ISSP, which began in 1985, is an ongoing survey conducted annually for a sample within thirty-nine countries. The emphasis for the survey varies each year, as do the participating countries.[13] In each survey, standardized questions are asked about social atitudes as well as respondents' age, sex, schooling years, earnings, and weekly working hours. In the ISSP data, the earnings variable is defined in either gross earnings (before taxes) or net earnings (after taxes), and it is calculated as monthly or annual earnings. Table 2-1 presents summary statistics for mean sample size and mean schooling level. As can be seen from the table,

[12] Card (1999) gives out more detailed descriptions of the two issues related to the specifications of the Mincer earnings function.

[13] The ISSP surveys topics on Role of Government in 1985, 1990, and 1996, Social Networks in 1986, Social Inequality in 1987, 1992, and 1999, Family and Changing Gender Roles in 1988, 1994, and 2002, Work Orientations in 1989, 1997, and 2005, Religion in 1991, and 1998, Environment in 1993, and 2000, National Identity in 1995, and 2003, Citizenship in 2004, and Social Relations and Support Systems in 2001. Data are downloadable from Inter-University Consortium for Political and Social Research (ICPSR), except for years of 1999, 2001 and years after 2002.

OECD countries account for a large proportion of the sample, and available years vary a great deal across countries. The mean schooling level displays a lot of heterogeneity, from less than 8 years of mean schooling in Bangladesh and Brazil to about 14 years of mean schooling in Canada, France, and the United States.

(Insert of Table 2-1 here)

The LIS is a collection of household data compiled from ongoing statistical surveys in twenty-nine countries widely spread across Europe, America, Asia and Oceania.[14] It began in 1983 and is now jointly sponsored by the Luxembourg government and the Centre for Population, Poverty and Policy Studies (CEPS), the Centre Universitaire (CU) de Luxembourg. The data are standardized in order to facilitate comparative research. Data include country-specific labor force surveys over various labor market structures. These data provide demographic, income and expenditure information on three different levels: household, person and child. I concentrate on extracting age, sex, education level, earnings, and weekly working hours data from the LIS person files. Again, the earnings variable is defined in either gross earnings (before taxex) or net earnings (after taxes), but it is always computed as annual earnings.[15] The same summary statistics of the LIS data are presented in Table 2-1A. The sample of countries and years in the LIS is much smaller, but each country-year has a much larger sample of observations. As usual, the mean schooling level is quite heterogenous across countries.

(Insert of Table 2-1A here)

Rates of Return Estimates

This study follows Trostel et al. (2002) and Denny et al. (2001), estimating rates of return based on the Mincer earnings function. The exact functional form used here is an extended Mincer earnings function from Blau and Kahn (2003), which is

$$\ln y = \beta_0 + \beta_1 PART + \beta_2 HRPART + \beta_3 HRFULL + \alpha_1 S + \alpha_2 t + \alpha_3 t^2 + e$$

[14] There are twenty-one countries in my regression sample. Other eight countries are not included because they have missing information of some key variable.

[15] For more information on earnings definitions for each sample country, see appendix 1 for the ISSP data and appendix 2 for the LIS data.

where y is the earnings, defined as monthly or annually; PART is a dummy variable for part-time employment, defined as working less than 30 hours per week;[16] HRPART and HRFULL are interactions of weekly working hours with part-time and full-time working status; S is years of schooling; t is potential working experience, defined as age-S-6.[17] The PART, HRPART, and HRFULL variables are used to adjust the effects of part-time employment and heterogeneity in working hours on earnings.

In the labor market, it is often observed that for the female group and the male group, different wages are attached to their comparable skills. As a result, many studies estimate rates of return separately for females and males. However, it is still not obvious whether the observed difference represents the wage difference for the same quality workers or is because females are deficient in some unobserved human capital that eventually cause the observed wage difference. For this reason, I add an estimated rate of return for the sample of both sexes for each country-year, which is absent from the previous two studies. The Ordinary Least Squares (OLS) regressions based on the above specification are run separately for the samples of male, female, and both sexes for each country and year.[18] As usual, α_1 is interpreted as the average marginal rate of return to education. The mean results of returns are shown in Table 2-2 for the ISSP data and in Table 2-2A for the LIS data.

(Insert of Table 2-2 and Table 2-2A here)

As shown in Table 2-2, returns to education vary significantly across countries. Bangladesh has the greatest rates of return, which are above 20 percent. It is followed by Brazil, Chile, Northern Ireland, and Philippines that all have returns well above the other countries. On the other hand, Demark, Finland, Italy, Netherlands, and Sweden all have rates of return below 5 percent. Another observation from the table is that returns to education are generally higher for females, which verifies the finding from the previous studies. The results in Table 2-2A suggest that the LIS estimates are normally higher than those from Table 2-2. When examined across countries, returns appear to be relatively low in Australia, Belgium, Netherlands, and Sweden, whereas they are

[16] It is defined as less than 35 hours per week in Blau and Kahn (2003). I change it to 30 hours following the introduction of the 30-hour cutoff by OECD in 1997.

[17] Trostel et al. (2002) and Denny et al. (2001) define the dependent variable as natural log of hourly earnings. But, the information is not available on weeks worked that is necessary to compute the hourly earnings.

[18] In the regressions for both sexes, a female dummy is added to the above specification in order to catch the gender wage differential.

relatively high in Austria, Finland, Hungary, Luxembourg, Mexico, Russia, and Spain. The finding that females have higher returns largely holds in the LIS data.

The Instrumental Variables Estimates

One complication arises with the above simple OLS results when measured schooling is expected to be endogenous: the OLS results become biased. The endogeneity can occur for a few reasons, but the most obvious reason is that the ability measure is omitted, which biases the rate of return upward when the omitted ability variable is positively correlated with both schooling and earnings.[19] A lot of researchers have addressed this endogeneity bias, and two popular ways to deal with the problem are through instrumental variables and using samples of twins. Family background variables (e.g. parental education or spouse education) are used by many studies as the proper instruments (e.g. Ashenfelter and Zimmerman, 1997; Card, 1995). Various samples of twins also appear in the literature to correct for the ability bias in estimating returns to education (e.g. Ashenfelter and Rouse, 1998; Isacsson, 1997).[20]

In recognition of this potential bias, I re-estimate rates of return to education using the instrumental variable method. Following Trostel et al. (2002), the education of spouse, father, and mother are chosen as instruments for the schooling variable in the ISSP data. On the other hand, the education of spouse is the only available instrument in the LIS data. The results of instrumental variables estimation are shown in Appendix 8 through Appendix 10. As can be seen from the appendixes, the sample of the estimates is much smaller because data on these variables are often unavailable. The estimated results are generally higher than the simple OLS estimates, which is consistent with the finding in many other studies.

(Insert of Appendix 8 through 10 here)

However, as pointed out in the conclusions of the literature survey, "evidence from the latest studies of identical twins suggests a small upward bias (on the order of 10%) in the simple OLS estimates [while] IV estimates of the return to education based on family background are

[19] See Trostel et al. (2002) for other reasons why schooling can be endogenous.
[20] For more examples on the empirical studies, see a survey in Card (1999) and the issue 4 in Labour Economics (1999).

systematically higher than corresponding OLS estimates and probably contain a bigger upward ability bias than the OLS estimates" (Card, 1999, p 1855). For these reasons, I stick to the more conservative estimation results- the simple OLS estimates- to conduct my cross-country comparison of returns to education.[21]

IV. The Bivariate Comparison of Cross-Country Variations in the Returns to Education

The Regression Results

The majority of the current literature explains variations in returns to education through bivariate comparisons. The early examples by Psacharopoulos (1985 and 1994) point out several bivariate patterns examined by subsequent studies. As we can see from the literature review, both Trostel et al. (2002) and Denny et al. (2001) lend support to these bivariate patterns: countries with higher GDP per capita tend to have lower rates of return; females are likely to possess higher returns to education than their male counterparts; the mean schooling level is negatively correlated with the returns.

Because this study extends the data time period in Trostel et al. (2002) and Denny et al. (2001) to cover the more recent years, it is worth examining those patterns again in a bigger sample of data. Furthermore, as to cross-country time-series data it is important to account for the country effect, because unobserved country characteristics can easily bias our estimates. In the following, I run bivariate regressions first without countries dummies and then with country dummies to explain the variations in the returns to education. As a further test of robustness, the above regressions are run using two samples of data: the estimated returns from the ISSP data and those from a combination of the ISSP and LIS data.[22] The generated results based on the ISSP data are shown in Table 2-3 and those based on the two datasets are shown in Table 2-3A.

[21] Another important reason is that the sample size of simple OLS results is much bigger than that of the instrumental variables estimates.

[22] This study does not use the LIS dataset as an independent regression sample due to its relatively small sample size. The regression results based on this dataset are much weaker than those from the ISSP dataset, especially in the multivariate regressions where most variables fail to show statistical significance.

(Insert of Table 2-3 here)

From Table 2-3, there are five explanatory variables and ten models.[23] Each independent variable corresponds to two models, with the first one without countries dummies and the second with the dummies. The dependent variable is measured based on the samples including both sexes.[24] The exceptions are the first pair of models, where the estimated rates of return from both the male samples and the female samples are included in order to test whether females have higher returns. Regardless of the model specification, the results from both models highly suggest that it is more profitable for females to invest in education, with a premium in returns about 1 percent. The GDP per capita variable also receives both statistically significant results, which once again lends support to the argument that the rate of return to education is negatively associated with a country's development level.

However, the other three variables fail to show statistical significance and even change their signs after adjusting for country specific effects. Denny et al. (2001) finds average schooling in population aged 15-64 to be negatively correlated with the rates of return in the bivariate model, but the finding disappears in the multivariate regression where the proportion of population with third-level education is positively related to the returns. Their results together with mine in model 2A suggest that mean schooling level will not necessarily decrease a country's rate of return.[25] Expenditure on education is also found to reduce returns to education from a simple correlation in Trostel et al. (2002), echoing my result in model 4. However, these results are puzzling, because Card and Krueger (1992a and 1992b) both imply a higher rate of return in response to high education qualities. The result in model 4A, despite its insignificance, seems to convey the same information contained in Card and Krueger (1992a and 1992b). Finally, the top marginal income tax rate variable tends to reduce returns to education in model 5. This result is obtained from a sample of country-years defined in net earnings.[26] Trostel et al. (2002) constructs an earnings

[23] The GDP per capita variable is based on purchasing power parity (PPP) in constant 1995 international dollars. The expenditure on education variable is defined as public expenditure on public education and subsidies to private education. Both of these two variables are from World Development Indicators, World Bank CD-ROM, 2004. The top marginal income tax rate variable is from Gwartney and Lawson (2004).

[24] Besides the reason I mentioned in the previous section, empirical evidence shows the estimated rates of return based on both sexes are highly correlated with those estimated separately for males and females (the correlation coefficients are about .95), which is another reason why I use the overall rates of return for my comparative study.

[25] One potential explanation is skill-biased technical change, which will be explained in detail later on in this study.

[26] Theoretically and empirically, top marginal income tax rate has almost no effect on the returns in the sample

dummy - one for net earnings and zero for gross earnings- and finds its coefficient negative, implying that income taxes are progressive. The negative coefficient of top marginal income tax rate in model 5 corroborates the finding in Trostel et al. (2002). Two implications can be drawn: First, income taxes are progressive, because top marginal income tax rate would have no effect on the returns if income taxes are flat. Second, high earners (the more educated) are disproportionally affected by income taxes and thereby their realized return to education is smaller when top marginal income tax rate is higher. However, this negative effect is washed out in model 5A, probably because the main effect of top marginal income tax rate comes from the cross-country heterogeneity.

(Insert of Table 2-3A here)

Table 2-3A has the exact setup as Table 2-3, except that it is based on the ISSP and LIS data rather than the ISSP data and a LIS dummy is used to account for the difference between two datasets. The coefficients of the LIS dummy show that the estimates from the LIS data are generally larger by 1.5 to 2 percent. As can be seen from Table 2-3A, most of the results are very close to those in Table 2-3, both in directions and magnitudes. The only differences come from the mean schooling and top marginal income tax rate variables: the first variable becomes statistically significant and the second variable turns to be negative in the second models. These two changes enhance my previous propositions regarding to these two variables.

The Graphic Depiction

As a final step in the bivariate comparison, I plot rates of return to education against each of these explanatory variables to give a graphic depiction of the above results.[27] One simplification is to use a single data point for each country in the graph, so every observation is labeled by a different country name. In this case, the average over years for each country is employed. Also, each graph contains a fitted line mirroring the linear prediction. The results corresponding to the

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defined in gross earnings. However, it is empirically found to have a negative impact on the returns in the sample combining both net earnings and gross earnings. Because country-years defined in net earnings account for a smaller proportion of the total sample, I will not restrict my sample to the net earnings in the multivariate regressions. Rather, the whole sample is used and a gross earnings dummy is employed to adjust for the difference in earnings in that step.

[27] It is not applicable to plot the female dummy in the two-way graph.

ISSP data are displayed in Figure 2-1 through Figure 2-4, while those corresponding to both datasets are in Figure 2-1A through Figure 2-4A.

(Insert of Figure 2-1 to 2-4 and Figure 2-1A to 2-4A here)

These two-way graphs clearly bear out cross-country predictions. Countries with higher mean schooling levels have smaller rates of return (Figure 2-1 and 2-1A). Countries with greater GDP per capita have smaller rates of return (Figure 2-2 and 2-2A). More education expenditures lead countries to have smaller rates of return (Figure 2-3 and 2-3A). Finally, countries with lower top marginal income tax rates have bigger rates of return (Figure 2-4 and 2-4A). The above graphs are obtained without adjusting for the country effect, so we cannot observe the positive effect of the mean schooling and expenditure on education variables. A closer examination reveals that Bangladesh stands out as an "outlier" in all the figures. However, little modification in predictions is found when it is taken out from the group.

V. The Multivariate Comparison of Cross-Country Variations in the Returns to Education

International Trade and the Returns to Education

Since the early 1980s, almost all developed countries have experienced a rise in wage premiums to skilled workers (Katz and Murphy, 1992; Gottschalk and Smeeding, 1997; OECD, 1997). Accompanied by this trend is rapid globalization – falling barriers to international trade, particularly between developed and developing countries, or North and South countries. The trade theory (namely the Stolper- Samuelson theorem) suggests that under this increasing body of trade between the North and the South, developed countries will increasingly produce skill-intensive goods while developing countries increasingly produce labor-intensive goods. These changes eventually reduce demand for unskilled workers in the developed countries. As a result, their relative wages to fall. Many studies either theoretically or empirically support the above causal link (Borjas and Ramey 1993; Sachs and Shatz., 1994; Wood, 1994 and 1998; Anderton and Brenton, 1999). This body of literature can easily be extended to depict the impact of trade on

returns to education since larger skill premiums directly imply bigger rates of return.

It is worthwhile to pay closer attention to the Stolper-Samuelson theorem, which constitutes the key in the above causal link. This theorem answers a central question in international trade: what is the effect of changes in the prices of goods on the prices of factors of production? The theorem can be explained as follows. Suppose in an economy there are two sectors, one produces exports and the other produces import-competing goods. Suppose the import-competing sector uses a relatively higher ratio of unskilled labor to skilled labor than the export sector. Now, for some reason the tariff on imported goods is decreased, which reduces the relative price of the import competing sector's output. As a result, the import-competing sector shrinks and the export sector expands, at the same time raising the demand for skilled labor and pressing downward the wage of unskilled labor. This description mirrors the previously mentioned situation in the developed countries described in the literature.

A few studies empirically estimate the impact of trade upon returns to education. Taylor (2002) studies the influence of globalization (in terms of import intensity, defined as import expenditure as a proportion of value added) on the returns to education in Great Britain over the period 1973 to 1994. In a regression using log of earnings as the dependent variable, the interactions between education dummies and trade intensity are found to be statistically significant, implying that returns to education are actually affected by trade.[28] However, instead of a priori expectations of positive interactions, these coefficients are negative meaning that educated people are adversely affected by trade in Great Britain. As previously mentioned, Denny et al. (2001) examines how trade affects returns to education through three trade measures: trade openness, trade protection, and FDI net inflows. The findings indicate both trade openness and trade protection increase the returns to education while FDI net inflows decrease the returns. However, these results contradict each other because trade openness is the opposite side of trade protection, so they are expected to have different signs instead.

The above two studies have shown the significant role of trade in influencing returns to education, but both of them somehow fail to make predictions in the right directions. One possible explanation could be their measures of trade. The Stolper-Samuelson theorem requires our

[28] Every education dummy represents an education level, with the reference group defined as people without qualifications.

knowledge of the nature of imported goods in order to predict the effect of trade on skill premiums. In other words, we need to know whether the imported goods are skill-intensive or labor-intensive; the skill premiums of home country will fall (rise) if imports are skill-intensive (labor intensive). Following the Stolper-Samuelson theorem, the ideal measurement of trade should differentiate between skill-intensive imports and labor-intensive imports. However, neither the import intensity measure nor the trade openness measure is constructed this way: both of these two measures mix all types of imports together. Therefore, the contradictory results obtained by these studies are not surprising.

To better suit the Stolper-Samuelson theorem, this study adopts two trade measures that separately calculate imports produced by skilled employees (skill-intensive) and by unskilled employees (labor-intensive). These measures are taken from Wang (2005), which are defined as "income of production factor g in aggregated foreign country created by imports of home country from aggregated foreign country as share of gross domestic product of home country within a year in percent" (p 8), where g refers to skilled employees and unskilled employees. Following the author, these two variables are named import-induced foreign value-added ratio of production factor skilled employees (IFRs) and import-induced foreign value-added ratio of production factor unskilled employees (IFRu). It is predicted that IFRs (IFRu) negatively (positively) affects domestic returns to education.

Skill-Biased Technical Change and the Returns to Education

The skill-biased technical change argument is another competing explanation for rising skilled-workers wage premiums in developed countries. A rapid technological change has been witnessed in OECD countries since the 1980s, and many studies argue that these new technologies are skill-biased which have increased demand for high skilled workers (Mincer, 1991; Bound and Johnson, 1992; Berman, Bound and Griliches, 1994; Johnson, 1997; Autor, Katz, and Krueger, 1998). According to this explanation, new technologies are by nature complementary to skills and skill-biased technical change can always exist. In the short run, a large increase in supply of college graduates (high skilled workers) can depress the skill premium because of substitution

effect. But in the long run, this supply change also increases the market size for technologies complementary to skills, which induces a change in the direction of technical progress and makes the short run demand curve shift to the right. This directed technical change effect can dominate the substitution effect, leading to an increase in the skill premium (Acemoglu, 1998, p1057).

Under this skill-biased technical change argument, a significant proportion of empirical studies examine how the use of computers affects the skill premiums. Using Current Population Survey data, Krueger (1993) finds that on-the-job computer use increases a wage premium about 10 to 15 percent after holding workers characteristics. Furthermore, one-third to one-half of the increase in returns to education in the 1980s can be accounted for by the expansion in computer use during that time period.[29] After controlling for more ability measures, Bell (1996) still computes a wage premium around 5-10 percent for workers using computers in Great Britain. Employing a dataset that matches data on individuals and their firms, Entorf and Kramarz (1997) finds a wage premium around 1 percent for the computer users from their fixed-effects estimation.[30] Following this group of literature, this study adopts use of computers as one variable to examine the impact of skill-biased technical change on the returns to education.

Another employed variable is high-technology exports as a proportion of manufactured exports. Under the assumption that high-technology goods are produced by skilled workers, this variable conveys information regarding the relative importance of skilled workers in manufactured export.[31] Meanwhile, skill-biased technical change expects that the larger the proportion of skilled workers, the higher the demand for skilled-biased technical change. As a result, high-technology exports as a proportion of manufactured exports are positively associated with demand for skill, and thereby this variable is positively related to returns to education.

Many studies have debated whether trade or skill-biased technical change accounts for the rising of wage premiums for skilled workers. Desjonqueres et al. (1999) summaries three stylized facts that conflict with the trade argument. First, the ratio of skilled to unskilled employment has

[29] Using the Germany micro-data, DiNardo and Pischke (1997) reexamines whether computer users have the wage premium. Their findings suggest that on-the-job use of calculators, telephones, pens or pencils can lead to wage premiums as well. They conclude that new technologies go to skilled workers and the unobserved ability really explains the wage premium.

[30] See Franzen (2001) for more examples in this literature.

[31] High-technology exports are products with high R&D intensity, such as in aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery.

risen in all sectors, rather than only in skill-intensive sectors. Second, skill premiums have increased in developing countries as well as in developed countries. Third, the price of labor-intensive goods has not declined significantly in developed countries. On the other hand, Card and DiNardo (2002) questions skill-biased technical change mainly based on the observation that wage inequality stabilized in the 1990s despite continuing advances in computer technologies.[32] Whereas some other studies tie together these two potential explanations, arguing that the trade liberalization leads to the skill-biased technical change, which in turn raises the skill premiums (Acemoglu, 2002; Ekholm and Midelfart, 2005). This study incorporates both the trade and the skill-biased technical change explanations, and empirically tests whether they can affect the returns to education.

The Regression Results

Table 2-4 shows summary statistics of all explanatory variables that are used in the following multivariate regressions.[33] The summary is based on both datasets, but the variables means from the ISSP data are very close to those values in Table 2-4. As can be easily seen, all variables more or less have missing values (the total observation is 330 which can be seen from the LIS dummy variable). Another shared commonality among these variables is that they all vary a great deal, clearly revealed by their minimum and maximum values. The information of GDP per capita variable suggests that the regression sample includes both advanced industrial countries and developing countries, but it puts more weight on the former group. The two trade variables indicate unskilled employees produce a larger proportion of imports than skilled employees. Finally, the mean of LIS dummy shows the LIS dataset accounts for about one-forth of the total observations.

