Positive or Negative?
Migrant Workers’ Self Selection Revisited

Eran Yashiv∗
Tel Aviv University, CEPR, IZA, and CEP (LSE)

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Abstract

With an increasing flow of low-skilled workers from developing economies to developed ones, migration is an issue of major interest. The Roy (1951) self-selection model has been suggested to explain migrant identity, a crucial factor in this context. But empirical work in this area has been subject to different and conflicting interpretations. This paper revisits the issue, using a unique data set on Palestinian workers, which offers the possibility to directly study the predictions of the model.

The data used encompass both migrants and stayers, sampled in a consistent way within a single survey. The results offer a nuanced view of migrant self-selection. Estimation results on observables show that migrants are less skilled than stayers. Specifically, a substantial migration premium lures migrant workers, while very low returns to skills in the foreign economy deter skilled workers, leading to negative self-selection. At the same time, on unobservables, migrants are found to be positively self-selected.

The results on both dimensions may be explained by the fact that migrants come from a relatively poor economy and are offered work in low-skill occupational tasks in a relatively rich economy.

Key words: self-selection, migrant workers, skill premia, migration premium, unobservable skills.

JEL classification: J3, J6, F2.

∗E-mail: yashiv@post.tau.ac.il
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1 Introduction

Against the background of an increasing flow of low-skilled workers from developing economies to developed ones, low-skilled migration has become a major issue. It animates political debates and ranks high on the political and economic agendas in many countries. A major concern in this discussion is the effect of migrants on the host economy and its workers. In this context, the identity of migrant workers is crucial. It is therefore important to determine what types of workers choose to migrate.

There is an ongoing debate in the literature on this issue. Borjas (1987) has suggested using the Roy (1951) self-selection model to tackle the subject of migrant identity. The empirical work on migrant self-selection and on the performance of migrants in the host economy has been subject to different and conflicting interpretations. For example, in U.S. data and in reference to Mexican migration, Borjas (1999) surveys findings of different studies indicating negative self selection. In contrast, Chiquiar and Hanson (2005) find that these migrants are more educated than non-migrants in Mexico and that they would have been concentrated in the middle of Mexico’s wage distribution had they not migrated.

This paper revisits the issue of the self selection of migrant workers. It does so using a unique data set, which offers the possibility to directly study the predictions of the model. The data used encompass both migrants and stayers, i.e., the two groups are sampled in a consistent way within a single survey. In some of the better cases in the literature, two different data sets (such as census data) have been used to compare migrants and stayers. These are quarterly labor force survey data on Palestinian workers who worked in Israel and those who worked in the local economy.

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Some evidence is presented below; for detailed reviews see Stalker (2000) and Zlotnik (1998).
While this case of migrant workers has some unique characteristics, employment of these workers bears similarity, in terms of occupations and position in the wage distribution, to the employment of Hispanic workers in the U.S. and North African workers in Western Europe.\(^3\) The data are particularly consistent with the formulations of the self-selection model, which describes workers as choosing among occupational tasks. Hence the paper is able to undertake a direct test of the migrant self-selection model and examine all of its implications. In particular, it provides estimates of the moments of the unobserved skills distributions, which are crucial for the determination of the patterns of self-selection. Doing so it derives new results and re-interprets existing findings, generating a consistent picture of the (rich) patterns of migrant self-selection. It shows in what sense migrant workers are negatively selected, as found in many studies, and in what sense they are, concurrently, positively selected.

The paper examines migrant self-selection by estimating wage equations derived from the model. The basic idea is as follows: workers select where to work according to the principle of maximizing income. Income depends on the return to the individual’s skills (both observed skills, like education or experience, and unobserved skills) and on market prices for a suitably defined labor supply aggregate. Individuals sort themselves into the local or host economy and the data are conditioned on their selection decisions. Estimation corrects for sample selection bias, which is inherent in the model.