(Insert of Table 2-4 here)

The multivariate regressions are based on fixed effects model for the reason previously

[32] Krugman (2000) and Leamer (2000) constitute another pair of studies that debate around these two arguments. The former study concludes the trade argument to be an entirely justified procedure when carefully applied, whereas the latter one rejects the important role of trade in raising wage inequalities.

[33] The summary of mean schooling can be found in Table 2-1 and Table 2-1A. Also, mean values of the dependent variable are available in Table 2-2 and Table 2-2A.

mentioned. As usual, two tables are constructed with regard to two data samples; Table 2-5 contains results for the ISSP data and Table 2-5A for the ISSP and LIS data. In each table, four pairs of models are estimated. The second model of each pair adds a year variable to control for unmeasured time effect.[34] The first pair of models addresses how international trade influences a country's returns to education. The second pair examines the impact of skill-biased technical change. By separately estimating the effects of these two groups of variables, I can test whether they individually influence returns to education. Their combined effects are shown in next two models. This step is to see how their effects can compete with each other. The last two models include all explanatory variables in this study to test the robustness. Because both trade and skill-biased technical change address the demand side for skill, it is important to account for effects from the supply side in the regressions as well. For this purpose, the mean schooling and GDP per capita variables are added in each of the above models.[35]

(Insert of Table 2-5 here)

The results in Table 2-5 generally bear out my expectations of these variables. First, IFRu is positive and statistically significant in Model 1 and 1A, meaning that domestic rates of return to education would rise when there is an increase in imports produced by unskilled workers abroad. This result exactly follows the Stolper-Samuelson theorem which predicts an increase in skill premiums when facing an increase in imports of labor-intensive goods. The same story applies to the negative coefficients of IFRs: domestic rates of return will fall as a result of an increase in imports produced by skilled workers abroad. These two variables together strongly support the trade argument that international trade is a driving force to raise the skill premiums in developed countries (as long as the dominant effect comes from the IFRu side in these countries). Second, as revealed in Model 2 and 2A, my empirical results for the skill-biased technical change explanation do not seem to be as strong as those for the trade argument. The only significant variable is the high technology exports as a proportion of manufactured exports. The variable measuring use of computer fails to show statistical significance in both models, even though it is in the predicted direction. This is probably because use of computer does not capture the real change in new

[34] In the returns to education literature, there is a debate regarding the time trend of rates of return. The year variable here is intended to test the time trend in my data sample.

[35] Expenditure on education is another variable addressing the supply side, but it is not included because of too many missing values with this variable.

technologies that induce the increased demand for high skilled workers.[36] On the other hand, the high technology exports variable is expected to convey more information on the demand a country has for skilled workers. This statement holds when skilled workers produce these high technology goods. The positive and statistically significant coefficients of this variable show that returns to education positively depend upon the proportion of high technology exports in manufactured exports. As a conclusion from Model 2 and 2A, the skill-biased technical change argument is partially supported.

The results of IFRs and IFRu are strongly held in Model 3 and 3A, whereas there only remains some weak evidence regarding the personal computers and high technology exports variables. After adjusting for the trade effects, the high technology exports variable fails to show any statistical significance while the personal computers variable becomes significant in model 3A. In Model 4 and 4A where all explanatory variables are included, the previous patterns largely persist: both IFRs and IFRu remain statistically significant while only the high technology exports variable shows its significance.

The mean schooling and GDP per capita variables remain consistent across all models: the GDP per capita is expected to reduce returns to education, while the mean schooling tends to increase the returns. As predicted, top marginal income tax rates are likely to decrease the rates of returns. Expenditure on education, on the other hand, displays no pattern. These results are similar to the findings from bivariate comparisons. Finally, the time trend of returns to education is not clear in this study. Despite its negative and statistically significant coefficient in the final model, the year variable has mixed insignificant results in all other cases. At best, it seems rates of return follow a declining time trend in my sample.[37]

(Insert of Table 2-5A here)

Table 2-5A is used as a test of robustness of the results in Table 2-5. As can be seen from the table, the major conclusions from Table 2-5 largely hold. IFRu and IFRs retain their strong

[36] There are a few other variables available to measure the extent to which new technologies are developed, such as investment in R&D and expenditure on information and communication technologies. However, these variables also fail to show statistical significance in the regressions and there are a lot more missing values with these variables.

[37] I also use a few year dummies to find the time pattern of rates of return. Specifically, I keep the years 1985, 1990, 1995, and 2000 and assign three year dummies. It turns out neither of these year dummies is statistically significant, suggesting the time trend is weak.

predictions in all the models. However, the high technology exports variable has weaker results here: it only shows statistical significance in the final two models. Similarly, the personal computers variable never turns to significance in all models. One big change occurs with the mean schooling variable: it becomes statistically significant in three-fourths of the cases. If skill-biased technical change increases highly educated workers in the long run, the positive coefficients of this variable would constitute evidence supportive of this argument. The other variables remain very similar results. One final note is for the LIS dummy, which suggests estimated rates of return are generally 2.5 percent higher in the LIS data.

VI. Conclusion

This study uses country characteristics to examine cross-country variations in rates of return to education. It begins with estimating returns to education for a large sample of countries, using the ISSP data from 1985 to 2002 and the LIS data covering a similar time period. The bivariate comparisons support a number of existent patterns: females have higher rates of return; returns to education decline in GDP per capita, in mean schooling level, in expenditure on education, and in top marginal income tax rate. However, the mean schooling and expenditure on education variables were found to increase the returns after accounting for the country effect. In the multivariate regressions, two trade variables (IFRu and IFRs) possess persistent effects on the returns: IFRu raises domestic returns to education while IFRs reduce the returns. Meanwhile, the results of personal computers and high technology exports are sensitive to regression specifications, although they tend to increase the returns in a large number of cases. Finally, there is no clear time pattern for returns to education in this study.

This paper makes two contributions. First, it clarifies mixed empirical results regarding trade by using better trade measures. Second, it introduces skill-biased technical change into the systemic study of returns to education.[38] While the trade measures successfully explain variations in returns to education, the technology measures do not yield consistent results. The latter finding

[38] Another possible explanation for the cross-country variations in returns to education is immigration (e.g. Borjas et al., 1997; Barrett et al., 2000). However, the relevant data are unavailable.

implies either these measures are not sufficient or that skill-biased technical change is not a strong explanation. Future research is needed to find better measures of technologies to sort out the above two possibilities.

Table 2-1: Mean Sample Size and Schooling Level, ISSP Data

Country	Number of Years	Men		Women		Both Sexes	
		Mean Sample Size	Mean Schooling Level	Mean Sample Size	Mean Schooling Level	Mean Sample Size	Mean Schooling Level
Australia	11	599	11.92	420	11.99	1018	11.95
Austria	11	278	10.89	230	10.63	508	10.78
Bangladesh	1	21	6.86	59	7.44	80	7.29
Brazil	1	463	7.26	292	8.82	755	7.86
Bulgaria	7	225	12.42	207	12.61	431	12.51
Canada	8	355	14.71	325	14.58	680	14.64
Chile	3	397	10.58	230	11.29	627	10.84
Cyprus	4	363	12.26	242	12.67	605	12.43
Czech Republic	7	241	13.16	203	12.74	444	12.95
Denmark	4	313	12.19	334	12.63	647	12.40
East Germany	9	173	11.34	154	11.38	327	11.36
Finland	2	305	12.94	324	13.22	629	13.08
Flanders	1	104	12.89	65	14.08	169	13.35
France	4	348	13.89	400	14.15	748	14.01
Germany (West)	14	331	10.74	223	10.69	554	10.72
Hungary	9	307	11.44	321	11.45	628	11.43
Ireland	9	371	11.23	331	11.81	702	11.48
Israel	5	311	12.99	324	13.65	635	13.33
Italy	11	293	11.68	166	11.77	459	11.71
Japan	8	373	12.65	282	12.13	655	12.42
Latvia	5	243	12.67	264	13.38	507	13.04
Mexico	2	312	9.56	228	10.33	540	9.85
Netherlands	6	440	13.47	324	13.06	764	13.30
New Zealand	7	314	13.00	287	12.97	601	12.99
Northern Ireland	5	167	10.80	145	11.14	312	10.97
Norway	12	524	12.81	476	12.75	999	12.78
Philippines	5	387	9.08	193	9.82	580	9.33
Poland	9	317	11.08	290	11.70	607	11.38
Portugal	3	274	8.24	297	7.95	571	8.09
Russia	10	408	12.26	439	12.49	846	12.37
Slovak Republic	3	357	12.67	325	12.65	682	12.66
Slovenia	8	219	11.55	203	11.77	421	11.66
Spain	6	265	11.23	146	11.97	411	11.48
Sweden	7	401	11.90	398	12.35	800	12.13
Switzerland	5	441	11.81	327	11.32	768	11.61
Taiwan	1	701	11.27	519	11.47	1220	11.36
United Kingdom	16	308	11.96	283	11.95	592	11.96
United States	16	386	13.68	378	13.61	764	13.65

Table 2-1A: Mean Sample Size and Schooling Level, LIS Data

Country	Number of Years	Men		Women		Both Sexes	
		Mean Sample Size	Mean Schooling Level	Mean Sample Size	Mean Schooling Level	Mean Sample Size	Mean Schooling Level
Australia	2	6393	11.07	4864	10.51	11257	10.82
Austria	3	1585	11.79	1072	11.62	2658	11.72
Belgium	5	2343	12.34	1495	12.75	3837	12.51
Canada	6	15281	12.88	13582	13.30	28863	13.08
Czech Republic	1	16458	12.19	14173	11.72	30631	11.97
Finland	1	7743	9.92	7313	10.05	15056	9.98
France	1	5678	9.30	4847	9.99	10525	9.62
Germany (West)	4	3695	11.04	2731	10.90	6426	10.98
Hungary	3	759	11.94	778	11.97	1537	11.96
Ireland	4	1472	11.50	1062	12.09	2535	11.75
Israel	4	2987	12.49	2109	13.06	5096	12.71
Italy	7	4076	10.18	2498	11.05	6574	10.51
Luxembourg	5	1345	11.53	800	11.35	2144	11.46
Mexico	8	8469	8.79	3540	9.98	12009	9.13
Netherlands	4	2545	11.15	1757	11.27	4302	11.20
Russia	3	1953	12.31	2053	12.70	4006	12.52
Spain	2	2630	11.14	1534	12.33	4164	11.58
Sweden	2	6374	11.39	6239	11.59	12613	11.49
Switzerland	1	1726	11.33	1014	10.79	2740	11.13
United Kingdom	5	6314	10.94	5950	10.88	12264	10.91
United States	6	26889	13.00	24332	13.06	51221	13.03

Table 2-2: Mean Rates of Return to Schooling based on OLS Estimation, ISSP Data

Country	Number of Years	Men	Women	Both Sexes
Australia	10	.073	.066	.071
Austria	11	.067	.089	.077
Bangladesh	1		.284	.221
Brazil	1	.128	.120	.126
Bulgaria	7	.068	.076	.070
Canada	8	.063	.079	.070
Chile	3	.135	.123	.130
Cyprus	4	.044	.090	.055
Czech Republic	7	.053	.065	.056
Denmark	4	.041	.043	.042
East Germany	9	.047	.061	.053
Finland	2	.037	.031	.033
Flanders	1	.054		.057
France	4	.095	.082	.089
Germany (West)	14	.064	.070	.066
Hungary	9	.083	.084	.084
Ireland	9	.096	.097	.094
Israel	5	.064	.080	.071
Italy	10	.043	.065	.046
Japan	8	.091	.123	.105
Latvia	5	.060	.062	.060
Mexico	2	.095	.095	.096
Netherlands	6	.038	.035	.036
New Zealand	7	.053	.050	.053
Northern Ireland	5	.135	.140	.141
Norway	12	.051	.059	.055
Philippines	5	.127	.125	.127
Poland	9	.093	.092	.091
Portugal	3	.078	.101	.090
Russia	10	.064	.061	.063
Slovak Republic	3	.054	.072	.061
Slovenia	8	.096	.101	.098
Spain	6	.063	.067	.065
Sweden	7	.045	.038	.042
Switzerland	5	.068	.069	.068
Taiwan	1	.075	.088	.078
United Kingdom	16	.090	.100	.096
United States	16	.092	.115	.102

Note:

a): The estimates of returns are negative in Australia 1985 and Italy 1992, which are not included in the sample.

b): The estimates of returns are statistically insignificant for men in Bangladesh 1997, Cyprus 1997, and Czech Republic 2002, for women in Flanders 2002, Ireland 1998, Italy 1986, 1997 and 1998, and for both sexes in Czech Republic 2002. These country-years are not included in the sample.

Table 2-2A: Mean Rates of Return to Schooling based on OLS Estimation, LIS Data

Country	Number of Years	Men	Women	Both Sexes
Australia	2	.050	.046	.049
Austria	3	.124	.109	.119
Belgium	5	.058	.064	.062
Canada	6	.070	.094	.080
Czech Republic	1	.074	.083	.078
Finland	1	.125	.101	.112
France	1	.064	.064	.064
Germany (West)	4	.083	.089	.087
Hungary	3	.105	.111	.108
Ireland	4	.095	.131	.110
Israel	4	.091	.087	.091
Italy	7	.075	.084	.079
Luxembourg	5	.091	.106	.099
Mexico	8	.138	.155	.143
Netherlands	4	.068	.067	.068
Russia	3	.057	.067	.062
Spain	2	.083	.106	.092
Sweden	2	.075	.060	.069
Switzerland	1	.094	.048	.084
United Kingdom	5	.089	.104	.095
United States	6	.110	.125	.116

Table 2-3: Bivariate Regression Results, ISSP Data

	Rates of Return to Education (ISSP Data)									
Explanatory Variables	Model 1	Model 1A	Model 2	Model 2A	Model 3	Model 3A	Model 4	Model 4A	Model 5	Model 5A
Female Dummy	.009***	.008***								
	(.003)	(.002)								
Mean Schooling			-.005***	.002						
			(.001)	(.002)						
GDP Per Capita, PPP 1995					-8.52e-07***	-2.62e-06***				
					(2.72e-07)	(7.34e-07)				
Expenditure on Education, as a Proportion of GDP							-.008***	.002		
							(.002)	(.003)		
Top Marginal Income Tax Rate									-.001***	.0001
									(.0002)	(.0005)
Constant	.073***	.073***	.140***	.048*	.091***	.122***	.120***	.064***	.107***	.067***
	(.002)	(.001)	(.018)	(.028)	(.005)	(.013)	(.009)	(.016)	(.012)	(.026)
Country Dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Number of Observations	498	498	252	252	235	235	195	195	87	87
Probability>F	.0028	.0002	.0004	.3097	.0020	.0005	.0000	.4845	.0028	.9073

Note:

a): *** denotes P<.01, **denotes P< .05, * denotes P< .10. Standard errors are in parentheses.

b): Robust standard errors are experimented, and the statistical significance of the variables holds in most cases, despite of small fall in the t-values.

c): The estimated rates of return from both the male samples and the female samples are included in the dependent variable in Model 1 and 1A, while the estimates based on the samples of both sexes are used as the dependent variable in rest of the models.

d): The sample is restricted to country-years defined in net earnings in Model 5 and 5A.

Table 2-3A: Bivariate Regression Results, ISSP and LIS Data

	Rates of Return to Education (ISSP and LIS Data)									
Explanatory Variables	Model 1	Model 1A	Model 2	Model 2A	Model 3	Model 3A	Model 4	Model 4A	Model 5	Model 5A
Female Dummy	.009***	.008***								
	(.003)	(.002)								
Mean Schooling			-.005***	.004**						
			(.001)	(.002)						
GDP Per Capita, PPP 1995					-8.10e-07***	-1.04e-06**				
					(2.26e-07)	(4.81e-07)				
Expenditure on Education, as a Proportion of GDP							-.007***	.002		
							(.001)	(.002)		
Top Marginal Income Tax Rate									-.001***	-.0003
									(.0002)	(.0003)
LIS Dummy	.017***	.018***	.015***	.021***	.020***	.020***	.016***	.017***	.022***	.030***
	(.003)	(.002)	(.004)	(.003)	(.004)	(.003)	(.004)	(.003)	(.005)	(.005)
Constant	.073***	.073***	.140***	.032*	.090***	.094***	.111***	.067***	.108***	.083***
	(.002)	(.001)	(.015)	(.019)	(.004)	(.009)	(.008)	(.012)	(.010)	(.017)
Country Dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Number of Observations	654	654	330	330	312	312	269	269	117	117
Probability>F	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000

Note:

a): *** denotes P<.01, **denotes P< .05, * denotes P< .10. Standard errors are in parentheses.

b): Robust standard errors are experimented, and the statistical significance of the variables holds in most cases, despite of small fall in the t-values.

c): The estimated rates of return from both the male samples and the female samples are included in the dependent variable in Model 1 and 1A, while the estimates based on the samples of both sexes are used as the dependent variable in rest of the models.

d): The sample is restricted to country-years defined in net earnings in Model 5 and 5A.

Table 2-4: Variable Summaries based on ISSP and LIS Data

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
GDP Per Capita, PPP 1995	312	17902.12	7347.877	1291.002	51636.82
Expenditure on Education	269	5.241	1.252	2.318	8.321
Top Marginal Income Tax Rate	299	48.209	10.228	13	78
IFRs	226	6.608	3.168	1.38	18.51
IFRu	226	12.951	6.131	2.73	36.61
Personal Computers	293	169.404	143.082	.243	708.668
High Technology exports	262	16.827	12.337	.01	72.58
LIS Dummy	330	.236	.425	0	1

Note:

a): Variable Definition and Data Sources

GDP Per Capita, PPP 1995: The GDP per capita based on purchasing power parity (PPP) in constant 1995 international dollars. Source: World Development Indicators, World Bank CD-ROM, 2004.

Expenditure on Education: Public expenditure on public education and subsidies to private education as a proportion as GDP. Source: World Development Indicators, World Bank CD-ROM, 2004.

Top Marginal Income Tax Rate: Top marginal income tax rate in percentage. Source: Chapter 3: Country Data Tables, Gwartney and Lawson (2004). Data are available at 5-year intervals. Linear interpolation is used to create a time series.

IFRs: Import-generated income of the foreign production factor skilled employees as a share of GDP in the domestic economy. Source: Table A-9, Wang (2005).

IFRu: Import-generated income of the foreign production factor unskilled employees as a share of GDP in the domestic economy. Source: Table A-9, Wang (2005).

Personal Computers: Personal computers per 1,000 persons. Source: World Development Indicators, World Bank CD-ROM, 2004.

High Technology exports: Exports of products with high R&D intensity as a proportion of manufactured exports. Source: World Development Indicators, World Bank CD-ROM, 2004.

LIS Dummy: Equals one if the dependent variable is computed from LIS data and zero if it is from ISSP data.

Table 2-5: Multivariate Regression Results, ISSP Data

	Rates of Return to Education (ISSP Data)							
Explanatory Variables	Model 1	Model 1A	Model 2	Model 2A	Model 3	Model 3A	Model 4	Model 4A
IFRs	-.047***	-.039**			-.035**	-.040**	-.050***	-.066***
	(.014)	(.016)			(.016)	(.016)	(.019)	(.020)
IFRu	.027***	.022**			.019**	.022**	.026**	.034***
	(.008)	(.009)			(.008)	(.009)	(.010)	(.011)
Personal Computers			.00004	.00005	.00006	.00008*	.00004	.00009
			(.00003)	(.00004)	(.00004)	(.00004)	(.00005)	(.00006)
High Technology exports			.001*	.001**	.0004	.0006	.002*	.002**
			(.0004)	(.0004)	(.0005)	(.0005)	(.0009)	(.0009)
Mean Schooling	.004	.003	.003	.003	.003	.004	.0002	.002
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.004)	(.004)
GDP Per Capita, PPP 1995	-4.79e-06***	-6.97e-06***	-5.20e-06***	-4.44e-06**	-8.22e-06***	-6.56e-06**	-8.47e-06**	-4.05e-06
	(1.25e-06)	(2.44e-06)	(1.86e-06)	(2.08e-06)	(2.79e-06)	(3.30e-06)	(3.44e-06)	(3.93e-06)
Expenditure on Education, as a Proportion of GDP							-.001	.0002
							(.004)	(.004)
Top Marginal Income Tax Rate							-.001*	-.002**
							(.0007)	(.0007)
Year		.001		-.001		-.001		-.004**
		(.001)		(.001)		(.001)		(.002)
Constant	.084**	-2.278	.118***	2.085	.142***	2.876	.241***	8.467**
	(.034)	(2.275)	(.037)	(2.377)	(.045)	(2.915)	(.075)	(3.762)
Country Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	171	171	202	202	169	169	126	126
Probability>F	.0000	.0000	.0084	.0137	.0000	.0000	.0000	.0000

Note:

a): *** denotes P<.01, **denotes P< .05, * denotes P< .10. Standard errors are in parentheses.

b): Robust standard errors are experimented, and the statistical significance of the variables holds in most cases, despite of small fall in the t-values.

c): A gross earnings dummy is included in Model 4 and 4A, defined as one if the earnings variable is calculated before income tax and zero after income tax.

Table 2-5A: Multivariate Regression Results, ISSP and LIS Data

	Rates of Return to Education (ISSP and LIS Data)							
Explanatory Variables	Model 1	Model 1A	Model 2	Model 2A	Model 3	Model 3A	Model 4	Model 4A
IFRs	-.029**	-.028**			-.026*	-.032**	-.046***	-.061***
	(.012)	(.014)			(.014)	(.015)	(.016)	(.017)
IFRu	.016**	.016**			.014*	.017**	.023***	.031***
	(.006)	(.008)			(.008)	(.008)	(.009)	(.009)
Personal Computers			.00002	.00003	.00002	.00004	-.00001	.00006
			(.00002)	(.00003)	(.00003)	(.00003)	(.00004)	(.00004)
High Technology exports			.0003	.0004	.0001	.0003	.0014*	.0017**
			(.0003)	(.0004)	(.0004)	(.0005)	(.0007)	(.0007)
Mean Schooling	.004**	.004**	.004**	.005**	.004*	.005**	.002	.004
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.003)	(.003)
GDP Per Capita, PPP 1995	-3.40e-06***	-3.61e-06**	-3.61e-06***	-3.16e-06**	-4.07e-06**	-2.93e-06	-2.22e-06	1.05e-07
	(1.04e-06)	(1.68e-06)	(1.30e-06)	(1.40e-06)	(1.89e-06)	(2.06e-06)	(2.10e-06)	(2.24e-06)
Expenditure on Education, as a Proportion of GDP							.002	.004
							(.003)	(.003)
Top Marginal Income Tax Rate							-.0007	-.0013**
							(.0006)	(.0006)
LIS Dummy	.025***	.025***	.026***	.026***	.026***	.026***	.021***	.023***
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.004)	(.004)
Year		.0001		-.0008		-.001		-.004***
		(.0008)		(.0009)		(.001)		(.002)
Constant	.070***	-.192	.080***	1.607	.088***	3.007	.093	8.022***
	(.025)	(1.641)	(.028)	(1.830)	(.034)	(2.118)	(.062)	(3.024)
Country Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	226	226	259	259	222	222	171	171
Probability>F	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000

Note:

a): *** denotes P<.01, **denotes P< .05, * denotes P< .10. Standard errors are in parentheses.

b): Robust standard errors are experimented, and the statistical significance of the variables holds in most cases, despite of small fall in the t-values.

c): A gross earnings dummy is included in Model 4 and 4A, defined as one if the earnings variable is calculated before income tax and zero after income tax.

Figure 2-1: Rates of Return versus Mean Schooling, ISSP Data

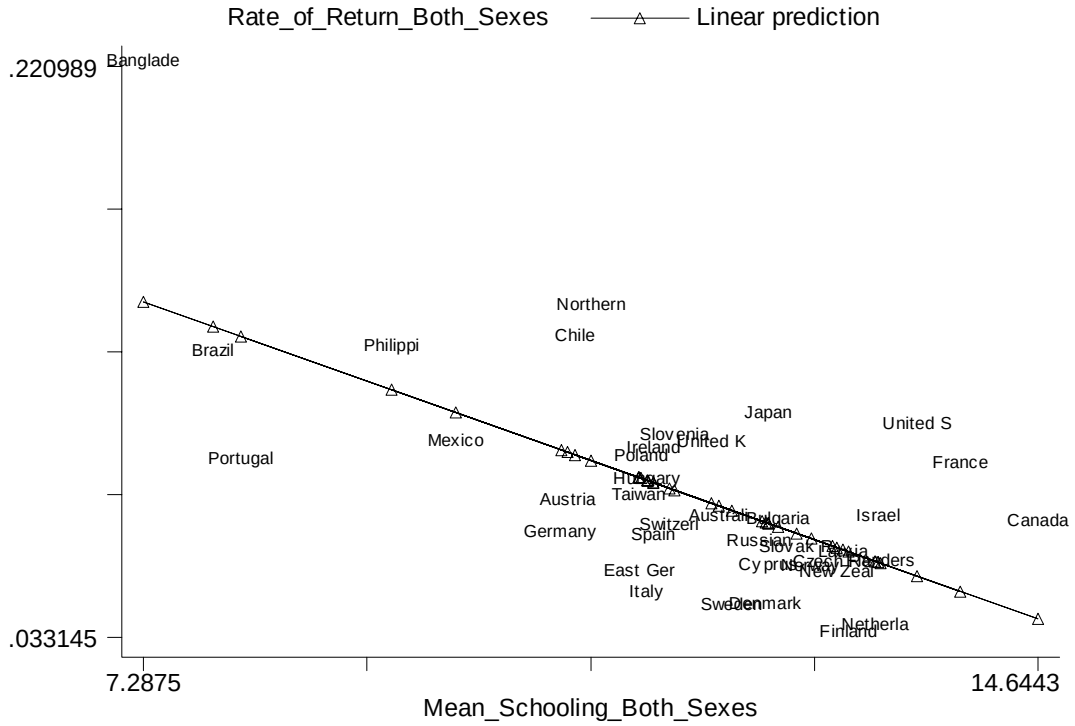


Figure 2-1A: Rates of Return versus Mean Schooling, ISSP and LIS Data

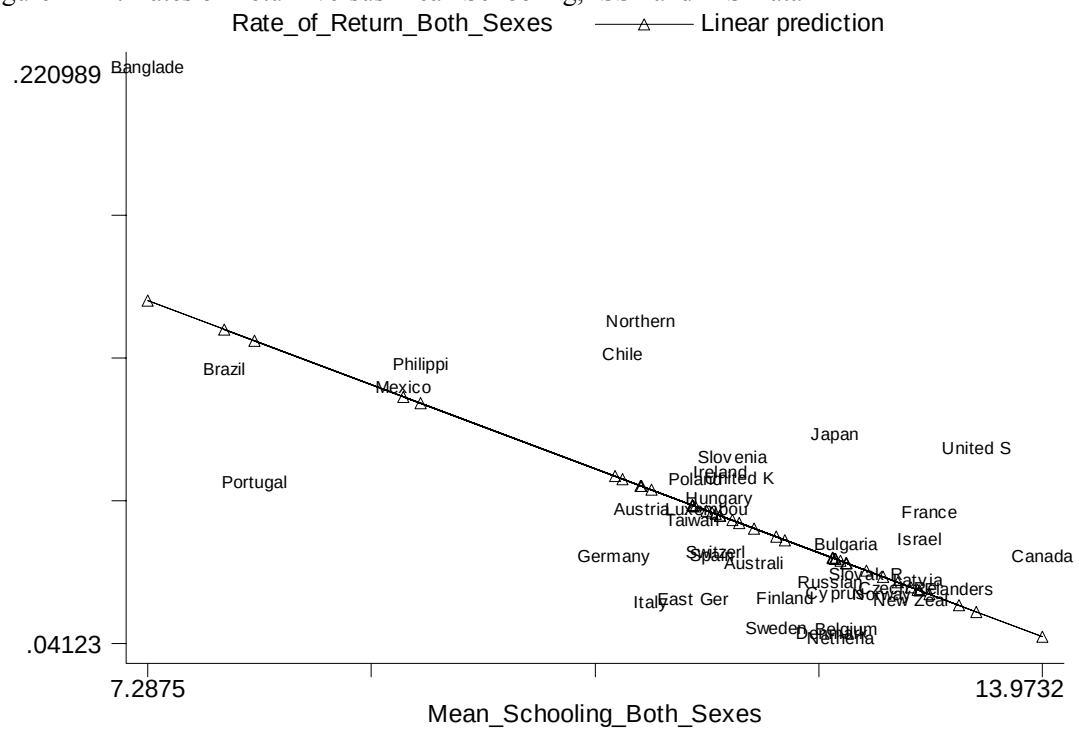


Figure 2-2: Rates of Return versus GDP Per Capita (PPP 1995), ISSP Data

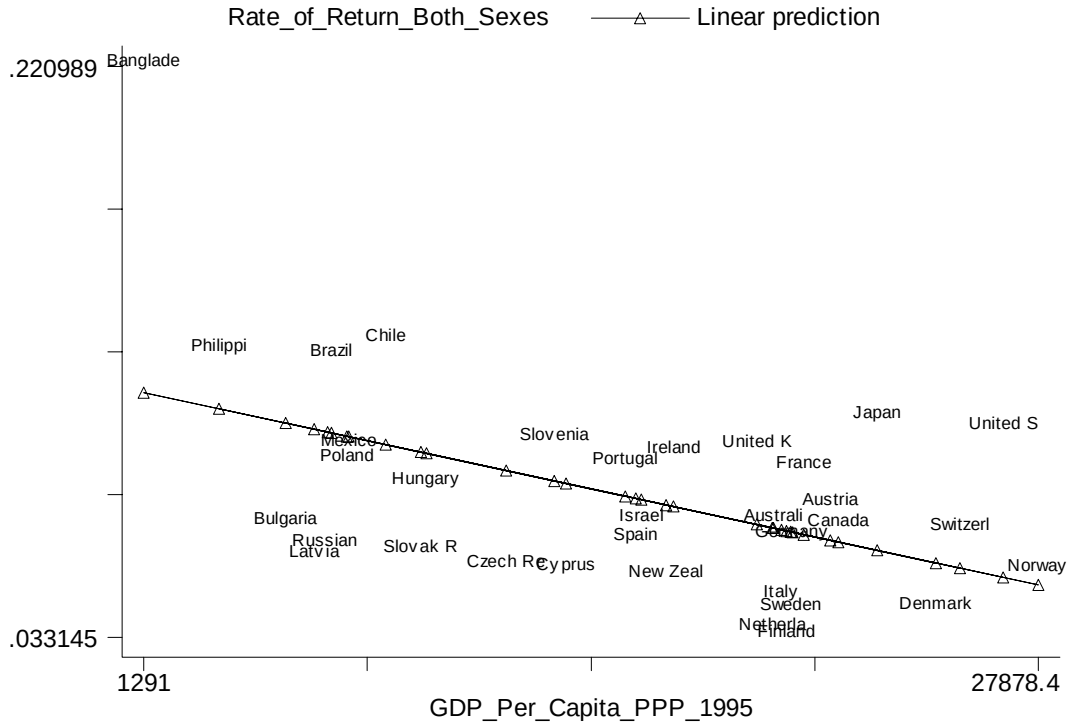


Figure 2-2A: Rates of Return versus GDP Per Capita (PPP 1995), ISSP and LIS Data

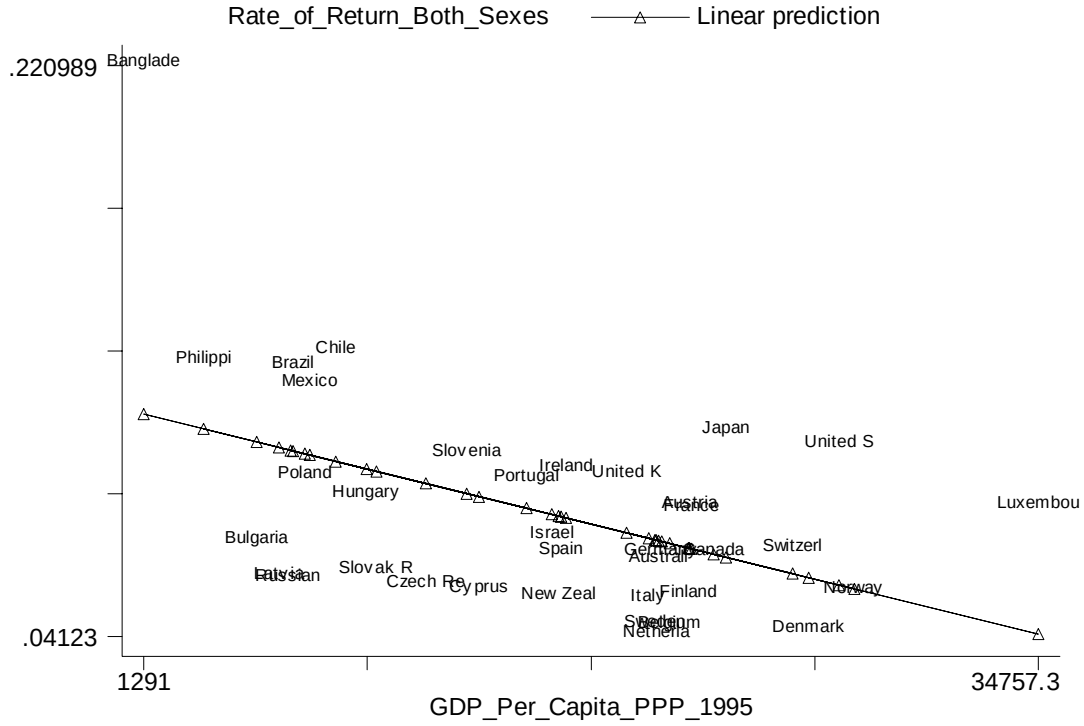


Figure 2-3: Rates of Return versus Expenditure on Education as a Proportion of GDP, ISSP Data

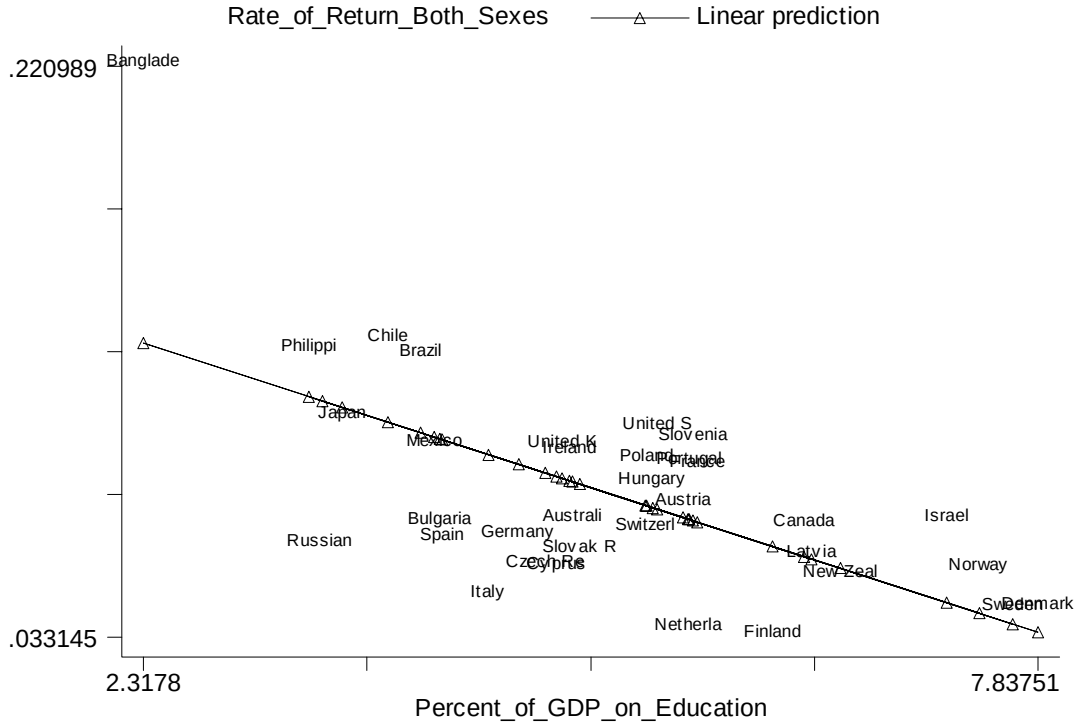


Figure 2-3A: Rates of Return versus Expenditure on Education as a Proportion of GDP, ISSP and LIS Data

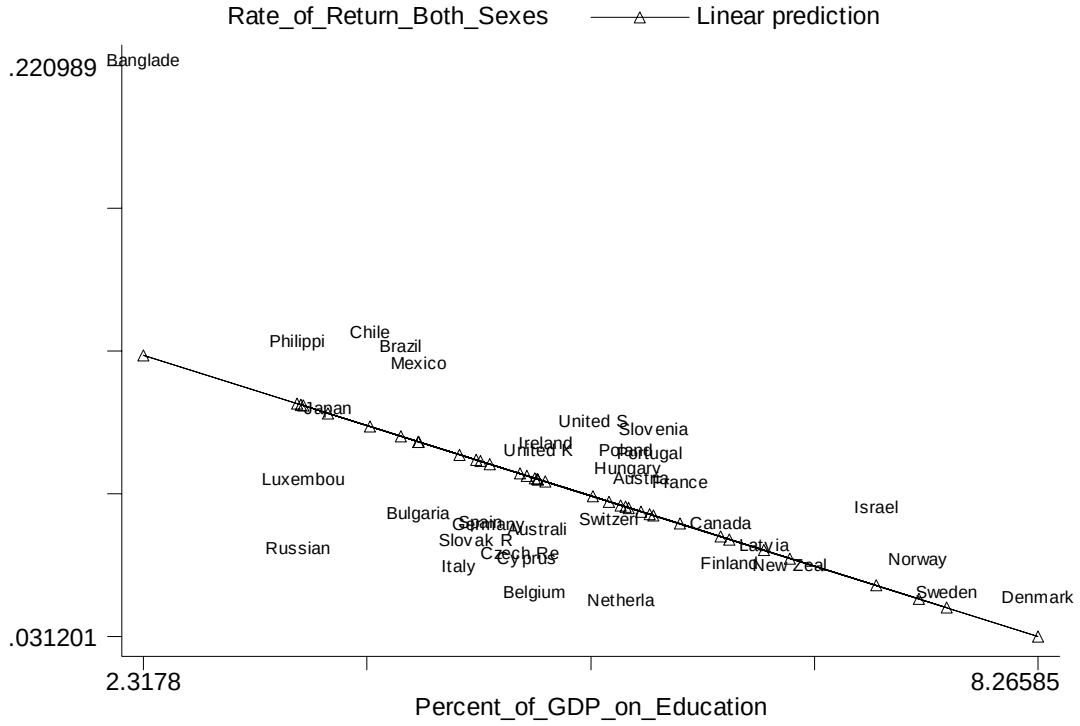


Figure 2-4: Rates of Return versus Top Marginal Income Tax Rate, ISSP Data

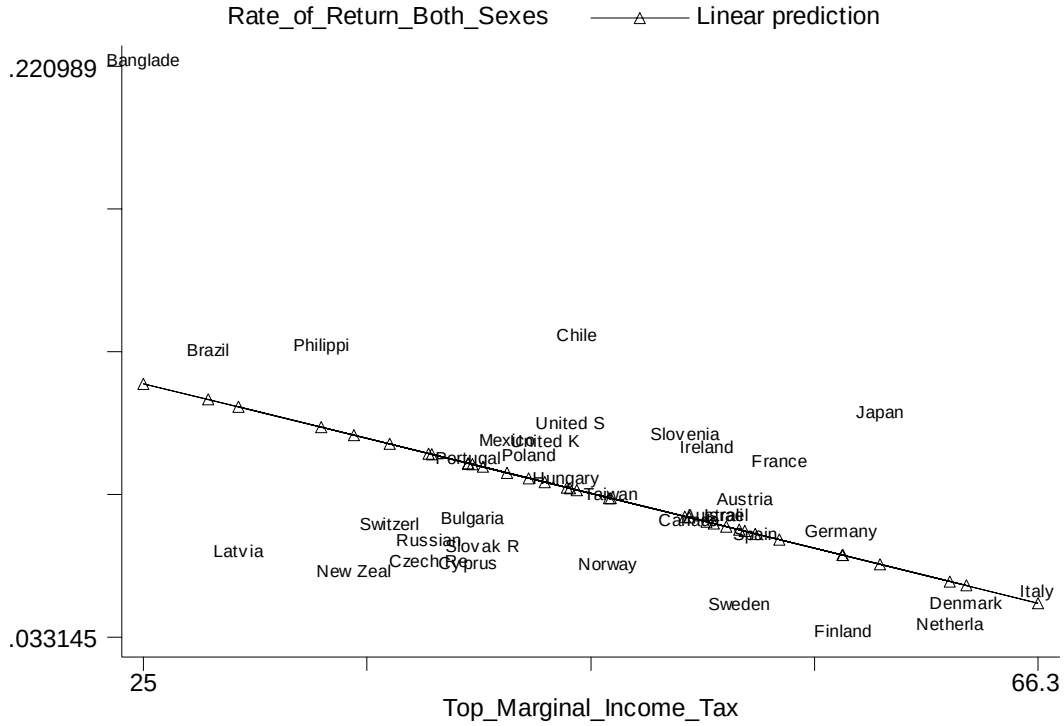
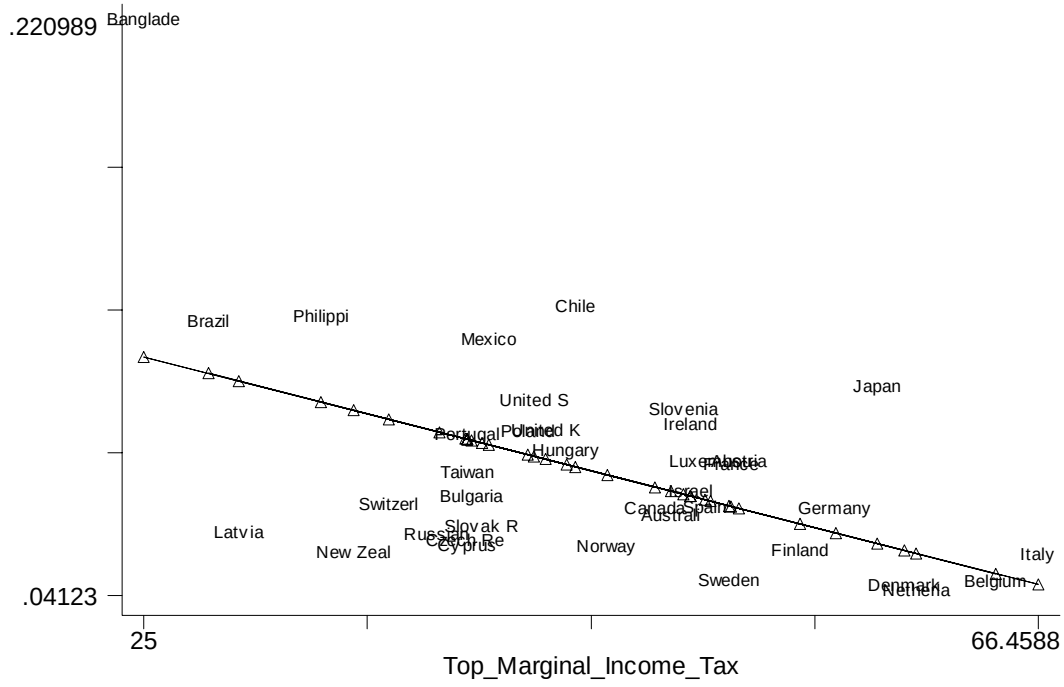


Figure 2-4A: Rates of Return versus Top Marginal Income Tax Rate, ISSP and LIS Data



CHAPTER III

THE EFFECTS OF INCOMPLETE EMPLOYEE WAGE INFORMATION: A CROSS-COUNTRY ANALYSIS[1]

I. Introduction

Tikva Lecker's main research centers on two issues. First, she concentrated on earnings -- particularly earnings of migrants including earnings of Arabs in Israel. Second, she worked on policies affecting legal and illegal immigrant flows. As will be explained, this paper marries these two topics: immigration and earnings. It does so in a unique way. The paper goes back to George Stigler's (1961, 1962) path breaking seminal work on incomplete information and applies earnings function concepts along with frontier estimation techniques to devise a measure of incomplete information, which we parameterize as the degree employees end up receiving wages less than their potential, given their skills. Then, once we estimate incomplete information, we explore how institutional factors, such as unemployment insurance and foreign worker inflows, affect incomplete information across eleven countries.