These wage equations – for workers employed locally and in Israel – demonstrate that self-selection needs to be understood along two dimensions. Both of these pertain to the fact that migrants come from a relatively poor economy and are offered work in low-skill occupational tasks in a relatively rich economy. In terms of observables, substantially different return profiles for experience and education existed in the local economy and in the host economy. While in the former they assumed a standard shape, in the latter they were low and relatively flat. However, Israel, a richer economy, lured workers by offering higher baseline wages, a ‘migration premium.’ This led to the self-selection of younger, less educated workers to the Israeli economy. Hence migrants

\(^3\)Thus, for example, Borjas and Katz (2005) report (see their Table 3, p.50) the “top ten” occupations of Mexican migrants in the U.S. As they note (p.10) “low-skill occupations as laborers, farm laborers, gardeners and cooks, dominate the occupational distribution of Mexican immigrants.” It is shown below that this is also the case for Palestinian migrant workers in Israel.
were negatively selected on experience and education. The estimates with respect to unobservables lead to another conclusion. They uncover moments of the latent skill distributions in the local and host economies, conditional on the afore-mentioned observed skills, that are very reasonable: unobserved skills across the two economies are very weakly correlated and the home distribution is more dispersed. This structure is to be expected given that migrant work in the host economy is concentrated in low-skill occupational tasks, while in the local economy occupations are more varied and also include relatively high-skilled tasks. Therefore, for reasons to be elaborated below, in terms of these conditional unobservables, migrant workers are positively selected.

The paper makes the following three contributions:

First, it identifies the self-selection patterns of migrant workers. As discussed, it differentiates between selection on observables and on unobservables. The availability of consistent data on migrants and stayers places this analysis on more solid footing relative to the existing literature on the self-selection of migrants.

Second, the results show the implications of sorting via self-selection for wages. In particular, selection on unobservables is found to be positive and to generate a wage premium. Findings from other studies are reviewed and it is shown that these empirical results are in fact similar. This new interpretation is due to the fact that the paper directly estimates the relevant second moments of the unobserved skill distribution, which are crucial for determining self selection patterns.

Third, it quantifies wage determination in a developing economy, including the earnings of its migrant workers. The paper uncovers an aggregation bias: using aggregate, rather than sectorial data, gives a misleading characterization of skill returns. This point may have implications for the issue of job outsourcing to other economies, which has recently aroused much interest.

The paper proceeds as follows: Section 2 presents the model and delineates the types of self-selection processes involved. In particular, it defines the role of observable skill premia and the role of the unobservable skills distributions in dictating self-selection. Section 3 discusses the modelling of Palestinian workers as migrants. Section 4 presents the data and the econometric methodology, including identification and specification issues. It then reports the results. The essential contributions are provided in the subsequent sections: Section 5 discusses the implications of the results for selection patterns both in terms of observables and in terms of unobservables.
These include issues such as the migration premium, returns to observed skills, and the non-hierarchical patterns of selection on unobservable skills. Section 6 examines the magnitudes involved in the self selection process (in terms of wages). It decomposes the wage differential between local employment and employment in Israel, highlighting the offsetting effects of the migration premium and skill premia. Section 7 concludes.

2 The Model

The model used is based on the seminal work of Roy (1951) on self-selection. The model has been applied to labor market issues on many occasions, with important first steps being taken by Rosen (1978) and Willis and Rosen (1979). Its application to the migration context has been elaborated by Borjas (1987). An extensive analysis of the empirical content of the model has been provided by Heckman and Honore (1990). Applications to the U.S. economy, as well as theoretical extensions, are presented in Heckman and Sedlacek (1985, 1990), whose notation is followed here.

While this model is well known, the brief discussion here is presented in order to clarify what is being estimated in the empirical work and to indicate how the estimates depict the patterns of migrant self selection. In sub-section 2.1 the basic model is presented [for more elaborate presentations see the afore-cited references]. In sub-section 2.2, alternative possible outcomes of the self-selection process are examined.