Incomplete information leads workers to accept wages below what they could have attained had they full information about each potential employer's pay.[2] Workers could improve their wage by prolonging job search, but information about available jobs is costly. To find a job, workers search the market, but normally terminate their search before discovering the very highest paying job available. As explained by Nelson (1970), Mortonsen (1970), McCall (1970) and others,

[1] This is a joint paper with Solomon W. Polachek.

[2] Katz and Ziderman (1986) argue that incomplete information also affects the complete wage package including non-wage benefits. Given unobserved worker characteristics, employers provide specific non-wage amenities to attract worker with desired but unobserved characteristics, thereby affecting the equilibrium wage. Unfortunately we do not have sufficient data to consider non-wage fringes.

individuals set a reservation wage, and search until offered a job at least equal to this reservation wage. On average, the higher the reservation wage the longer the search, but invariably the accepted wage is almost always less than the best possible market wage available for a person of their skill level.

Receiving a wage less than the maximum possible wage (given one's skill) is an important phenomenon because it illustrates an effect of incomplete information that arises from costly search. Collectively, over the whole economy, it reflects foregone gross national product, since so many within the economy are similarly receiving less than they could potentially earn. Therefore in the aggregate, this wage gap reflects incomplete information's cost to the economy. Measuring the effects of incomplete information is significant for at least two reasons. First, as just noted, one can gauge the overall economic losses associated with costly information. Second, having a measure of these losses, one can assess appropriate policies needed to reduce search costs, thereby increasing efficiency within the economy.

One result regarding policy seems pretty much universal in past literature: Unemployment insurance (measured by the replacement rate) subsidizes employee search, which lengthens unemployment duration (e.g., Mofiftt and Nicholson (1982) and Meyer (1990)). The resulting extra search enables workers to obtain more information and higher wages (e.g., Ehrenberg and Oaxaca, (1976)). A gigantic body of literature corroborates these findings regarding UI, both for the U.S. and other countries (e.g., Jurajda and Tannery (2003), Fourgere, Pradel, and Roger (1998), Van den Berg and van der Klaauw (2001), Micklewright and Nagy (1995), Card and Levine (1998), Beach and Kaliski (1983), Ham and Rea (1987), Arellano, Bentolila and Bover (1998), Belzil (1995) and Gonzalo, Maria Teresa Gonzalo (2002)).

This paper differs from past empirical research in three ways. First, rather than concentrate on unemployment duration, it examines worker wages. It focuses on the extent to which workers receive a wage less than what they could be paid based on their skill level. This focus enables the paper to get a metric defining the monetary effect (and indeed a measure of) incomplete information. Second, the paper examines incomplete information from an international perspective. Rather than examine incomplete information for one single country, it obtains measures for eleven countries over several time-periods. Third, by looking across countries, the paper is able to explain

how inter-country institutional differences affect incomplete information.

In testing our model, we first corroborate past findings on unemployment insurance. We show that an employee's incomplete information is smaller where UI is a larger proportion of GDP. Then second, we test whether institutional factors lead to differences in incomplete employee information. In this context, we show that geographic considerations as well as industrial structure likely affect search costs, and hence incomplete information. Third, given Tikva Lecker's interest in immigration, the paper culminates by examining how foreign migrant workers affect overall employee incomplete information. In this context, we determine that an influx of foreign workers into an economy decreases the effectiveness workers search, thereby increasing the degree of incomplete information within the labor market.[3]

Background

A country's distribution of wages defines the benefits of job search. The more dispersed are wages, the greater are the gains from search. Higher search gains lead to relatively higher reservation wages, which in turn leads to more search. But as a consequence, earnings dispersion narrows, and the degree of incomplete information diminishes. At the same time the amount of search is related to search costs. Individual characteristics, such as a worker's location vis-à-vis jobs or a worker's opportunity costs (which would be higher for those already at work) affect search costs. Higher search costs diminish search, leading to wider earnings dispersion.

The whole search process provides job seekers with wage (and amenity) information, but clearly information remains imperfect because search is costly.[4] Creating an index of the degree of incomplete information is important because, as already mentioned, incomplete information leads to lost opportunities and diminished GNP. But in addition, the level of incomplete information is

[3] Beyond the scope of this paper is how institutional characteristics affect employer (as opposed to employee) incomplete information. To answer this latter question, one would need to adopt a two-tier estimation technique (Polachek-Yoon, 1987). However, at this point, the two-tier algorithm is not available to use with LIS data, since all statistical analysis must be done on the LIS computer with standard statistical software (SAS, SPSS, and STATA).

[4] At this point we are abstracting from life cycle considerations, particularly training and other opportunities available on the job. As will be illustrated later, the estimation procedure accounts for these factors by including life cycle variables. Differences in information between "inside" and "outside" employees may also be a consideration, but getting at these is more difficult. Not all "inside" information is acted upon, and hence it is more difficult to measure. For example, the perspicacious peregrinator (Polachek-Horvath, 1977) searches on-the-job for more beneficial opportunities. The information he/she gathers is unobservable until acted upon, which doesn't occur until the perspicacious peregrinator actually moves.

an indicator of market competition. Whereas prices collapse to a unique single equilibrium in purely competitive full-information markets, this is not the case in imperfect competition where there are multiple prices. But even markets for homogeneous easily transferable commodities contain price variability when there is imperfect information.

The amount of market imperfection can also be related to institutional factors. These institutions might include information networks, such as nationally based bargaining units (e.g., Germany) and the availability of unemployment insurance (most developed countries), but they also could include other institutions, such as inflows of foreign workers (who might have little information) into an economy. There is much research on how migrants affect the labor market. These analyses include the effect of immigrants on wages. Some of this research looks at how quickly (in terms of number of generations) migrants achieve success equal to natives (Chiswick, 1978). Other of this research examines how this rate of assimilation depends on migrant quality, particularly concentrating on the skills migrants possess upon entering a country (Borjas, 1985). However, almost no research assesses workers' overall knowledge of wage offer distributions. Similarly, almost no research assesses the effects of foreign workers on incomplete information within a particular labor market. This paper examines both. It develops a metric defining the effects of incomplete information. It assesses the impact of institutional factors including unemployment insurance and population density. Then, in memory of Tikva Lecker, it assesses how in-migration of foreign workers affects the amount of information workers have regarding the labor market. All this is done with international labor market data on eleven countries obtained from the Luxembourg Income Study (LIS).

Incomplete Information

There is a large literature on the theory of equilibrium prices. Most is theoretical, and most concerns defining the conditions under which there is an equilibrium price distribution (e.g., Reinganum (1979), Burdett and Judd (1983), Bester (1986), Arnold (2000), and Kamiya and Sato (2004)). There is also a small but growing body of literature that is empirical. That literature relies on overall price variation to measure the degree if incomplete information (e.g., Stigler

(1961), Stigler and Kindahl (1970), Lach and Tsiddon (1992), and Sorensen (2000)).

As recognized by Stigler and others, there is a major drawback of merely using price (or wage) dispersion as a measure of incomplete information. Price dispersion can vary for many reasons other than incomplete information. These include differences in worker quality, differences in worker-firm bargaining power such as through unions, but they also can result from noisy data. Dispersion measures do not get at these considerations because they don't net out these effects. Regression models suffer the same biases because the dispersion measures they use as the dependent variable do not net out random price variations, nor do they distinguish between a worker's (seller's) and a firm's (buyer's) incomplete information. Thus these past more traditional measures do not reflect accurate estimates of incomplete information.

One technique to get at incomplete information that can net out worker quality as well as pure measurement error, yet get a measure of the effect of incomplete employee information, is given in Hofler-Polachek (1985), and Polachek-Yoon (1987). The technique is relatively simple to implement. Basically, it measures worker incomplete information as a parameter obtained from estimating an earnings function using frontier estimation techniques. Essentially, this parameter depicts the degree workers receive wages that are less than they could obtain, had they known the specific firms paying the highest wages. Hofler and Murphy (1992) employ this technique to compute the average worker shortfall using the 1983 U.S. Current Population Survey (CPS). Gaynor and Polachek (1994) apply the technique to compute incomplete information about physician prices. Daneshvary et al. (1992) use the technique to get at assimilation of foreign workers in the U.S., and Lang (2004) uses it to get at assimilation of German immigrants. Groot and Oosterbeek (1994) corroborate the validity of the approach using a 1985 Dutch national sample of employees. Finally Polachek and Robst (1998) confirm the technique's power by showing how the technique's incomplete information measures match those independently obtained from the World of Work test administered to a group of workers in the 1966U.S.National Longitudinal Survey of Young Men (NLSYM).

But to date, no one has systematically studied how the degree of incomplete information differs across countries. Part of the problem is the paucity of data for enough countries to be able to draw valid conclusions. Comparative cross-country micro-data were simply not available.

However, new data are now obtainable from the Luxembourg Income Study (LIS) for a sufficient number of countries to get meaningful results. This paper applies the techniques mentioned above to estimate the amount of employees' incomplete information. It then looks at different institutional factors across countries to determine how these institutional factors affect incomplete information.

Approach

We use Luxembourg Income Study (LIS) data to examine incomplete information by country.[5] The LIS is a collection of household data compiled from ongoing statistical surveys in approximately 29 countries widely spread across Europe, America, Asia and Oceania. The data are standardized in order to facilitate comparative research. The LIS began in 1983 and is now jointly sponsored by the Luxembourg government and the Centre for Population, Poverty and Policy Studies (CEPS), the Centre Universitaire (CU) de Luxembourg.

Data include country-specific labor force surveys over various labor market structures. These data provide demographic, income and expenditure information on three different levels: household, person and child. We concentrate on extracting earnings, education and age data from the LIS person files for ten OECD countries. In addition, we include Israel, given that this is the location of the conference honoring Tikva Lecker.

For each country we use an econometric frontier estimation technique developed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), originally employed by Hofler and Polachek (1985) to estimate a numeric index of incomplete worker information. Next we look at institutional factors within countries to establish which of these institutions affect incomplete information. First standard institutions such as UI are considered. Then, we concentrate on population density, the proportion of rural employment, the proportion of industrial employment, and finally the influx of foreign workers into an economy.

[5] We do not use ISSP data partially because the earnings are reported in categories in many country-years. This earnings smoothing is likely to distort information regarding incomplete information. However, future work can include those country-years that do not report earnings in categories to extend our current study sample.

II. Modeling Incomplete Information

Assume a labor market with a wage offer distribution such that wages for a worker of given skill vary from a low of $w_{\min}$ to a maximum of $w_{\max}$.[6] A worker entering this job arena is motivated to seek a job at the firm paying the highest possible wage. The only problem is that the worker does not know which firms pay high wages. Indeed, given that firm heterogeneity is not uniform across jobs (so that some firms may pay high wages for one particular skill, but low wages for another), wages vary across firms in uneasy to detect ways, *a priori*. Given this incomplete information, the worker must search. To do this, the worker sets a reservation wage w_i^R, which is the minimum wage the worker will accept when searching. This reservation wage is based on perceived costs and benefits of search. On average, a worker searches more the higher the reservation wage, and less the lower the reservation wage. The greater the search, the more likely the worker achieves a wage closer to the maximum $w_{\max}$.

Suppose worker i finds a job paying a wage w_i^0, such that $w_{\max} \geq w_i^0 \geq w_i^R$. The gap between $w_{\max}$ and w_i^0 will vary across individuals, depending upon relative success in the worker's job search. The greater one's knowledge of the labor market the more likely the chance w_i^0 is closer to $w_{\max}$, barring the impact of luck (which we'll talk about shortly). Let u_i be the (logarithmic) gap between $w_{\max}$ and the wage one actually receives (w_i^0). This gap represents the proportion by which one could enhance one's current wage through continued search for the highest possible wage. The variable u_i can be expressed as

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[6] Wage level w is dependent on the worker's skill level x and a variable θ that will be defined shortly, so that $w = w(x, \theta)$. This wage can vary somewhat because companies differ in how they use comparably skilled workers. Some, perhaps with good management and/or higher physical capital (both indexed by θ) pay more, while other less efficient companies pay lower amount for comparable workers. This results in a distribution of potential wages, for example W ~ N $(\overline{w}, \theta)$, given the firms' heterogeneity of utilization of workers of given quality x. Accordingly, there are high wage firms, the maximum wage being $w_{\max}(x)$, and low wage firms, the minimum being $w_{\min}(x)$. For now, since we are talking about a worker of a particular skill level, we suppress the vector of worker characteristics (x), defining these available wages as $w_{\min}$ and $w_{\max}$.

$$u_i = \ln w_{\max} - \ln w_i^0 + \omega_i \quad (1)$$

and reflects the cost to a worker of incomplete information. In (1) ω_i reflects luck, which for the sake of assumption can be normally distributed with zero mean. The average $u = \sum_i u_i / N$, over all workers (N) in the market, depicts the mean effect of worker incomplete information. Note that since $E(\omega_i) = 0$ luck cancels out when computing average incomplete information for all workers.

Using similar logic, a firm pays more than necessary to the i[th] worker, since it pays w_i^0 despite the worker's willingness to work at w_i^R. The gap ($\ln w_i^0$ - $\ln w_i^R$) $\geq$ 0 reflects the effect of the firm's incomplete information regarding worker i (neglecting luck). But, in reality, worker i need not be the lowest reservation waged worker, so that the true effect of the firm's incomplete information is $\eta_i = \ln w_i^0 - \ln w_{\min}$, where $w_{\min}$ is the minimum reservation wage for all comparable workers who satisfy the job's requirements. The average $\eta = \sum_i \eta_i / N$, across all workers (N), depicts the mean effect of firm incomplete information.

Polachek and Yoon (1987) tested search theory's implications by computing average u and η for various groups of workers. They used the Panel Study of Income Dynamics (PSID) for the U.S. in 1981, and found smaller u values for workers who received UI benefits before their current job. This finding illustrated the efficiency UI brings about through enhanced worker search. Similarly, using the January 1983 Current Populations Survey (CPS), Hofler and Murphy (1992: 516) found that workers in areas paying relatively higher unemployment benefits exhibit a smaller u. Groot and Oosterbeek (1994) found that "males have more labor market information than females [which is] probably caused by the greater market attachment of males, which makes the opportunity costs of ignorance [i.e., incomplete information] greater for males than females (p. 388)." They also found that "employees in the public sector possess more market information than workers in the private sector … probably due to the fact that wage policies in the private sector are in general less public knowledge and more individually based (p. 388)." Polachek and Robst (1998)

found that workers scoring high on World of Work tests had more information than those with lower World of Work scores. Finally Gaynor and Polachek (1994) applied the technique to the medical profession, and there too found that "measured incomplete information is higher when … search costs are higher (p.830)." But to date no one has done a comprehensive study across more than one country. Nor have they examined whether in-migration affects incomplete information.

III. Estimation Procedure

The LIS data require all computations be done on the Luxembourg computer. At this time limitations on canned STATA and SAS software preclude estimating both employer and employee information simultaneously. However, Groot and Oosterbeek (1994) find employer incomplete information to be relatively constant across economic sectors, as does Polachek and Yoon (1987). This result means that incomplete *employee* information varies far more than incomplete *employer* information. So, because incomplete employer information varies little with institutional characteristics, we concentrate solely on incomplete *worker* information (u_i).

To put meat on the discussion, we now derive the econometric specification. However, first a word regarding the underpinnings of an individual's maximum possible wage, $w_{\max}(x)$ defined earlier in footnote 6. Various models can describe the underlying factors of an individual's wage potential. For example, the human capital model argues that a worker's wage potential is determined by human capital acquisition. Productivity enhancing contract models suggest contracts whereby a worker's ability to supply effort affects wage. Finally, collective bargaining implies that union power is important when negotiating a viable contract. Each of these underpinnings can be represented by a vector of an employee's own individual and his or her firm's characteristics, which we denote as vector x_i.[7] As such, a worker's maximum potential

[7] The LIS data do not contain employer characteristics. Thus, such information is omitted from x_i. To the extent these omitted variables influence u_i, our worker incomplete information estimates may be biased. However, *differences* in these measures across countries are unaffected by this bias. These *differences* are akin to serially correlated errors in fixed-effects panel estimates being better than cross-sectional estimates. (See Bound and Krueger (1991).) Economy-wide institutional variables are included later in the analysis when comparing incomplete information across countries.

wage (w_i^p) is related to x_i , plus measurement error.[8] In logarithmic form,

$$\ln \; w_{\max} \mid_{x_i} = \ln w_i^p = \ln(g(x_i)) + v_i \tag{2}$$

Taking a linear model for $g(x_i)$,

$$\ln w_i^p = x_i \beta + v_i \,, \tag{3}$$

where the dependent variable represents the individual's maximum potential wage offer; x_i denotes a vector of individual characteristics defining the worker i's skill level; and v_i is a disturbance distributed as $N(0, \sigma_v^2)$. With *perfect* information regarding what each firm pays, a worker would be able to locate the firm paying his or her maximum potential wage w_i^p . However, in a world of *incomplete* information, where search is costly, the typical worker defines a reservation wage w_i^R below his or her potential wage. As indicated above, the offer wage one accepts $w_i^0 \geq w_i^R$.

Combining (1) and (2), a worker's observed wage can be represented as:

$$\ln w_i^0 \; = \; \ln w_i^p - u_i \tag{4}$$

where $u_i \geq 0$. This one-sided residual u_i represents the extent incomplete information causes one to accept a wage lower than the market's potential wage. It reflects a monetary measure of incomplete information. Substituting (3) into (4) yields

$$\ln w_i^0 = x_i \beta + \varepsilon_i \tag{5}$$

[8] This is the measurement error omitted from past studies of incomplete information that simply use wage (or price) dispersion measures to get at incomplete information.

where $\varepsilon_i = v_i - u_i$. As already indicated $v_i \sim N(0, \sigma_v^2)$. We also assume that $u_i \sim N^+(\mu_{\mu_i}, \sigma_{\mu_i}^2)$, as is typical in frontier estimation.[9]

Based on the above assumptions, the composite error ($\varepsilon = v - u$) must be rightward skewed for the approach to be valid. Therefore before proceeding, we test for skewness in ε. To do this, we follow Schmidt and Lin (1984) to obtain residuals from OLS regressions of (5) for each country and year. The specific test[10] we adopt was developed by Royston (1991) and is a test for normality which combines two tests, one based on skewness and another based on kurtosis, into an overall test statistic. In no country or year do the test results supports the normality assumption (with p-value less than 0.1%). Therefore, our hypothesis about the skewness of the residuals is strongly upheld justifying that we can proceed with estimation of (5) using frontier techniques to disentangle u_i and v_i. To do this, we adopt the maximum likelihood approach to estimate (5) that incorporates a composed error term first proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). It assumes a non-negative one-sided error term, u_i, in addition to the traditional normally distributed error term, v_i. To understand the approach rewrite (5) as:

$$w_i^0 = g(x_i).\exp\{-u_i + v_i\}, \tag{6}$$

where w_i^0 is the actual observed earnings, as already defined, and $g(x_i)$ is the potential maximum earnings achievable barring random errors v_i. Actual earnings (w_i^0) are less than potential maximum earnings ($g(x_i)$) by the proportion (1- $\exp\{-u_i\}$). In other words, (1- $\exp\{-u_i\}$) is the effect of incomplete information.

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[9] It is not necessary to assume $u_i \sim N^+(\mu_{\mu_i}, \sigma_{\mu_i}^2)$. Other common distributions used in this context include the exponential, the Gamma, and lognormal. However, past studies found little qualitative difference between results using these different distributions. See Olson, Schmidt, and Waldman (1980) and Byeong-Ho Gong and Robin C. Sickles (1992).

[10] The skewness and kurtosis test for normality (sktest) is described in the STATA reference manual, p. 226-228.

As is standard in the literature we specify the x_i vector to adhere to typical earnings functions. [11] Based on current literature regarding functional form of earnings equations (Mincer, 1974, Heckman and Polachek, 1974, and Murphy and Welch, 1990), we express an individual's potential wage as

$$g(x_i) = \exp(\alpha_0 + \alpha_1 S_i + \alpha_2 t_i + \alpha_3 t_i^2 + \alpha_4 F_i) \tag{7}$$

where,

S_i is the individual worker i's completed highest schooling level,

t_i is the individual worker i's potential working experience,

t_i^2 is the quadratic term of i's experience level, and

F_i is the individual worker i's gender dummy, 1 for female and 0 otherwise.

The above equation (7) gives a worker's potential wage in the absence of the incomplete information. In reality, because of the limits of finite search, a worker receives less than his or her potential maximum wage, and gets an observed wage w_i^o. To incorporate incomplete information, substitute (7) into (6) to obtain

$$w_i^o = g(x_i).\exp\{-u_i + v_i\} \quad = \exp(\alpha_0 + \alpha_1 S_i + \alpha_2 t_i + \alpha_3 t_i^2 + \alpha_4 F_i) \cdot \exp(-u_i + v_i) \tag{8}$$

After taking the logarithm, it becomes:

$$\ln w_i^o = \alpha_0 + \alpha_1 S_i + \alpha_2 t_i + \alpha_3 t_i^2 + \alpha_4 F_i - u_i + v_i \tag{9}$$

[11] As already noted, data on employers were not available, and hence omitted. However, in the latter cross-country analysis, the effect of these omitted variables are smaller, the more uniformly distributed these variables are across countries. Also, without data on tenure it is impossible to examine incomplete information differences between insider and outsider workers. However, were tenure data available one could compare information measures of recently hired workers to workers with longer tenure to ascertain the role on-the-job search of "insiders" within the firm. Preliminary evidence on this solely for the U.S. (Polachek-Yoon, 1987, Table 2) indicates that tenured employees have less incomplete information. Similarly were enough panel data available one could employ the techniques utilized by Polachek-Yoon (1997) to net out person-specific heterogeneity.

The common approach is to estimate (9) using the (ln) likelihood function

$$\ln \quad L(w_i^0 \xi \beta, \lambda, \sigma^2) = N \ln \frac{\sqrt{2}}{\sqrt{\Pi}} + N \ln \sigma^{-1} + \sum_{i=1}^{N} \ln[1 - F(\varepsilon_i \lambda \sigma^{-1})] - \frac{1}{2\sigma^2} \sum_{i=1}^{N} \varepsilon_i^2 \quad (10)$$

proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977), where

$$\sigma^2 = \sigma_u^2 + \sigma_v^2$$

$$\lambda = \frac{\sigma_u}{\sigma_v}$$

and where f and F are respectively the standard normal density and distribution functions.[12] The expected value of the composite error is

$$E(\varepsilon) = -E(u) = -\frac{\sqrt{2}}{\sqrt{\Pi}} \sigma_u \quad (11)$$

the mean of the one-sided error term.

A problem with the above approach is it assumes u_i to be unrelated to any of the independent variables. So, following Wang's (2002) strategy, we take account of how the independent variables can influence incomplete information by parameterizing u_i to be a function of gender, marital status, race, schooling and experience, because each these variables affects a worker's opportunity costs of search. Thus, we assume

$$u_i \sim N^+(\mu_{ui}, \sigma_{ui}^2) \quad (12)$$

[12] Note that based on Weinstein (1964), the likelihood function is based on the ε_i distribution being

$$f(\varepsilon) = \frac{2}{\sigma} f(\frac{\varepsilon}{\sigma})[1 - F(\varepsilon \lambda \sigma^{-1}) .$$

$$\mu_{ui} = \delta_0 + \delta_1 F_i + \delta_2 M_{1i} + \delta_3 M_{2i} + \delta_4 R_i + \delta_5 S_i + \delta_6 t_i \quad (13)$$

$$\sigma_{ui}^2 = \exp\{\gamma_0 + \gamma_1 F_i + \gamma_2 M_{1i} + \gamma_3 M_{2i} + \gamma_4 R_i + \gamma_5 S_i + \gamma_6 t_i\} \quad (14)$$

$$v_i \sim N(0, \sigma_v^2) \quad (15)$$

where

u_i is truncated normally distributed with mean μ_{ui} and variance σ_{ui}^2,

M_{1i} is the individual worker i's marital status, 1 for married and 0 otherwise,

M_{2i} is the individual worker i's marital status, 1 for divorced, widowed, separated and 0 otherwise, and

R_i is the individual worker i's race, 1 for white and 0 otherwise. (For countries other than U.S., 1 for the majority ethnic group and 0 otherwise).

The empirical estimate of the u_i is obtained through its conditional expectation on the total error term ε_i, which is defined as

$$\varepsilon_i = -u_i + v_i . \quad (16)$$

As noted by a referee, our choice of independent variables in (9), (13) and (14) is an important issue. Omitting key earnings determinants from (9) that are included in (13) and (14) can bias our estimates of incomplete information (μ). Take an example: Suppose education affects earnings positively. Then, including education in equation (9) implies lower potential earnings for the less educated, and higher potential earnings for the more educated. On the other hand, omitting education from equation (9) implies a single potential earnings measure for all. But given the frontier estimation adopted in likelihood function (10), potential earnings in this latter case are those of the most educated group. As a result, the gap between the potential wage and the actual wage is smaller for the more educated and larger for the less educated. Thus, incorporating education in (13) but not in (9) would imply a smaller μ for the most educated workers (hence less incomplete information) simply because the gap between the potential wage and the actual

wage is smaller for the more educated when in reality frontier wages for the less educated should be lower than frontier wages for the more educated.

In this paper we adopt the Mincer earnings specification for (9). Here education, experience, and experience-squared identify potential earnings. In addition, we incorporate gender because gender is known to affect wage level. On the other hand, we include marital status and race in (13) and (14) but not (9) because marital status does not affect wage uniformly. For women marital status appears to lower earnings, whereas for men it appears to raise earnings. Similarly we incorporate race in (13) and (14) but not (9). The LIS data (which we describe later) includes majority ethnic group rather than race. For the U.S. this ethnicity variable denotes race, but not for the other countries. Blacks in the U.S. are earn less than white people. However, there is no strong evidence outside the U.S. that minority ethnic groups earn less than the majority ethnicity groups. Thus we hesitate to include this ethnicity variable in the wage equation. As for the incomplete information equation, marriage and race are included because married, widowed/divorced, and majority ethnicity groups are assumed to have different search behaviors. We expect these groups to search more not only because their marginal gains for an additional search are higher, but also because their search costs are lower. The determinants of search do not always perfectly match those of earning patterns and therefore, the variables in the two equations are not required to be the same.

We admit some biases can creep in because of difficulty in specifying the variables that affect μ but not w, and vice versa. Mostly for this reason, later in the paper, we adopt an additional approach to identify country institutional factors that affect μ. In this latter approach (comparable to differences-in-differences) the above type errors cancel out as long as they are uniform across countries.

Maximum likelihood is used to estimate equation (17), given assumptions (12) to (16).[13] The log likelihood function for a sample of N workers is

$$\ln L(w_i^0 \mid \beta, \lambda, \sigma) = C - \sum_i \ln \sigma_i - \sum_i \ln \Phi(\frac{\mu_{ui}}{\sigma_{ui}}) + \sum_i \ln \Phi(\frac{\mu_{ui}}{\sigma_i \lambda_i} - \frac{\varepsilon_i \lambda_i}{\sigma_i}) - \frac{1}{2} \sum_i (\frac{\varepsilon_i + \mu_{ui}}{\sigma_i})^2 \quad (17)$$

[13] See Stevenson (1980).

where

$$\sigma_i = (\sigma_{ui}^2 + \sigma_v^2)^{1/2} \tag{18}$$

$$\lambda_i = \sigma_{ui} / \sigma_v \tag{19}$$

As discussed above, we use 1- $E(\exp\{-u_i\}|\varepsilon_i)$ as a measure of a worker's incomplete information. The advantage of this measure is that it is bounded by (0,1), which is easily interpreted as the proportion of the potential maximum wage a worker gives up due to the incomplete information. So the bigger the 1- $E(\exp\{-u_i\}|\varepsilon_i)$, the more incomplete one's knowledge of available wages. The formula to obtain each worker's incomplete information is

$$1 - E(\exp\{-u_i\} \mid \varepsilon_i) = 1 - \frac{1 - \Phi[\sigma_{*i} - (\tilde{\mu}_i / \sigma_{*i})]}{1 - \Phi[(-\tilde{\mu}_i) / \sigma_{*i}]} . \exp\{(-\tilde{\mu}_i) + \frac{1}{2}\sigma_{*i}^2\} \tag{20}$$

where

$$\sigma_{*i}^2 = \sigma_{ui}^2 \sigma_v^2 / \sigma_i^2 \tag{21}$$

$$\tilde{\mu}_i = (-\sigma_{ui}^2 \varepsilon_i + \mu_{ui} \sigma_v^2) / \sigma_i^2 \tag{22}$$

The estimate of incomplete information is the average of all workers' incomplete information. So each country year's incomplete information is

$$\mu_j = \frac{1}{N_j} \sum_{i=1}^{N_j} [1 - E(\exp\{-u_i\}|\varepsilon_i)] \tag{23}$$

where N_j is the total number of workers for country year j.

IV. The Data

Our first task is to compute each worker's incomplete information defined in equation (20), using the maximum likelihood estimation formulated in equation (17). In the LIS data, there are three data files for each country and year. We use the personal file, which has information on work

status, personal income, education as well as other basic individual characteristics. For each of the 29 countries, the number of available years differs, ranging from one year for Estonia to nine years for Canada and the United States. For two reasons, we use only part of the available countries for the analysis. First, our final goal is to understand how institutional differences explain variations in incomplete information across countries. However, crucial variables to test hypotheses related to institutional perspectives are not available for all LIS countries and years. Generally LIS has sufficient data for many, but not all OECD countries. So for this reason we first restrict our analysis to the OECD countries and years, which contain the full complement of demographic information that we need for analysis. (As mentioned before, we also include Israel – our only non-OECD country – because LIS contains the relevant information, and because Israel is the site of the Tikva Lecker conference.) Second, we only include countries and years for which the nonlinear maximum likelihood estimation of equation (17) converged. Of the 23 potential OECD countries (and Israel), this left 11 countries for which we have sufficient data. They are the United States, Canada, the United Kingdom, Germany, Sweden, Finland, Ireland, Norway, Netherlands, Czech Republic and finally Israel. They span North America and all parts of Europe.

V. Within Country Regression Results

Summary statistics are provided in Table 3-1. For most countries and years, the average schooling is around 11 to 12 years, and the average potential experience is between 20 and 25 years. So, across these OECD countries, most workers have relatively comparable educational backgrounds, and are similar in age. Also, female workers constitute about half of the population interviewed. (Though, not shown in the table, a greater proportion of women did not work for pay.) The ethnicity variable depicts the proportion of the population constituting a country's majority racial or ethnic group. In the US, this is the proportion white. Married workers are around 60% of the population, and divorced or widowed workers are in the 5-20% range. Mean wages are contained in the last column, and are defined either as hourly wages or annual earnings, depending on the available data. We expect more variation in annual earnings because hourly wages fluctuate less as work hours vary. In the statistical analysis to follow, we add a dummy categorical variable

to signify country-years with hourly wage data.

Table 3-2 contains the regression results of equation (9). Columns (1) and (2) give the country and year; columns (3) through (6) give the coefficient values for schooling, potential experience, potential experience-squared, and gender; and finally column (7) gives estimates of the extent of incomplete information obtained from equation (23). We begin by explaining Columns (3) through (6) since they reflect earnings function parameters typically obtained when estimating Mincer earnings functions.

The schooling variable coefficient depicts the average rate of return for an additional year of school. For more than half of the countries, this rate of return is increasing over time. (Only a few counties have decreasing rates of return.) This pattern is consistent with other data sets as well as with technological change. It implies that the more educated absorb advanced technology easily, and that their rate of pay per year of schooling is increasing secularly.[14] The experience coefficients yield concave earning profiles, shown by the consistently negative squared-term. The female dummy variable is uniformly negative, suggesting that in all the countries (that we consider), women earn less than men, given adjustments for schooling and experience. Overall, these earnings function parameters are typical of those found in the literature.

Estimates of incomplete information, based on equation (23), are given in Column 7. They range from 0.16 to 0.58, but average about 0.3. This means that incomplete information causes the average worker to get about 30% less than his or her potential. An examination of the values indicates strong consistency within countries, since these values differ more country-to-country than within countries. Within countries incomplete information measures do not reveal any apparent time pattern. Incomplete information seems to be increasing in Sweden, Czechoslovakia, Finland, Germany, Netherlands and Israel, while in Norway it is decreasing. On the other hand, time trends are relatively flat for the United States, the United Kingdom, Canada and Ireland. Usually technological improvements mirror time trends. The lack of a time trend might suggest that technological improvements are not necessarily associated with decreasing incomplete

[14] As schooling levels rise, the wage distribution becomes wider. Although a wider earnings distribution increases search gains, it need not imply more information since search costs also rise. Perhaps this is the reason we see no time trends regarding incomplete information.

information, as common sense might have implied.[15]

What factors affect the level and distribution of incomplete information within each country? To answer this question, we adopt Wang's (2002) method to compute marginal effects of μ_{ui} 's covariates listed in equation (13) (Table 3-3) and σ_{ui}^2 's covariates given in equation (14) (Table 3-4).[16] Beginning with Table 3-3, we see a number of trends. For example, the mostly negative marginal effects of school indicate that additional schooling reduces a worker's incomplete information. This finding is consistent with Stephenson's (1976) argument that workers with more education gather more wage information by searching more efficiently. Similarly, about three-quarters of the cases show married workers, and two-thirds of the cases show that widowed and divorced workers, have more information than singles. This result is consistent with higher married and widowed labor force participation rates (Taubman, 1976), which leads to larger marginal gains from search.

Further, as hypothesized (McCall, 1973) blacks exhibit lower labor force participation and possibly higher search costs, so they might acquire less information than whites. In our international data, we show that on average minority ethnic groups have less complete information than majority groups, which is an extension of McCall's argument. Also, from Table 3-3, potential experience reduces workers' incomplete information in over 80% of the observations. Finally, incomplete information is larger among female workers than male workers, again consistent with less lifetime female labor force participation.

Another observation regarding these marginal effects in Table 3-3 is that the patterns are more consistent within a specific country, than across countries. As such, any covariate's marginal effect is likely to have a uniform sign within a particular country, but not necessarily across countries. This uniformity within countries underscores the importance of using cross-country institutional differences to explain how incomplete information differs from country-to-country.

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[15] Whereas technological improvement provides the opportunity for more search, the whole search process can become more overwhelming, making the job choice decision more complicated. For instance, by intensively searching through the internet, individuals decrease search costs. These decreased search costs might imply more search but less real information if, for example, wages are not posted. Thus technology could leave workers with less real information.

[16] For the details, see equation (9) and equation (10) in Wang's paper.

Recall from equation (5) that σ_{ui}^2 depicts the dispersion of incomplete information. How individual characteristics affect this dispersion is parameterized in equation (15). The impacts of these characteristics on σ_{ui}^2 are given in Table 3-4. They indicate the degree incomplete information fluctuates across socioeconomic groups. As an example, take race. From Table 3-3, incomplete information is smaller for whites than for blacks. But, the negative ethnicity coefficient in Table 3-4 implies that whites exhibit smaller dispersion in incomplete information than blacks. This implies a relatively wider range in incomplete information for blacks than whites. Thus the variance of incomplete information is greater for blacks than whites. Similarly, though on average females garner less information in total, they exhibit greater variance in the amount of information they gather, as well. For the most part being older (having more potential experience) reduces this dispersion, as does being married or widowed, and as does having more education (except for the United Kingdom, Germany, The Netherlands and Israel).

VI. Why Incomplete Information Differs Across Countries? An Examination of Institutional Factors

So far we have estimated incomplete information and examined how it varies within countries. We have seen that an employee's characteristics, especially those characteristics affecting one's incentive to search, influence the amount of wage related information one acquires. However, a country's institutions may also be important, but identifying the impact of these institutions is difficult to discern with a limited number of cross-sections for a given country. For this reason, we now do a comparative analysis by contrasting institutional differences across each of the eleven countries to explain inter-country differences in incomplete information.

UI and Incomplete Information

Perhaps unemployment insurance (UI) is the most studied institution regarding information

and search. Ehrenberg and Oaxaca (1976), Jurajda and Tannery (2003), and numerous other studies find that UI increases unemployment duration, job search and post-unemployment wage. Hofler-Polachek (1985), Polachek-Yoon (1987) and Hofler-Murphy (1992) corroborate this result using one of the frontier estimation techniques described above. They find that having received UI leads to less incomplete information. As already mentioned, this finding is consistent with search theory explanations that UI subsidizes search costs leading to longer search, better wages, and more information (less incomplete information). Whereas these studies test this proposition with U.S. data, to the best of our knowledge, none examine other countries; nor do any do comparative analysis across countries. In what follows, we perform a comparative analysis using the eleven countries mentioned above. We test whether variations in UI are related to worker incomplete information.

To achieve this goal, we need UI information for these countries. One measure, found in the "OECD Employment Outlook," is a country's public expenditure as a percentage of GDP. The advantage of this measurement is that we have each country's actual expenditures on UI, instead of some nominal benefit measure that might not be implemented exactly for each worker. The disadvantage is that this measure might reflect a country's business cycle rather than how it subsides an individual's search. Because UI (as a proportion of GDP) is narrowly distributed (most of the UI expenditures are less than 2 percent of countries' GDP, with a few over 3 percent), we convert the UI variable to a logarithm. This assumption is consistent with UI's impact being nonlinear. A logarithmic specification implies a larger impact when UI is initially small, which is what we expect.

Other Institutional Factors

Besides UI, we examine several other institutional factors that might contribute to the explanation of workers' incomplete information. These variables are population density, proportion of employment in industry, rural population and the inflow of foreign workers.[17] Information on each of these is obtained from World Bank data.

[17] Please refer to Table 3-5 for definitions of these variables.

The first three variables get at how information is concentrated among the population. As such they reflect the costs of search, since we presume that search costs rise when information is dispersed more widely and harder to find. So for example, a more dense population implies quicker access to information networks. Also, a more dense population probably means that jobs are closer in proximity. A large rural population implies the opposite, namely sparse harder to find information, with jobs spread over wider distances. Sandell (1980) suggests that geographically concentrated opportunities lowers search costs, which prolongs search, and reduces incomplete information. In contrast to urban areas, rural regions are less concentrated with job opportunities, and therefore likely result in more incomplete information.

Unionization rates rise as a country's industrial employment increases (Polachek, 2004). Also unions provide information to employers and employees regarding wages and jobs (Polachek and Yoon, 1987) and unions compress wage distributions (Freeman, 1980). Thus because industrialized countries are more unionized, we expect workers in more industrial countries to be more informed and have *less* incomplete information.

Finally, in honor of Tikva Lecker, we examine the inflow of foreign workers. A considerable body of research examines the relative success of immigrants. For example, past studies of U.S. immigration note that wages of newly arrived immigrants lag behind native wages (Chiswick, 1978), but that the assimilation process can cause earnings of the foreign born to eventually overtake U.S. natives (Chiswick, 1986), though there remains some debate on the issue (Borjas, 1985). In any case, the whole assimilation process involves increased acquisition of information on domestic labor markets, and the use of this information in the search process (Daneshvary, *et al*., 1992). Further, new lower-waged foreign workers, who come to a country with less initial knowledge of wage structures can affect the overall distribution of wages. Since generally, having less information implies that immigrant workers receive lower wages than natives, wage dispersion increases, as does skewness. Thus the effect of foreign workers is likely to be a more left-skewed earnings distribution, resulting from incomplete information (holding skills constant). But this result is not always found. A study of German immigrants, using data from 2000, finds natives and immigrants at about the same distance from the frontier (Lang, 2004). For this reason, the effect of foreign in-migration on incomplete information is still an open question.

Table 3-5 gives a detailed summary of these variables. Column (1) contains the variable name and definition. Column (2) contains the number of country-year cells for which data are available. Columns (3) – (6) contain summary statistics. Rows (1) through (7) contain statistics for each of the institutional variables just mentioned. Generally data are available for most of the time periods and countries. The exceptions are for UI (which is missing eight of 45 observations) and foreign worker inflows (which is missing 24 observations). This latter restriction necessitates running separate analysis of foreign worker inflow effects. Row (8) gives estimates of the incomplete information variable (obtained from Table 3-2). Because the effects of incomplete information are affected by using annual instead of hourly wages, we normalize those 18 observations that were based on annual instead of hourly wages. This normalization unifies the incomplete information measurement to make it consistent across counties so that inter-country comparisons can be made. These values are given in row (10).[18]

Cross-country Analysis

Cross-country regression results are given in Table 3-6. Country (and year) specific incomplete information measures derived from (23) are the dependent variables, and the country-specific institutional variables just described serve as independent variables.[19] We present five models that explain incomplete information as a function of these institutional factors. Model (1) concentrates on UI. Model (2) concentrates on the population density and industrial structure variables. Models (3) and (4) concentrate on the inflow of foreign workers. Finally, Model (5) integrates most of the institutional factors into one model.[20] We present four parameters for each independent variable. The first is the simple OLS coefficient. The second is the t-statistic based on the robust standard error. The third is the marginal effect caused by a one standard deviation change in the independent variable. Finally the fourth is an elasticity measure describing the

[18] We adjust the 18 incomplete information estimates by the hourly wage dummy coefficient in a regression of incomplete information on the hourly wage dummy variable.