2.1 Self-Selection

There are two market sectors $i(= 1, 2)$ in which workers can work. In the current context these are the host (Israel) and source (Palestinian) economies. Agents are free to enter the sector that gives them the highest income but are limited to work in only one sector at a time. Each sector requires a unique sector-specific task $t_i$. Each worker is endowed with a vector of skills $(S)$ which enable him or her to perform sector-specific tasks. The vector $S$ is continuously distributed with density $g(S \mid \Theta)$ where $\Theta$ is a vector of parameters. $t_i(S)$ is a non-negative function that expresses the amount of task a worker with the given skill endowment $S$ can perform and is continuously differentiable in $S$. Note that there is a distinction here between tasks, which are the object of firms’ demand,
and skills, which reflect the endowments of workers. Packages of skills cannot be unbundled, and different skills are used in different tasks, though some skills could be equally productive in all tasks.

Aggregating the micro supply of task to sector $i$ yields:

$$T_i = \int t_i(S) g(S \mid \Theta) dS \quad (1)$$

The output of sector $i$ is given by:

$$Y_i = F^i(T_i, A_i) \quad (2)$$

where $A$ is a vector of non-labor inputs. The production function $F$ is assumed to be twice continuously differentiable and strictly concave in all its arguments. For a given output price $P_i$, the equilibrium price of task $i$ equals the value of the marginal product of a unit of the task in sector $i$. This task price will be denoted by $\pi_i$ and is assumed independent of the skill distribution:

$$\pi_i = P_i \frac{\partial F^i}{\partial T_i} \quad (3)$$

Wages in this set-up are given by:

$$\ln w_i(S) = \ln \pi_i + \ln t_i(S) \quad (4)$$

Additionally, I postulate – to make the model consistent with the data to be examined – that the individual has travel costs to work. These depend on a vector of variables related to location, to be denoted $L$, and are formulated as a fraction $k_i(L)$ of wages (so as to make their units of measure be in wage terms):

$$\text{travel costs} = k_i(L) w_i$$

I discuss these variables in the empirical work below.

An income-maximizing individual chooses the sector $i$ that satisfies:

$$w_i(1 - k_i(L)) > w_j(1 - k_j(L)) \quad (5)$$
Hence:

\[ \pi_i t_i(S) [1 - k_i(L)] > \pi_j t_j(S) [1 - k_j(L)] \quad i \neq j; i, j = 1, 2 \quad (6) \]

Further analysis requires the adoption of specific functional forms for the density of skills \( g \) and the function mapping skills to tasks \( t \). Roy (1951) assumed that these are such that the tasks are log-normal i.e. \((\ln t_1, \ln t_2)\) have a mean \((\mu_1, \mu_2)\) and co-variance matrix \( \Sigma \) (with elements denoted by \( \sigma_{ij} \)). Denoting a zero-mean, normal vector by \((u_1, u_2)\) the workers choose between two wages:

\[
\ln w_1 = \ln \pi_1 + \mu_1 + u_1 \\
\ln w_2 = \ln \pi_2 + \mu_2 + u_2
\]  

(7)

If \( \ln w_1 + \ln [1 - k_1(L)] > \ln w_2 + \ln [1 - k_2(L)] \), the worker enters sector 1. If the converse is true, the worker enters sector 2.

With these functional specifications the proportion of workers in sector \( i \) is given by:

\[
pr(i) = P(\ln w_i + \ln [1 - k_i(L)] > \ln w_j + \ln [1 - k_j(L)]) = \Phi(c_i)
\]

(8)

\[
i \neq j; i, j = 1, 2
\]

where \( \Phi(\cdot) \) is the cdf of a standard normal variable and

\[
c_i = \frac{\ln \frac{\pi_i}{\pi_j} + \ln \frac{[1 - k_i(L)]}{[1 - k_j(L)]} + \mu_i - \mu_j}{\sigma^*}, \quad i \neq j
\]

(9)

\[
\sigma^* = \sqrt{\text{var}(u_i - u_j)}
\]

The proportion of workers in sector \( i \) will increase as the task price \( \pi_i \) in that sector gets relatively higher, as relative travel costs for the sector \( k_i(L) \) decline, or as the mean of the task \( \mu_i \) gets relatively bigger. In addition it depends on the variance and co-variance terms in \( \Sigma \) via \( \sigma^* \).