[19] It is argued that our estimates could be biased by unadjusted time-invariant country effects when these effects are correlated with the independent variables. However, the small sample sizes of our regressions - between 21 to 42 observations – prevent us from using country dummies: we will lose about ten degrees of freedom after country dummies are implemented, which would make our regression results much weaker.

[20] Foreign worker inflows cannot be integrated because the limited number of observations on this variable precludes sufficient degrees of freedom. In addition, we eliminated the industrial employment variable because it becomes insignificant.

percent change in incomplete information caused by a one percent change in the independent institutional characteristic. To distinguish between incomplete information variables derived from annual versus incomplete information measures derived from hourly wage data, we adjust for hours of work.[21]

The first model focuses on how UI impacts incomplete information. A one-unit increase in the logarithm of a country's UI expenditures (relative to GDP) reduces incomplete information by .05. This means that a one extra logarithm unit of UI spending (relative to GDP) induces workers to get 5% closer to their maximum attainable wage. The -.036 coefficient implies that a one standard deviation increase in a country's logarithm of UI (relative to GDP) causes workers to get 3.6% closer to their potential wage. Finally the -.048 elasticity measure indicates that a doubling of the logarithm of UI spending (from its mean value) leads to 4.8 percentage decrease in worker incomplete information (from its mean value). Most important, these coefficients substantiate search theory. Increasing UI reduces search costs. Lower search costs increase search leading to more worker information on the wage structure.

The second model focuses on population density, rural population, and industrial employment. If, as we postulate, each of these influences search costs, then we should expect these variables to have an effect on worker incomplete information. Indeed, this is precisely what we find. Both a more dense population and a high level of industrial employment provide information networks, and thus decrease incomplete information. A large rural population increases distances, thereby increasing information costs. This leads to decreases in employee information, and hence a greater level of employee incomplete information.

The marginal effect of a one standard deviation change in each of these three variables is very similar in magnitude (0.03). This means that a one standard deviation increase in either population density or industrial employment decreases a country's incomplete information by about 10%.[22] Analogously, one could look at this another way: Incomplete information of about 0.30 (the mean reported in Table 3-5) implies that employees on average earn about 70% of their maximum possible wage. A one standard deviation increase in population density raises employee

[21] This adjustment is omitted from Models (3) and (4) because each of the 21 observations contains incomplete information measures derived solely from hourly wage data.

[22] According to Table 3-5, average adjusted employee incomplete information is about 0.30. A 0.03 change is about 10%.

information (lowers employee incomplete information) by about 10%. Thus workers in (a one standard deviation) denser area get wages 3% closer to their maximum. Though this analysis is performed across countries, it is well known that urban areas pay higher wages, and often for unexplainable reasons. Perhaps one reason is that better information networks lead to less employee incomplete information.[23]

Models (3) and (4) incorporate the inflow of foreign workers. Both these models show that a growing foreign workforce decreases worker information. A standard deviation increase in inflow of foreign workers yields a 3.7% wage loss in model (3) and a 2.4% loss in model (4). The elasticity measurements for these two models are .049 and .116 respectively. Thus doubling the inflow of foreign workers induces a 4.9% increase in incomplete information in model (3), and a 11.6% increase in model (4).[24] Thus, despite major contributions foreign workers probably contribute to a host country's economic development, they also affect the wage distribution, which becomes more skewed to the left. As such, the average worker receives a wage proportionally lower than the maximum available wage. These lower wages are consistent with an increase in incomplete information.

Combining all variables (Model (5)) does not alter the results.[25] Again, UI is associated with significantly increased worker wages, relative to potential wages. This is consistent with increased worker information. Also, a more dispersed population is associated with wages being lower relative to potential wages. In contrast with UI, this is consistent with *less* employee information.

From a policy perspective, these results show that a country can reduce its incomplete information through governmental efforts, such as spending more on UI. Also, from a policy perspective, the results are consistent with information dissemination being linked to economic development. As a country develops, its geographical structure often changes, so that rural

[23] The large industrial employment and rural population elasticities (Table 3-6) at first surprised us. However, an examination of the means (or median for population density) and standard deviations of these variables reveals values respectively five-times the size and twice the size of their standard deviations. So these two elasticity measures are really very consistent with the marginal effects.

[24] More specifically, a doubling of foreign workers (i.e., a new inflow of 77,700 foreign workers for a country already with 77,700 (median value from Table 3-5) foreign workers and incomplete information of 0.359) will increase incomplete information by .018 units, which is 4.9% of .359. Similarly, increasing the proportion of foreign workers from 0.161% to 0.322% yields an increase in incomplete information by 0.142, which is 11.6% of 0.359.

[25] As noted in footnote #20, an insufficient number of observations precludes including the foreign worker inflow. The industrial employment variable has the correct sign, is statistically insignificant. Thus we also eliminate this variable in Model (5).

(relative to urban) population is reduced. From the above coefficients, relative rural population reductions are associated with more worker information.

In making these claims, it is important to note that information rises because the overall wage distribution becomes more left-skewed, not because wages simply rise equally across the whole distribution. Thus, we are not making a trivial statement regarding development and wage levels. While it is very well known that economic development raises a society's wages, a rising overall wage does *not* constitute increasing information. By our original definition, incomplete information is based on changes in wage distribution skewness, and not on the distribution's overall mean wage level. Thus our proclaimed result goes beyond traditional development economics.

A Graphical Depiction

To get another view of the above results, we graph incomplete information against each of these explanatory variables (Figure 3-1 through Figure 3-6). Every observation is labeled by country name. Also, the graphs contain a fitted line mirroring each of the above model's predictions.

As easily seen, the cross-country predictions blatantly stand out. Nations with greater UI benefits (Figure 3-1) have less incomplete information (more employee information). Workers in more densely populated nations have less incomplete information (Figure 3-2). Nations with greater rural populations have more incomplete worker information (Figure 3-3). Industrialized nations have less incomplete information (Figure 3-4). Finally, nations with a greater influx of foreign workers have more incomplete information (Figures 3-5 and 3-6).

One interesting observation is noted from these graphs. Within-country results are not always as strong as the between country results. Take incomplete information versus the logarithm of UI (Figure 3-1). Whereas greater UI decreases incomplete information in the US, Canada, the UK, Israel, the Netherlands, Ireland and Sweden, it does not in Norway, Finland and Germany.[26] Rather, these latter within-country patterns seem to indicate rising incomplete information as UI

[26] Missing UI data preclude plotting Czechoslovakia in the Figure.

increases. These few counter examples imply that UI alone does not explain all changes of the within country incomplete information. Perhaps UI must be examined in conjunction with welfare policies, given the preponderance of Scandinavian countries among this latter group.

Probably because a country's population density and rural population change very slowly over short time periods, we observe similarly anomalous results for within-country comparisons in Figure 3-2 and Figure 3-3. As a result, we observe almost no within-country relationship in these Figures, even though the between country relation is significant.

On the other hand, the within country observations follow the cross-country trends in Figures 3-4, 3-5 and 3-6. Incomplete information decreases within a country when its industrial employment increases (Figure 3-4). Incomplete information tends to rise with inflows of foreign workers (Figures 3-5 and 3-6).

VII. Conclusion

In this paper, we define a tractable procedure to measure incomplete information in the labor market. The procedure is based on econometric frontier estimation techniques, and is consistent with search theory. It is an improvement over past measures because it holds individual characteristics constant and nets out random effects.

We apply the technique to eleven countries over various years. We find incomplete information leads workers to receive on average about 30-35% less pay than they otherwise would have earned, had they information on what each firm paid. Generally married men and women suffer less from incomplete information than the widowed or divorced, and singles suffer the most. Women suffer more than men do. Schooling and labor market experience reduce these losses. But institutions within a country matter, as well. For example, we find that workers in countries that strongly support unemployment insurance (UI) receive wages closer to their potential. Doubling UI decreases incomplete information and results in 5% higher wages. A more dense population reduces search costs leading to less incomplete information and higher wages. A more industrial economy disseminates wage information better, so that workers exhibit less incomplete information. Finally, in memory of Tikva Lecker, we examined the effect of foreign worker

inflows on incomplete information. Data within countries, as well as data from a cross-country comparison, yield comparable results. Foreign worker inflows skew wages to the left. In the short-run they increase incomplete information, and at the same time they reduce average wage levels.

In reaching these conclusions it is important to note that we achieve our estimates of incomplete information based on the skewness of the wage distribution and not on wage levels. Thus, whereas we find that individual characteristics such as race, gender and work experience lead to higher wage levels in their own right (i.e., these variables have a direct effect), they also do so through their effects on incomplete information. Similarly whereas we find that a country's institutional characteristics such as commitment to UI, sanctions against foreign workers, or a more developed industrial structure directly raise wages, these country characteristics also do so through their effects on incomplete information. These latter effects of incomplete information on wage level are obtained from wage distribution skewness, and not from symmetric movements in the entire wage distribution.

Table 3-1: Mean of the Variables from the Individual Country-Year Regressions**

Country	Year	School	Potential Experience	Female	Majority Ethnicity	Married	Divorced Widowed	Wage	Sample Size
CN*	1981	11.117	21.813	0.172				10.452	9063
CN*	1987	10.822	24.353	0.519		0.618	0.124	12.131	11976
CN*	1991	11.646	25.152	0.517		0.636	0.126	15.110	20514
CN*	1994	11.984	25.164	0.521		0.619	0.135	16.020	39635
CN*	1997	12.066	26.507	0.513		0.646	0.130	14.716	33052
CN*	1998	12.492	25.488	0.513		0.487	0.229	15.256	36566
CN*	2000	13.288	18.450	0.487		0.529	0.201	16.080	32548
CZ	1992	11.804	20.900	0.471		0.733	0.103	518.575	18910
CZ	1996	10.413	23.784	0.466	0.992	0.694	0.108	1140.721	31435
FI	1987	9.351	22.222	0.474	0.933	0.614	0.073	63344.97	18793
FI	1991	9.706	22.374	0.486	0.939	0.629		85465.26	17444
FI	1995	11.145	21.195	0.493	0.948	0.586	0.106	88175.4	12822
FI	2000	11.693	22.208	0.491	0.942	0.584	0.082	112289.7	14137
GE*	1984	7.638	29.046	0.511	0.821	0.638	0.125	19.146	4844
GE*	1989	8.483	28.992	0.504	0.804	0.634	0.132	25.493	3914
GE*	1994	8.780	29.558	0.519	0.813	0.649	0.135	34.482	5849
GE*	2000	12.607	27.399	0.516	0.937	0.629	0.196	24.574	5537
IE*	1994	9.481	29.716	0.500	0.997	0.628	0.105	5.035	2762
IE*	1995	9.471	30.007	0.501	0.993	0.621	0.108	5.217	2396
IE*	1996	9.492	29.905	0.495	0.995	0.611	0.116	5.239	2327
IS	1992	12.531	19.813	0.452	0.473	0.755	0.058	38082.47	5429
IS	1997	12.019	22.691	0.514	0.431	0.602	0.108	64932.53	5817
NL*	1983	9.881	22.597	0.102		0.793	0.053	21.685	2162
NL	1987	9.417	20.573	0.361		0.677	0.046	41329.14	3054
NL	1991	11.615	17.760	0.396		0.64	0.048	40200.91	3828
NL*	1994	10.868	26.795	0.526		0.648	0.113	26.229	4707
NL*	1999	12.693	19.441	0.463		0.612	0.071	29.216	5110
NW	1991	11.485	19.930	0.470		0.554	0.061	115304.8	12786
NW	1995	11.804	21.152	0.479		0.571	0.074	150085.6	13538
NW	2000	12.734	20.755	0.486	0.939	0.551	0.082	209902.6	19214
SW	1992	11.144	25.180	0.492	0.965	0.802		145644.9	15623
SW	1995	10.740	24.248	0.495	0.973	0.765		157548.8	16828
SW	2000	12.207	22.140	0.491	0.961	0.501	0.084	189576	17235
UK	1986	10.482	21.153	0.429				8121.4	6251
UK*	1991	10.744	21.295	0.478		0.659	0.140	6.277	6398
UK*	1994	10.283	31.504	0.528		0.615	0.225	7.295	21659
UK*	1995	11.094	22.043	0.504		0.649	0.180	7.474	5472
US	1969	11.491	20.311	0.421	0.885	0.658	0.099	5566.403	15715
US*	1974	11.327	23.539	0.535	0.815	0.610	0.151	4.650	12087
US*	1979	12.804	20.336	0.472				6.703	15470
US*	1986	12.227	23.362	0.535	0.785	0.554	0.175	9.737	13048
US*	1991	12.429	24.408	0.532	0.745	0.540	0.195	10.467	19636
US*	1994	12.598	24.130	0.531	0.733	0.517	0.203	11.962	79323
US*	1997	12.675	25.060	0.532	0.719	0.549	0.194	13.795	64369
US*	2000	12.818	25.219	0.521	0.701	0.581	0.158	15.320	63890

Data Source: Luxembourg Income Study

* Denotes countries with hourly wage, otherwise with annual wage data are given.
**The mean is based on those in the population with positive wages (earnings). Missing variables are denoted as blanks,
Variable definitions:
School is average years of schooling;
Potential Experience is average years of working experience, calculated by age-school-6;
Female is a gender dummy, 1 for female and 0 otherwise;
Majority Ethnicity is ethnicity dummy, 1 for majority ethnic group and 0 otherwise;
Married is marital status dummy, 1 for married and 0 otherwise;
Divorced/Widowed is a marital status dummy, 1 for divorced/widowed and 0 otherwise;
Wage is average wage, either specified as hourly wage or annual earnings.

Table 3-2: Within Country Regression Results

Country	Year	School	Potential Experience	Experience Square	Female	Incomplete Information
CN*	1981	0.050	0.024	-0.0003	-0.276	0.281
CN*	1987	0.066	0.031	-0.0004	-0.205	0.377
CN*	1991	0.067	0.021	-0.0002	-0.211	0.347
CN*	1994	0.070	0.024	-0.0002	-0.202	0.348
CN*	1997	0.080	0.024	-0.0002	-0.204	0.347
CN*	1998	0.103	0.036	-0.0004	-0.322	0.251
CN*	2000	0.098	-0.006	0.0002	-0.314	0.340
CZ	1992	0.077	0.023	-0.0004	-0.324	0.259
CZ	1996	0.093	0.020	-0.0003	-0.321	0.274
FI	1987	0.082	0.066	-0.0009	-0.413	0.535
FI	1991	0.083	0.056	-0.0007	-0.383	0.536
FI	1995	0.067	0.043	-0.0005	-0.381	0.563
FI	2000	0.065	0.043	-0.0005	-0.421	0.563
GE*	1984	0.089	0.030	-0.0004	-0.243	0.252
GE*	1989	0.073	0.021	-0.0002	-0.169	0.267
GE*	1994	0.067	0.013	-.0001**	-0.151	0.281
GE*	2000	0.105	0.020	-0.0002	-0.187	0.357
IE*	1994	0.098	0.041	-0.0004	-0.116	0.324
IE*	1995	0.087	0.038	-0.0004	-0.128	0.312
IE*	1996	0.091	0.038	-0.0004	-0.110	0.353
IS	1992	0.105	0.048	-0.0006	-0.486	0.320
IS	1997	0.128	0.042	-0.0005	-0.514	0.341
NL*	1983	0.083	0.048	-0.0006	-0.081	0.156
NL	1987	0.084	0.061	-0.0008	-0.172	0.256
NL	1991	0.064	0.038	-0.0005	-0.239	0.398
NL*	1994	0.060	0.025	-0.0002	-0.046	0.275
NL*	1999	0.065	0.026	-0.0003	-0.058	0.297
NW	1991	0.074	0.042	-0.0007	-0.416	0.581
NW	1995	0.069	0.046	-0.0007	-0.436	0.527
NW	2000	0.073	0.046	-0.0008	-0.460	0.484
SW	1992	0.068	0.037	-0.0005	-0.437	0.445
SW	1995	0.076	0.041	-0.0006	-0.443	0.469
SW	2000	0.092	0.036	-0.0005	-0.392	0.471
UK	1986	0.093	0.046	-0.0007	-0.396	0.304
UK*	1991	0.141	0.028	-0.0004	-0.405	0.187
UK*	1994	0.156	0.028	-0.0003	-0.390	0.207
UK*	1995	0.161	0.018	-.0001**	-0.368	0.204
US	1969	0.087	0.028	-0.0004	-0.533	0.495
US*	1974	0.076	0.028	-0.0004	-0.390	0.345
US*	1979	0.074	0.018	-0.0002	-0.476	0.288
US*	1986	0.092	0.035	-0.0004	-0.292	0.365
US*	1991	0.098	0.030	-0.0004	-0.275	0.405
US*	1994	0.113	0.035	-0.0004	-0.257	0.396
US*	1997	0.118	0.034	-0.0004	-0.301	0.384
US*	2000	0.116	0.027	-0.0003	-0.307	0.384

Data Source: Luxembourg Income Study

The dependent variable is hourly wage for countries with *; otherwise the dependent variable is annual earnings.
Coefficients with ** are not statistically significant at 5% p-value level, otherwise are statistically significant at least 5% p-value level.
Variable Definitions:
School denotes the rate of return to an additional year of schooling in equation (9);
Potential Experience is experience coefficient in equation (9);
Experience Square is experience square coefficient in equation (9);
Female is the female dummy variable coefficient in equation (9), 1 for female and 0 otherwise;
As computed from equation (23), incomplete Information is expressed as a percentage of potential maximum wages.

Table 3-3: Marginal Effect of Covariates on E(U) by Country and Year**

Country	Year	Female	Married	Divorced/ Widowed	Majority Ethnicity	School	Potential Experience
CN*	1981	0.139				-0.005	-0.002
CN*	1987	0.100	-0.162	-0.107		-0.106	-0.006
CN*	1991	0.135	-0.077	-0.143		-0.016	-0.008
CN*	1994	0.093	-0.088	-0.021		-0.012	-0.010
CN*	1997	0.120	-0.076	-0.098		-0.007	-0.011
CN*	1998	-0.049	-0.057	0.060		0.027	0.009
CN*	2000	-0.059	-0.077	-0.022		0.012	-0.012
CZ	1992	0.034	0.004	-0.004		-0.002	-0.015
CZ	1996	0.073	-0.026	-0.006	-0.119	0.004	-0.010
FI	1987	-0.262	0.038	-0.245	0.016	-0.081	-0.016
FI	1991	-0.236	0.081		0.018	-0.076	-0.034
FI	1995	-0.142	0.097	-0.032	0.032	-0.059	-0.044
FI	2000	-0.173	0.134	-0.067	-0.040	-0.061	-0.036
GE*	1984	0.095	-0.132	-0.344	-0.059	0.010	-0.042
GE*	1989	0.165	-0.045	0.142	0.059	0.014	-0.039
GE*	1994	0.083	0.053	0.032	0.138	0.008	-0.027
GE*	2000	0.089	0.032	0.067	0.035	0.006	-0.019
IE*	1994	0.219	-0.267	-0.198	-0.298	-0.008	0.003
IE*	1995	0.170	-0.270	-0.041	-0.258	-0.008	0.001
IE*	1996	0.256	-0.276	-0.068	-0.063	-0.007	0.007
IS	1992	0.132	-0.042	0.005	-0.162	0.034	-0.001
IS	1997	0.040	-0.156	0.088	-0.215	0.035	-0.018
NL*	1983	0.069	-0.236	-0.389		0.012	0.006
NL	1987	0.198	-0.162	0.107		0.015	0.009
NL	1991	0.486	-0.958	-0.804		-0.044	-0.055
NL*	1994	0.227	-0.713	-0.930		-0.014	-0.013
NL*	1999	0.141	-0.577	-0.196		-0.021	-0.028
NW	1991	-0.230	0.031	0.429		-0.055	-0.043
NW	1995	-0.170	-0.065	0.350		-0.054	-0.050
NW	2000	-0.119	-0.011	0.067	-0.152	-0.049	-0.031
SW	1992	-0.003	-0.086		-0.184	-0.025	-0.006
SW	1995	-0.019	-0.112		-0.389	-0.034	-0.034
SW	2000	0.086	0.031	0.119	-0.336	-0.003	-0.058
UK	1986	0.247				0.014	0.006
UK*	1991	-0.107	-0.042	-0.049		0.034	-0.001
UK*	1994	-0.023	0.071	0.079		0.050	0.004
UK*	1995	-0.058	-0.020	-0.005		0.048	-0.001
US	1969	0.452	-0.200	-0.183	-0.228	-0.046	-0.056
US*	1974	0.154	-0.147	-0.080	-0.072	-0.006	-0.028
US*	1979	-0.015				0.005	-0.002
US*	1986	0.136	-0.201	-0.183	-0.069	-0.013	-0.021
US*	1991	0.175	-0.128	-0.006	-0.088	-0.017	-0.020
US*	1994	0.134	-0.134	-0.005	-0.067	-0.012	-0.020
US*	1997	0.093	-0.128	-0.015	-0.067	-0.008	-0.020
US*	2000	0.073	-0.157	-0.035	-0.069	-0.012	-0.020

Data Source: Luxembourg Income Study

* Denotes computations based on hourly wage; otherwise computation based on with annual earnings.
** Marginal effect for each country year is the average marginal effect of individual workers within that country year.

Definitions of variables in Table 3-3:
Female is the gender dummy variable in equation (13), 1 for female and 0 otherwise;
Married is the marital status dummy variable in equation (13), 1 for married and 0 otherwise;
Divorced/Widowed is the marital status dummy variable in equation (13), 1 for divorced/widowed and 0 otherwise;
Majority Ethnicity is the race/ethnicity dummy in equation (13), 1 for majority ethnic group and 0 otherwise;
School is the years of schooling variable in equation (13);
Potential Experience is the years of working experience in equation (13), calculated as age-school-6.

Table 3-4: Marginal Effect of Covariates on V(U) by Country and Year**

Country	Year	Female	Married	Divorced/ Widowed	Majority Ethnicity	School	Potential Experience
CN*	1981	0.119				-0.004	-0.002
CN*	1987	0.074	-0.338	-0.208		-0.029	-0.014
CN*	1991	0.190	-0.117	-0.209		-0.025	-0.015
CN*	1994	0.115	-0.145	-0.030		-0.022	-0.022
CN*	1997	0.159	-0.117	-0.155		-0.016	-0.026
CN*	1998	0.004	0.076	0.067		0.013	0.005
CN*	2000	0.001	-0.009	0.001		0.007	0.003
CZ	1992	0.023	0.012	0.001		-0.002	-0.020
CZ	1996	0.062	-0.005	0.004	-0.107	-0.002	-0.017
FI	1987	-0.741	0.230	-0.485	0.005	0.138	0.031
FI	1991	-0.653	0.319		0.000	-0.127	-0.006
FI	1995	-0.380	0.197	-0.112	0.010	0.002	0.051
FI	2000	-0.475	0.420	0.015	-0.236	-0.003	0.050
GE*	1984	0.128	0.011	-0.048	-0.051	0.023	-0.006
GE*	1989	0.174	0.060	0.097	0.051	0.014	-0.006
GE*	1994	0.099	0.093	0.097	0.130	0.016	-0.001
GE*	2000	0.116	0.171	0.145	0.047	0.003	-0.001
IE*	1994	0.364	-0.365	-0.263	-0.444	-0.012	0.007
IE*	1995	0.324	-0.308	-0.052	-0.400	-0.010	0.010
IE*	1996	0.545	-0.450	-0.097	-0.148	-0.012	0.019
IS	1992	0.148	-0.043	0.006	-0.179	0.038	-0.001
IS	1997	0.163	-0.122	0.216	-0.381	0.063	0.001
NL*	1983	0.031	-0.081	-0.142		0.005	0.003
NL	1987	0.539	0.110	0.125		0.020	0.014
NL	1991	0.978	-0.343	-0.211		-0.032	-0.022
NL*	1994	0.332	-0.360	-0.480		-0.007	-0.002
NL*	1999	0.130	-0.448	-0.144		-0.017	-0.022
NW	1991	-0.527	0.567	0.946		-0.056	-0.001
NW	1995	-0.352	-0.071	0.278		-0.053	-0.024
NW	2000	-0.199	-0.074	0.030	-0.281	-0.058	-0.021
SW	1992	0.003	-0.167		-0.393	-0.057	-0.025
SW	1995	-0.041	-0.219		-0.761	-0.048	-0.041
SW	2000	0.188	-0.090	0.042	-0.600	0.013	-0.052
UK	1986	0.511				0.020	0.013
UK*	1991	-0.001	-0.008	-0.008		0.014	0.002
UK*	1994	0.015	0.079	0.080		0.038	0.009
UK*	1995	0.002	0.012	0.002		0.022	0.006
US	1969	0.986	0.008	-0.046	-0.402	-0.013	-0.012
US*	1974	0.210	-0.206	-0.112	-0.099	-0.009	-0.039
US*	1979	-0.012				0.004	-0.001
US*	1986	0.177	-0.493	-0.424	-0.133	-0.039	-0.057
US*	1991	0.429	-0.213	-0.018	-0.146	-0.006	0.001
US*	1994	0.287	-0.224	-0.039	-0.109	-0.001	-0.012
US*	1997	0.188	-0.224	-0.044	-0.120	-0.005	-0.024
US*	2000	0.154	-0.244	-0.085	-0.109	-0.004	-0.011

Data Source: Luxembourg Income Study

* Denotes computations based on hourly wage; otherwise computation based on with annual earnings.
** Marginal effect for each country year is the average marginal effect of individual workers within that country year.
Definitions of variables in Table 3-4:
Female is the gender dummy variable in equation (14), 1 for female and 0 otherwise;
Married is the marital status dummy variable in equation (14), 1 for married and 0 otherwise;
Divorced/Widowed is marital status dummy variable in equation (14), 1 for divorced/widowed and 0 otherwise;
Majority Ethnicity is race/ethnicity dummy variable in equation (14), 1 for majority ethnic group and 0 otherwise;
School is the years of schooling in equation (14);
Potential Experience is the years of working experience in equation (14), calculated by age-school-6.

Table 3-5: Statistic Summary of the Variables from the Cross Country Regressions

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Unemployment Insurance (Expenditure as a Percentage of GDP	37	1.779	1.181	0.26	5.6
Log of Unemployment Insurance	37	0.352	0.722	-1.347	1.723
Population Density (People Per sq km)	45	28.542*	147.464	2.7000	466.499
Industrial Employment (% of Total Employment)	42	27.764	5.644	21.5	45.1
Rural Population (% of Total Population)	45	22.107	9.822	8.841	42.283
Inflow of Foreign Worker (in Thousands)	21	77.700*	184.707	3.8	742.3
Inflow of Foreign Worker (% of Total Population)	21	0.161	0.108	0.033	0.412
Incomplete Information	45	0.359	0.108	0.156	0.581
Hourly Wage Dummy(1 for Hourly Wage)	45	0.600	0.495	0	1
Adjusted Incomplete Information	45	0.309	0.088	0.130	0.455

Data Source: Incomplete information is from Table 3-2; UI is from OECD Employment Outlook; the remaining variables are from World Bank data.
Industry includes mining and quarrying (including oil production), manufacturing, electricity, gas and water, and construction, corresponding to major divisions 2-5 (ISIC revision 2) or tabulation categories C-F (ISIC revision 3).
* denotes median.

Table 3-6: Regression Results of Country Attributes on Country workers' Average Incomplete Information of Wages (Robust Standard Error Used; T Value in Parentheses)

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.487 (20.62)	0.570 (8.94)	0.287 (17.01)	0.279 (10.23)	0.414 (12.00)
Wage Definition Dummy	-0.161 (-5.82)	-0.128 (-6.86)			-0.138 (-7.12)
Log of UI	-0.050 (-3.82) [-.036] {-.048}				-0.022 (-1.99) [-.016] {-.021}
Population Density		-0.0002 (-2.63) [-.030] {-.016}*			-0.0002 (-1.70) [-.028] {-.015}*
Rural Population		0.003 (2.65) [.030] {.184}			0.003 (3.05) [.031] {.180}
Industrial Employment		-0.006 (-2.64) [-.034] {-.464}			
Inflow of Foreign Workers(in Thousands)			0.0002 (3.30) [.037] {.049}*		
Inflow of Foreign Workers (Proportion of Total Population)				0.226 (2.03) [.023] {.116}	
N	37	42	21	21	37
R-squared	0.5185	0.7301	0.2922	0.1391	0.7787
Probability>F	0.0000	0.0000	0.0038	0.0561	0.0000

Note: [ ] contains the marginal effect of a standard deviation change in the variable.

{ }contains the elasticity defined as: Elasticity= $\frac{\partial y / \bar{y}}{\partial x / \bar{x}}$, where $\bar{y}$ and $\bar{x}$ are the means (or medians indicated by *) of the dependent variable and the independent variable respectively.

Figure 3-1: Adjusted Incomplete Information versus Logarithm of UI.

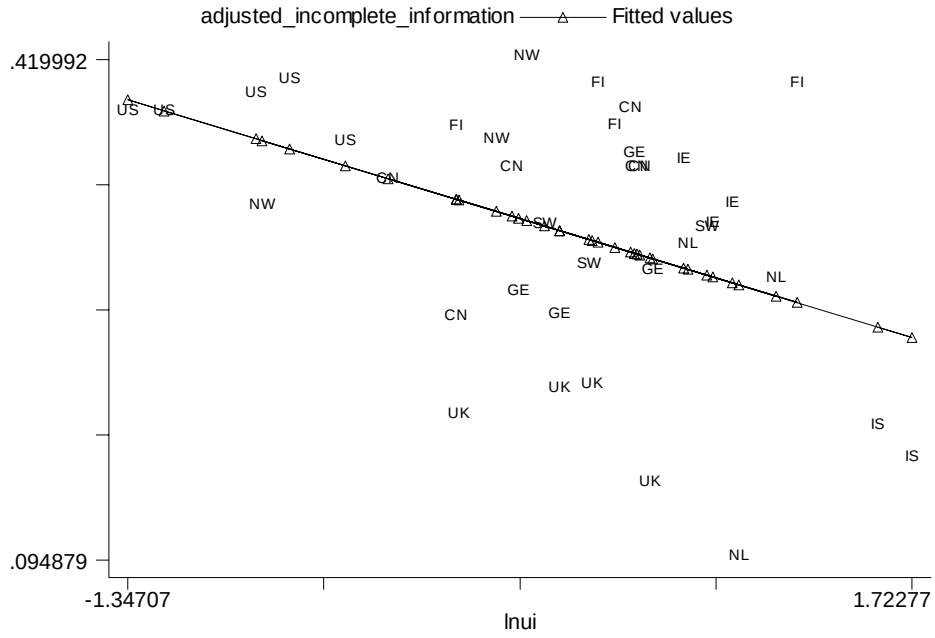

Figure 3-2: Adjusted Incomplete Information versus Population Density.

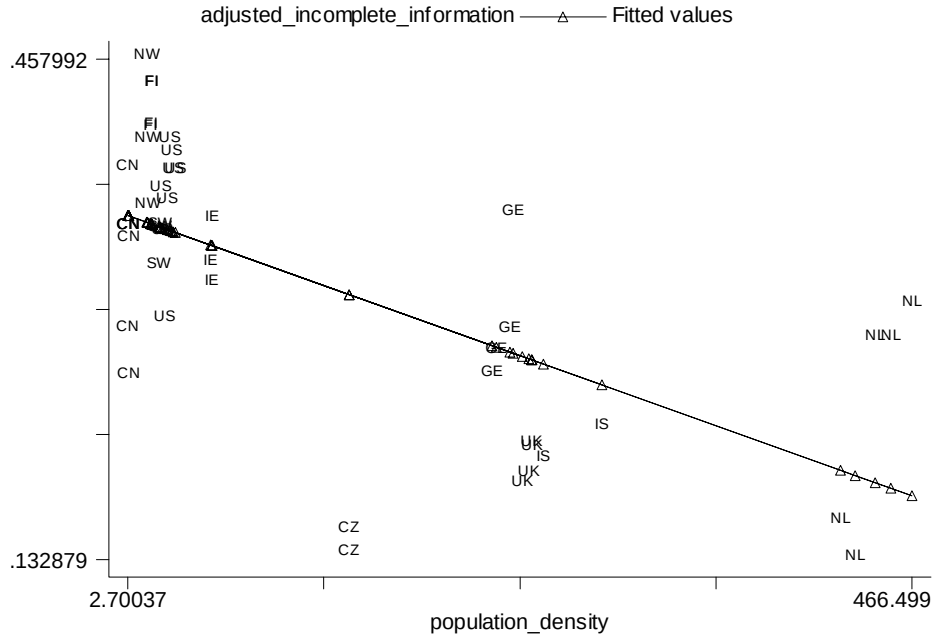

Figure 3-3: Adjusted Incomplete Information versus Rural Population.

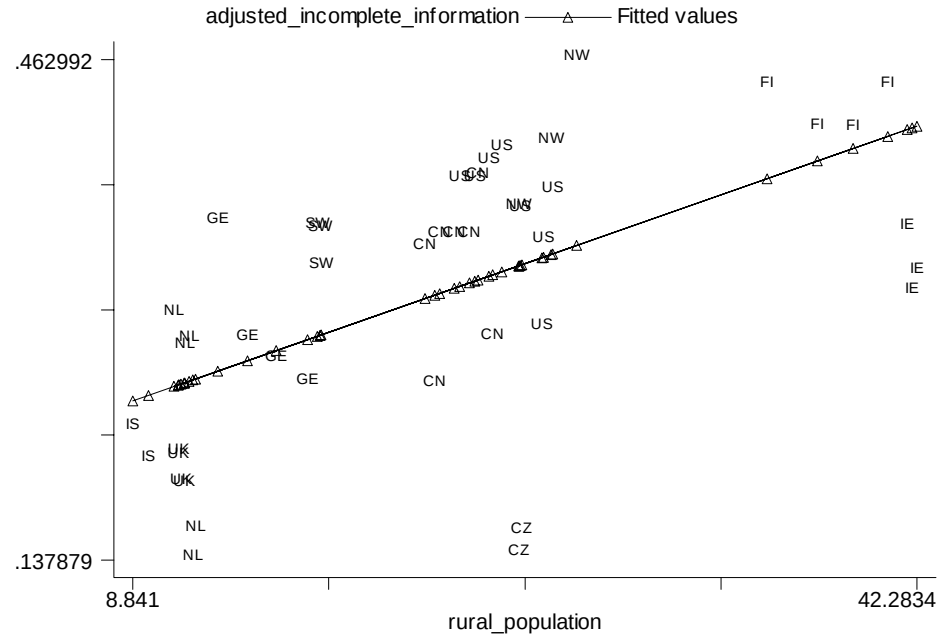

Figure 3-4: Adjusted Incomplete Information versus Industrial Employment.

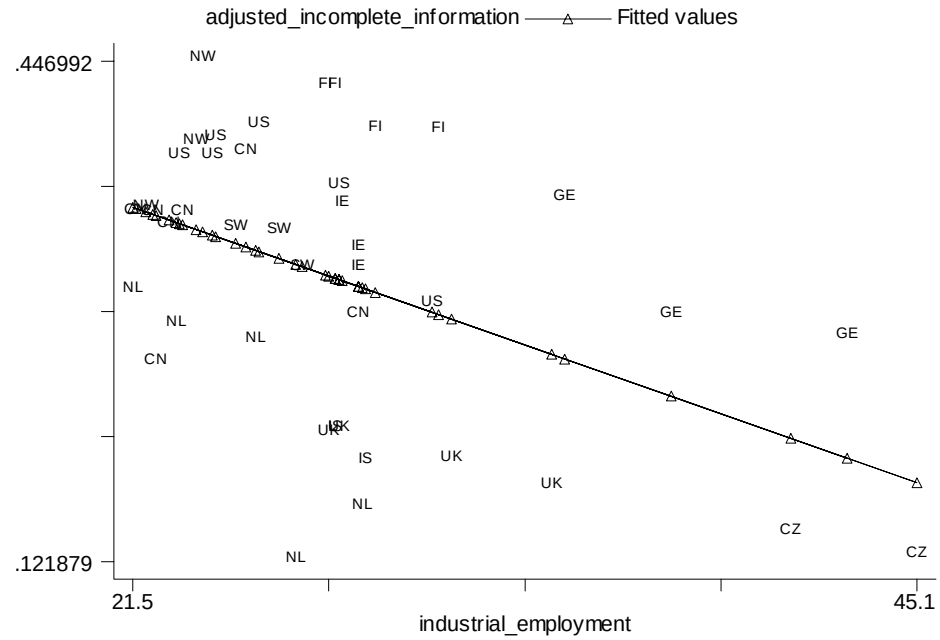

Figure 3-5: Adjusted Incomplete Information versus Inflow of Foreign Workers

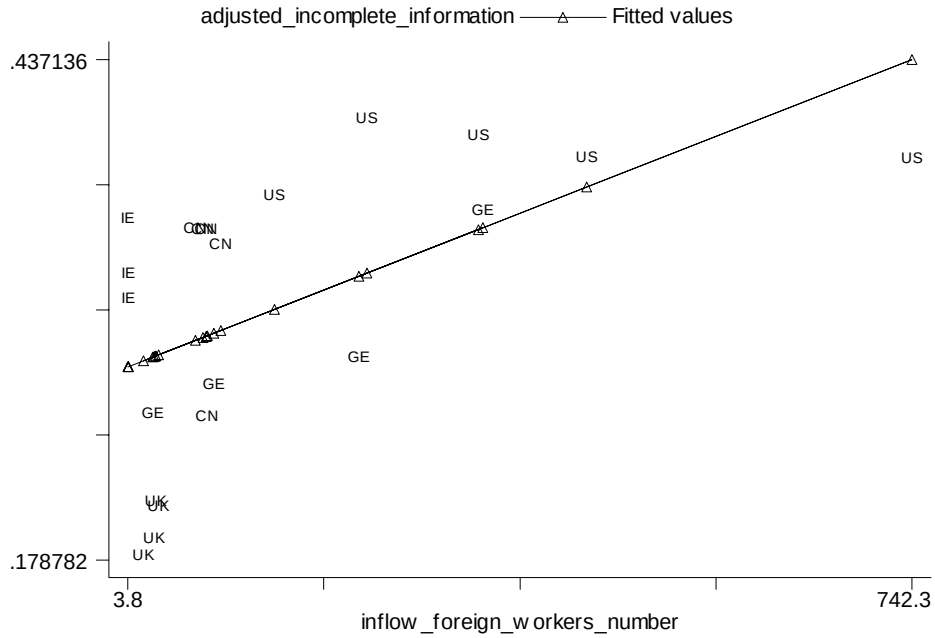

Figure 3-6: Adjusted Incomplete Information versus Proportional Inflow of Foreign Workers

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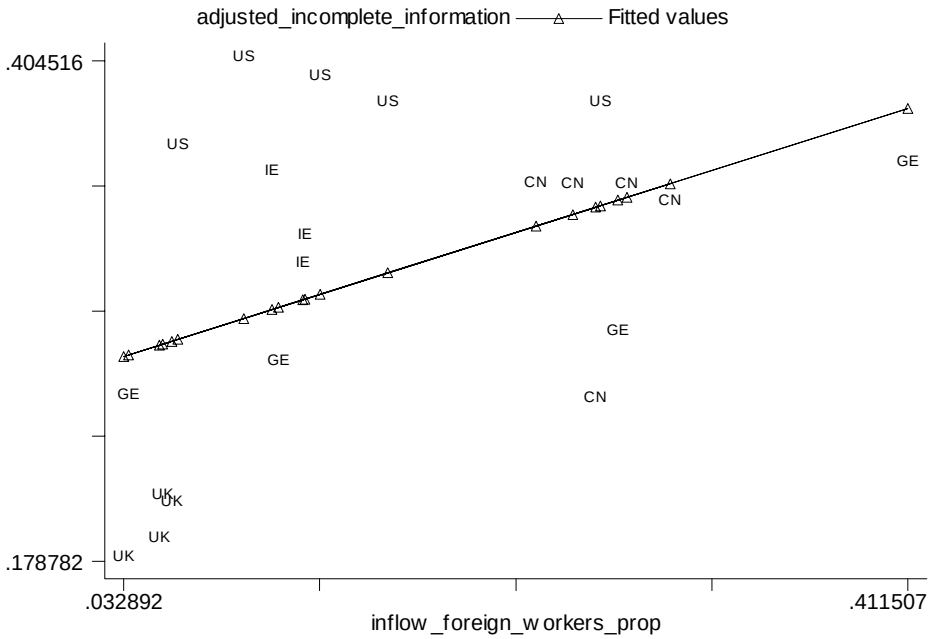

Appendix 1: Earnings Data Definitions, ISSP Data

Country	Years	Earnings definition
Australia	1986-87, 1990-92, 1994-96, 1998, 2002	Annual gross wage and salary income
Austria	1985-89, 1991-92, 1994-95, 1998, 2002	Monthly net earnings
Bangladesh	1997	Annual gross income
Brazil	2002	Monthly earnings
Bulgaria	1992, 1996-98, 2000, 2002	Monthly net earnings
Canada	1992-98, 2000	Annual gross personal income
Chile	1998, 2000, 2002	Monthly net income
Cyprus	1996-98, 2002	Monthly gross earnings
Czech Republic	1992, 1994-98, 2002	Monthly net income
Denmark	1997-98, 2000, 2002	Annual gross earnings
France	1996-98, 2002	Monthly earnings
East Germany	1990-93, 1995, 1997-98, 2000, 2002	Monthly net earnings
Germany (West)	1985-93, 1995, 1997-98, 2000, 2002	Monthly net earnings
Hungary	1990, 1992-98, 2002	Monthly net earnings
Ireland	1988-91, 1993-96, 1998	Annual gross earnings (1988-91, 1995-96); weekly net earnings (1993-94); weekly gross earnings (1998)
Israel	1993-94, 1996, 1998, 2000, 2002	Monthly net earnings
Italy	1986-94, 1997-98	Monthly net income
Japan	1993-98, 2000, 2002	Annual gross earnings
Latvia	1995-96, 1998, 2000, 2002	Monthly net income
Mexico	2000, 2002	Monthly earnings*
Netherlands	1988-89, 1993	Annual net earnings
New Zealand	1991-95, 2000, 2002	Annual gross income
Northern Ireland	1990-91, 1994, 2000, 2002	Annual gross earnings
Norway	1989-98, 2000, 2002	Annual gross earnings
Philippines	1996, 1998, 2000, 2002	Monthly earnings
Poland	1991-98, 2002	Monthly net earnings,
Portugal	1998, 2000, 2002	Monthly net income
Russia	1991-98, 2000, 2002	Monthly gross earnings
Slovak Republic	1995, 1998, 2002	Annual gross earnings
Slovenia	1993-98, 2000, 2002	Monthly net regular income
Spain	1993, 1995, 1997-98, 2000, 2002	Monthly gross earnings
Sweden	1994-98, 2000, 2002	Monthly gross earnings
Switzerland	1987, 1997-98, 2000, 2002	Monthly net income
Taiwan	2002	Monthly earnings*
United Kingdom	1985-98, 2000, 2002	Annual gross earnings
United States	1985-98, 2000, 2002	Annual gross earnings

Note:
a): All surveys are conducted by the ISSP group to its thirty-nine member countries.
b): The above data sample only includes country-years with both of the variables earnings and weekly working hours. Data are excluded for Australia (1985), Bulgaria (1993), Flanders (2002), Netherlands (1991, 1994-95), and Philippines (1992) because computed gender pay gaps in those country-years are negative which are inconsistent either with empirical evidence or with other years of data for that country. Data on Finland (2000, 2002) are also excluded because personal income is mixed with household income.
c): * denotes the information is not obtained directly from the codebooks, but is inferred from earnings data.
d): Gross earnings and net earnings refer to earnings before and after income taxes respectively.