\[ 4 \text{The following equations are based on the properties of incidentally truncated bivariate normal distributions.}\]
## 2.2 Patterns of Self-Selection

Post-selection the *conditional* mean and variance of the sectorial wage distribution can be characterized; note that these will also characterize the *observed* distribution if the model holds true:

\[
E(\ln w_i | \ln w_i + \ln [1 - k_i(L)] > \ln w_j + \ln [1 - k_j(L)]) = \ln \pi_i + \mu_i + \frac{\sigma_{ii} - \sigma_{ij}}{\sigma^*} \lambda(c_i) \tag{10}
\]

\[
\text{var}(\ln w_i | \ln w_i + \ln [1 - k_i(L)] > \ln w_j + \ln [1 - k_j(L)]) = \sigma_{ii} \left\{ \rho_i^2 [1 - c_i \lambda(c_i) - \lambda^2(c_i)] + (1 - \rho_i^2) \right\} \tag{11}
\]

where:

\[
\rho_i = \text{correl}(u_i, u_i - u_j), \quad i \neq j; \quad i, j = 1, 2
\]

\[
\lambda(c_i) = \frac{\phi(c_i)}{\Phi(c_i)}
\]

with \( \phi(\cdot) \) denoting the density of a standard normal variable.\(^5\)

This set-up provides for a rich set of outcomes. The focus here is on issues that will be relevant for the empirical work below. The discussion which follows refers to equations (10)-(11), i.e., to the two moments of the conditional log-normal wage distribution.

It is possible to classify the selection outcomes in terms of the relations between the elements

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\(^5\) The term \( \lambda(c) \), denoted the inverse of “Mill's ratio” or the hazard rate in reliability theory, has the following properties, sub-scripts denoting partial derivatives:

\[
\lambda(c) \geq 0
\]

\[
\lambda_c < 0 \quad \lambda_{cc} > 0
\]

\[
\lim_{c \to -\infty} \lambda(c) = 0 \quad \lim_{c \to -\infty} \lambda(c) = \infty
\]
of \( \Sigma: \sigma_{11}, \sigma_{22} \) and \( \sigma_{12} \) or alternatively between \( \sqrt{\sigma_{22}/\sigma_{11}} \) and \( \rho_{12} = \frac{\sigma_{12}}{\sqrt{\sigma_{11}\sigma_{22}}}. \) Assuming, without loss of generality, that \( \sigma_{22} \geq \sigma_{11}, \) the different outcomes depend on the relation between the ratio of the standard deviation in each sector \( \sqrt{\sigma_{11}/\sigma_{22}} \) and the correlation between the two sectorial distributions \( \rho_{12}. \)

Three cases are possible (remarking that \( \rho_{12} \) is bounded from above by \( 1 \leq \frac{\sqrt{\sigma_{22}}}{\sqrt{\sigma_{11}}} \)):

(i) The correlation between the sectors is positive and relatively high, i.e., \( \rho_{12} \geq \frac{\sqrt{\sigma_{11}}}{\sqrt{\sigma_{22}}}. \) In this case the term \( \frac{\sigma_{ii} - \sigma_{ij}}{\sigma^*} \) in equation (10) is positive for sector 2 and negative for sector 1. Thus the conditional mean in sector 2 (sector 1) is higher (lower) than the unconditional mean, \( \ln \pi + \mu_i \) (note that \( \lambda(c_i) \) is positive). Selection is positive in sector 2 and negative in sector 1. Note that the Roy model cannot have negative selection in the two sectors (as \( \sigma_{11} + \sigma_{22} - 2\sigma_{12} \geq 0 \)). Because of the high correlation, this is a comparative advantage case rather than absolute advantage, i.e., workers who do well in a certain sector may still select the other one and workers may select a sector that they do badly in.