Data Link: http://www.icpsr.com/ and search by "ISSP".

Appendix 2: Earnings Data Definitions, LIS Data

Country	Years	Earnings definition	Survey Name
Australia	1989, 1994	Annual gross wage/salary	Australian Income and Housing Survey
Austria	1994, 1997, 2000	Annual net wage/salary	European Community Household Panel (ECHP)
Belgium	1985, 1988, 1992, 1997, 2000	Annual net wage/salary (1985, 1988, and 2000); Annual gross wage/salary (1992 and 1997)	Socio-Economic Panel Survey (CBS -Centre for Social Policy) for 1997; Panel Study of Belgian Households (PSBH) for 2000
Canada	1987, 1991, 1994, 1997, 1998, 2000	Annual gross wage/salary	Survey of Consumer Finances for years before 1998; Survey of Labour and Income Dynamics for 1998 and 2000.
Czech Republic	1996	Annual gross wage/salary	Microcensus
Finland	1991	Annual gross wage/salary	Income Distribution Survey
France	1981, 1994	Annual net wage/salary	Family Budget Survey
Germany	1984, 1989, 1994, 2000	Annual gross wage/salary	German Social Economic Panel Study (GSOEP)
Hungary	1991, 1994, 1999	Annual net wage/salary	Hungarian Household Panel
Ireland	1994, 1995, 1996, 2000	Annual net wage/salary	European Community Household Panel (ECHP)
Israel	1986, 1992, 1997, 2001	Annual gross wage/salary	Family Expenditure Survey
Italy	1987, 1989, 1991, 1993, 1995, 1998, 2000	Annual net wage/salary	The Bank of Italy Survey (Indagine Campionaria sui Bilanci Delle Famiglie)
Luxembourg	1985, 1991, 1994, 1997, 2000	Annual net wage/salary	The Luxembourg Social Economic Panel Study "Liewen zu Letzebuerg"
Netherlands	1987, 1991, 1994, 1999	Annual gross wage/salary	Additional Enquiry on the Use of (Public) Services (AVO) for 1983; Socio-Economic Panel (SEP) for 1994 and 1999.
Russia	1992, 1995, 2000	Annual net wage/salary	Russian Longitudinal Monitoring Survey
Spain	1995, 2000	Annual net wage/salary	Expenditure and Income Survey
Sweden	1992, 1995	Annual gross wage/salary	Income Distribution Survey (Inkomstfördelningsundersokningen)
Switzerland	1992	Annual gross wage/salary	Swiss Poverty Survey
United Kingdom	1979, 1986, 1991, 1994, 1995, 1999	Annual gross wage/salary	The Family Expenditure Survey for 1991 and 1995; The Family Resources Survey for 1994 and 1999
United States	1974, 1986, 1991, 1994, 1997, 2000	Annual gross wage/salary	March Current Population Survey

Note:
a): The above data sample only includes country-years with both of the variables earnings and weekly working hours. Data of Mexico produce either negative or close to zero gender pay gaps that are inconsistent with empirical evidence, and they are omitted here.
b): Annual gross wage/salary includes cash wage and salary income, including employer bonuses, 13th month bonus, etc. It is recorded gross of employee social insurance contributions/taxes but net of employer social insurance contributions/taxes. In some cases employer provided sick pay is included in the wages.
Annual net wage/salary is the amount after taxes.

Data Link: http://www.lisproject.org/techdoc.htm

Appendix 3: Earnings Data Definitions and sources, OECD Statistics

Country	Years	Earnings definition	Original source	Publication/data provider
Australia	1976-95, 1997-2000	Gross weekly earnings in main job (all jobs prior to 1988) of full-time employees.	Household survey (annual supplement, usually in August, to monthly labour force survey).	Australian Bureau of Statistics, *Weekly Earnings of Employees (Distribution)*.
Austria	1980, 1987-94, 1996	Gross daily earnings, standardized to a monthly basis, taking into account the recorded number of days of insurance contributions (excluding civil servants).	Social security data.	Austrian Central Statistical Office.
Belgium	1985-95	Gross weekly earnings of full-time workers (including civil servants).	Social security data.	Belgium Institut national d'assurance maladie-invalidité (INAMI).
Canada	1967, 1973, 1980-94	Gross annual earnings of full-time, full-year workers.	Household survey (*Survey of Consumer Finances*).	Analytical Studies Branch, Statistics Canada.
Czech Republic	1996-99	Gross monthly earnings of full-time, full-year employees.	Enterprise survey (*Periodic Census of Employers)*.	Czech Statistical Office.
Finland	1977-80, 1982-84, 1986-99	Gross annual earnings of full-time, full-year workers.	Household survey (*Income Distribution Survey*).	Statistics Finland.
France	1950-98	Net annual earnings of full-time, full-year workers.	Salary records of enterprises. (*Déclarations Annuelles des Données Sociales*).	Institut national de la statistique et des études économiques (INSEE), *Séries longues sur les salaires*.
Germany (west)	1984-98	Gross monthly earnings of full-time workers.	Household survey (German Socio-Economic Panel).	Secretariat alculations.
Hungary	1989, 1992, 1994,1996, 1998-2000	Gross monthly earnings of full-time employees in May of each year.	Household survey (*Survey of Individual Wages and Earnings*).	National Labour Centre, Ministry of Labour.
Ireland	1994, 1997	Gross weekly earnings of full-time employees.	Household survey (*Living in Ireland Survey*).	The data and decile calculations were provided by Brian Nolan, Economic and Social Research Institute, Dublin.
Italy	1986-96	Gross monthly earnings of full-time employees.	Social security data collected by the Instituto Nazionale de Previdenza Sociale (INPS).	Data provided by Claudia Villosio, Ricerche e Progetti, Torino, based on the INPS Panel Data
Japan	1975-99	Scheduled monthly earnings of regular, full-time employees.	Entreprise Survey (*Basic Survey on Wage Structure*).	Policy Planning and Rresearch Department, Ministry of Labour, *Yearbook of Labour Statistics*.
Korea (South)	1975-99	Gross monthly earnings of full-time workers	Enterprise Survey (*Wage Structure Survey*).	Korean Ministry of Labour, *Yearbook of Labour Statistics* and data provided directly by the Korean authorities.
Netherlands	1977-99	Annual earnings of full-time, full-year equivalent workers.	Enterprise survey (*Survey of Earnings*).	Sociaal-Economische Maandstatistiek, Dutch Central Bureau of Statistics.
New Zealand	1984, 1986, 1988, 1990, 1992, 1994-97	Usual gross weekly earnings of full-time employees.	Household survey (*Household Economic Survey*).	Estimates provided by the New Zealand Department of Labour.
Poland	1991-99	Gross monthly earnings of full-time employees.	Enterprise survey.	Polish Central Statistical Office, Statistical Yearbook of Poland and *Earnings Distribution in the National Economy as of September 1995*.

Spain	1995	Gross annual earnings of full-time employees.	Entreprise survey (*Structure of Earnings Survey, 1995).*	Instituto Nacional de Estadistica.
Sweden	1975, 1978, 1980-98	Gross annual earnings of full-year, full-time workers.	Household survey *(Income Distribution Survey*). Statistics Sweden.	
Switzerland	1991-98	Annual earnings of full-time, full-year equivalent workers.	Household survey (Annual Swiss labour force survey, *Enquête Suisse de la Population Active* (EPSA)).	Swiss Office fédéral de la statistique.
United Kingdom (Great Britain)	1970-2000	Gross weekly earnings of all full-time workers (i.e. on adult or junior rates of pay).	Enterprise survey (*New Earnings Survey*).	(former) U.K. Department of Employment.
United States	1973-2000	Gross usual weekly earnings of full-time workers aged 16 and over.	Household survey (*Current Population Survey*).	U.S. Bureau of Labor Statistics.

Note:
a): Gross earnings and net earnings refer to earnings before and after income taxes respectively.

Data Link: http://www1.oecd.org/scripts/cde/members/lfsdataauthenticate.asp and query under the dataset named "Percentile distribution of gross earnings".

Appendix4: Estimates of the Gender Pay Gap at Mean, ISSP Data

Year / Country	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	2000	2002
Australia		.407	.372			.400	.345	.345		.278	.238	.299		.408		.209
Austria	.362	.437	.454	.454	.349		.314	.265		.253	.294			.398		.300
Bangladesh													1.361			
Brazil																.148
Bulgaria								.256				.393	.398	.401	.305	.437
Canada								.315	.345	.324	.203	.311	.169	.418	.140	
Chile														.205	.126	.256
Cyprus												.4511	.270	.313		.403
Czech Republic								.387		.421	.395	.337	.346	.450		.281
Denmark													.288	.223	.225	.244
France												.276	.269	.253		.351
East Germany						.253	.293	.222	.251		.204		.208	.118	.193	.199
Germany (West)	.522	.433	.477	.356	.326	.424	.456	.350	.456		.355		.360	.310	.334	.412
Hungary						.391		.286	.094	.238	.170	.175	.120	.161		.075
Ireland				.662	.807	.724	.720		.172	.182	.893	.893		.515		
Israel									.378	.403		.374		.380	.280	.299
Italy		.162	.162	.354	.354	.318	.318	.312	.250	.311			.196	.234		
Japan									1.002	.762	.753	.755	.932	.898	.916	.833
Latvia											.304	.228		.394	.364	.177
Mexico															.061	.248
Netherlands				.414	.337				.078							
New Zealand							.329	.225	.241	.360	.300				.249	.337
Northern Ireland						.371	.318			.476					.111	.174
Norway					.302	.343	.405	.336	.257	.290	.318	.332	.336	.268	.389	.413
Philippines												.238		.209	.261	.205
Poland							.321	.379	.156	.317	.282	.313	.274	.182		.159
Portugal														.277	.309	.272
Russia							.199	.414	.379	.359	.456	.439	.486	.492	.469	.312
Slovak Republic											.294			.325		.309
Slovenia									.319	.246	.177	.167	.055	.075	.095	.089
Spain									.084		.096		.383	.211	.347	.323
Sweden										.239	.218	.202	.234	.233	.241	.192

Switzerland			.536									.308	.264	.372	.325
Taiwan															.219
United Kingdom	.434	.483	.532	.477	.497	.432	.400	.306	.280	.298	.269	.319	.284	.267	.321	.274
United States	.632	.516	.482	.399	.507	.563	.452	.643	.431	.407	.229	.177	.150	.103	.441	.402

Appendix4A: Estimates of the Gender Pay Gap at 50th, ISSP Data

Year / Country	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	2000	2002
Australia		.383	.345			.375	.288	.288		.247	.143	.272		.379		.234
Austria	.201	.368	.619	.619	.310		.268	.268		.268	.336			.379		.236
Bangladesh													1.792			
Brazil																.182
Bulgaria								.405				.357	.416	.288	.288	.511
Canada								.288	.288	.288	.288	.511	.288	.288	.182	
Chile														.250	.200	.253
Cyprus												.693	.452	.201		.241
Czech Republic								.405		.368	.321	.313	.274	.452		.254
Denmark													.201	.201	.201	.201
France												.386	.386	.386		.386
East Germany						.182	.231	.100	.288		.511		0	.125	.140	.118
Germany (West)	.588	.336	.560	.318	.228	.368	.388	.381	.444		.336		.336	.314	.359	.379
Hungary						.408		.318	.105	.163	.140	.205	.113	.099		.138
Ireland				.619	.852	.852	.852		.336	0	1.204	1.204		.693		
Israel									.511	.336		.251		.511	.511	0
Italy		.134	.134	.251	.251	.201	.201	.201	.201	.368			.182	.190		
Japan									1.099	.588	.588	.588	.588	.588	.588	.588
Latvia											.288	.288		.223	.405	.241
Mexico															.087	.143
Netherlands				.379	.236				.134							
New Zealand							.442	.241	.241	.241	.241				0	.251
Northern Ireland						.383	.201			.405					.336	0
Norway					.249	.336	.588	.251	.251	.251	.251	.274	.262	.223	.332	.223
Philippines												.251		.288	.288	.223
Poland							.301	.357	.310	.336	.341	.319	.223	.223		.163
Portugal														0	.486	.486
Russia							.215	.405	.511	.288	.560	.470	.511	.348	.568	.405
Slovak Republic											.288			.375		.339
Slovenia									.151	.118	.095	.154	.085	.017	.049	.069
Spain									.357		0		.357	0	0	.336

Sweden										.336	0	.251	.164	.194	.163	.163
Switzerland			.241										.223	.442	.201	.233
Taiwan																.288
United Kingdom	.310	.492	.693	.588	.485	.463	.405	.405	.205	.405	.201	.271	.208	.342	.465	.265
United States	.547	.435	.547	.379	.526	.526	.383	.383	.258	.425	.201	.201	.201	.143	.457	.310

Appendix 5: Definitions and Sources of Independent Variables

Fertility Rate: The total fertility rate, defined as births per woman. Source: World Development Indicators, World Bank CD-ROM, 2004. Data are available for most years. Linear interpolation is used to create a time series.

Age Gap at the First Marriage: Mean age gap between husband and wife at the first marriage. Source: United Nations Women's Indicators and Statistics Database, version 4, United Nations 1999. Data on mean age at the first marriage by sex are available in 1970, 1980, 1990, and the latest year (around 1995). Linear interpolation is used to create a time series.

Top Marginal Income Tax Rate: Top marginal income tax rate in percentage. Source: Economic Freedom of the World 2004 Annual Report, James Gwartney and Robert Lawson (eds). Data are available at 5-year intervals. Linear interpolation is used to create a time series.

Female Educational Attainment: The ratio of female educational attainment over male educational attainment at the third level (educational attainment is originally defined as third level students per 1000,000 population by sex). Source: United Nations Women's Indicators and Statistics Database, version 4, United Nations 1999. Data on third level students per 1000,000 population by sex are available in 1970, 1980, 1990, and the latest year (around 1995). Linear interpolation is used to create a time series.

Bargaining Centralization: The Index of Centralization. Source: Torben Iversen, "Wage Bargaining, Central Bank Independence and the Real Effects of Money," *International Organization*, 52, summer 1998.

Economic Competition: The Economic Freedom Index. Source: Economic Freedom of the World 2004 Annual Report, James Gwartney and Robert Lawson (eds). Data are available at 5-year intervals. Linear interpolation is used to create a time series.

Public Employment Ratio: Civilian government employment as a percentage of the working age population (15-64). Source: Comparative Welfare States Dataset, 2004 (downloaded from Luxembourg Income Study). Find the Original Sources in the Comparative Welfare States Dataset.

Appendix 6: Effects of Women's Incentive for Labor Force Participation on the Gender Pay Gap, Based on the OECD data

Explanatory Variables	Gender Pay Gap_50th				Gender Pay Gap_Mean			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Fertility Rate	.151***				.177***			
	(.019)				(.012)			
Age Gap at the First Marriage		.188***				.171***		
		(.016)				(.018)		
Top Marginal Income Tax Rate			.003***				.004***	
			(.0002)				(.0003)	
Female Educational Attainment				-.387***				-.417***
				(.020)				(.024)
Constant	.047	-.182***	.114***	.654***	.057***	-.079*	.139***	.730***
	(.032)	(.041)	(.013)	(.018)	(.021)	(.046)	(.015)	(.021)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	290	287	273	265	312	301	287	275
Probability>F	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000

Note:

a): *** denotes P<.01, **denotes P< .05, * denotes P< .10. Standard errors are in parentheses.

b): Robust standard errors are experimented, and the statistical significance of the variables holds, despite of small fall in the t-values.

Appendix 7: The Effect of Top Marginal Income Tax Rate on the Gender Pay Gap Measured at Different Percentiles

	10^{th}	20^{th}	25^{th}	30^{th}	40^{th}	50^{th}	60^{th}	70^{th}	75^{th}	80^{th}	90^{th}
Top Marginal Income Tax Rate	-.0002	.0002	.0015***	.0004	.0007	.0012***	.0019***	.0022***	.0035***	.0021***	.0010
	(.0007)	(.0005)	(.0006)	(.0005)	(.0005)	(.0004)	(.0005)	(.0005)	(.0006)	(.0005)	(.0006)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	247	231	160	231	231	252	231	231	160	231	236
Probability>F	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000

Note:

a): *** denotes P<.01, **denotes P< .05, * denotes P< .10. Standard errors are in parentheses.

b): Robust standard errors are experimented, and the statistical significance of the variables holds, despite of small fall in the t-values.

c): In addition to top marginal income tax rate, the independent variables include fertility rate, age gap at the first marriage, and female educational attainment.

Appendix8: Mean Rates of Return to Schooling based on IV Estimation (Spouse's Schooling as the IV), ISSP Data

Country	Number of Years	Men	Women	Both Sexes
Australia	4	.067	.109	.065
Austria	7	.108	.136	.119
Czech Republic	1	.061	.058	.062
East Germany	2		.125	.061
Germany (West)	3	.072	.086	.078
Hungary	3	.093	.093	.095
Ireland	3	.142	.117	.130
Italy	7	.066	.094	.073
Netherlands	1	.076	.090	.080
Poland	3	.131	.179	.100
United States	9	.143	.179.	.145

Note:

a): The estimates of returns are negative in Australia 1985 and 1986, and Italy 1992, which are not included in the sample.

b): The estimates of returns are statistically insignificant for men in East Germany 1991 and 1992, Germany 1991, and Poland 1991, for women in Australia 1991 and 1992, Germany 1991, Poland 1993, and United States 1986 and 1988, and for both sexes in Germany 1991. These country-years are not included in the sample.

Appendix 8A: Mean Rates of Return to Schooling based on IV Estimation (Spouse's Schooling as the IV), LIS Data

Country	Number of Years	Men	Women	Both Sexes
Australia	2	.071	.066	.069
Austria	3	.134	.135	.138
Belgium	5	.077	.095	.084
Canada	6	.095	.150	.120
Czech Republic	1	.103	.118	.111
Finland	1	.148	.141	.144
France	1	.106	.103	.105
Germany (West)	4	.071	.145	.095
Hungary	3	.136	.138	.137
Ireland	4	.110	.152	.125
Israel	4	.110	.112	.111
Italy	7	.094	.111	.101
Luxembourg	5	.141	.158	.148
Mexico	8	.206	.250	.215
Netherlands	4	.065	.078	.063
Russia	3	.148	.120	.137
Spain	2	.128	.153	.136
Sweden	2	.085	.078	.080
United Kingdom	5	.114	.134	.123
United States	6	.114	.130	.120

Note:
a): The estimate of returns is statistically insignificant for men in Germany 1994, which is not included in the sample.
b): The number of observations in regressions is insufficient for men in Switzerland 1992, for women in Israel 1986 and Switzerland 1992, and for both sexes in Switzerland 1992. These country-years are not included in the sample.

Appendix 9: Mean Rates of Return to Schooling based on IV Estimation (Father's Schooling as the IV), ISSP Data

Country	Number of Years	Men	Women	Both Sexes
Australia	3	.072	.094	.079
Austria	4	.125	.155	.137
Czech Republic	1	.064	.118	.092
East Germany	1	.125		.065
Germany (West)	3	.068	.097	.084
Hungary	3	.095	.083	.087
Ireland	2	.128	.116	.118
Poland	3	.136	.156	.111
United States	6	.152	.178	.162

Note: The estimates of returns are statistically insignificant for men in Poland 1993, for women in East Germany 1992, and Poland 1991 and 1993. These country-years are not included in the sample.

Appendix 10: Mean Rates of Return to Schooling based on IV Estimation (Mother's Schooling as the IV), ISSP Data

Country	Number of Years	Men	Women	Both Sexes
Australia	3	.093	.222	.105
Austria	4	.132	.127	.117
Germany (West)	3	.107	.136	.076
Hungary	3	.086	.074	.080
Ireland	2	.133	.127	.136
Poland	2	.165	.121	.117
United States	6	.151	.179	.159

Note: The estimates of returns are statistically insignificant for men in Australia 1991 and 1992 Austria 1988 and 1991, Germany 1988 and 1992, Hungary 1990, Poland 1993, and United States 1992, for women in Germany 1992, and Poland 1993. These country-years are not included in the sample.

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