(ii) The correlation between the sectors is negative, i.e., \( \rho_{12} < 0. \) In this case the term \( \frac{\sigma_{ii} - \sigma_{ij}}{\sigma^*} \) in equation (10) is positive for each sector so the conditional mean in each sector is higher than the unconditional mean. This is a case of positive selection in the two sectors or of absolute advantage – each sector tends to be filled with the workers that perform best in the sector.

(iii) The correlation between the sectors is positive but relatively low, i.e., \( 0 \leq \rho_{12} < \frac{\sqrt{\sigma_{11}}}{\sqrt{\sigma_{22}}}. \) In this case too the term \( \frac{\sigma_{ii} - \sigma_{ij}}{\sigma^*} \) in equation (10) is positive for both sectors, and in each sector there is positive selection, though it is once more comparative and not absolute advantage which dictates selection. Note that this case includes \( \rho_{12} = 0, \) i.e., the endowment of tasks are uncorrelated.

One can interpret this set-up as follows: when the correlation \( \rho_{12} \) is negative, workers self-select in terms of absolute advantage, i.e., they go to the sector suited for their skills. When the

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\( ^6 \) Note the following definitions which will appear below:

\[
\begin{align*}
\rho_1 &= \frac{\sigma_{11} - \sigma_{12}}{\sqrt{\sigma_{11}\sigma^*}} \\
\rho_2 &= \frac{\sigma_{22} - \sigma_{12}}{\sqrt{\sigma_{22}\sigma^*}} \\
\rho_{12} &= \frac{\sigma_{12}}{\sqrt{\sigma_{11}\sigma_{22}}} 
\end{align*}
\]
correlation is positive, then comparative advantage applies. The latter case breaks down into two sub-cases: when the correlation is moderate, self-selection induces positive selection effects in the two sectors via worker sorting by comparative advantage. When the correlation is sufficiently high, some workers will work in a sector which is not well suited for them; hence there will be a negative selection effect for those workers. Case (i) would be more likely to occur than the other two, the lower is the variance in sector 1 \( (\sigma_{11}) \) or the higher is the co-variance between the sectors \( (\sigma_{12}) \).

Note that task prices and mean abilities operate through \( c \) and \( \lambda(c) \). They do not determine the afore cited selection patterns but they do affect the magnitude of selection.

Borjas (1987) offered a classification of the afore-cited outcomes in terms of immigration selection patterns:

a. Positive selection of immigrants – when the host economy has greater wage inequality (i.e., the higher \( \sigma_{ii} \)) and the correlation between economies \( (\rho_{12}) \) is relatively high, then the “best” workers leave the home economy and perform well in the host economy (i.e., negative selection at home and positive selection of migrants going to the host economy).

b. Negative selection of immigrants – when the home economy has the greater wage inequality and \( \rho_{12} \) is relatively high then the immigrants come from the lower tail of the home distribution and these immigrants do not perform well in the host economy (i.e., positive selection at home and negative selection of migrants going to the host economy).

Both these cases correspond to the one classified as (i) above, each case defining sector 1 and sector 2 differently. The key point here is that it matters which economy has the bigger wage inequality.

c. ‘Refugee sorting’ – the correlation is relatively low so the host economy draws below average immigrants but they do well in the (host) economy. These are cases (ii) and (iii) above with positive selection in each sector.

3 Palestinian Workers as Migrants

In the empirical work, I use data on Palestinian males working in the local economy and in Israel. A natural question that arises is to what extent can Palestinian workers be considered migrants. This section addresses the issue, providing some empirical details.
The West Bank and the Gaza Strip — the constituents of the Palestinian economy — are occupied by Israel since June 1967. There is a substantial difference in the degree of development between the economies: in the sample period, GDP per capita in the Palestinian economy was 16% of the Israeli figure. Men constitute the bulk of the Palestinian labor force. Labor force participation rates for men aged 14 and above were about 70%, while women had low participation rates, 7% on average.\footnote{For more details on this labor market, see Angrist (1996). For an analysis of the Israeli labor market see Yashiv (2000).}

In 1968 Palestinian workers started to flow to employment in Israel and the labor market turned out to be the major link between the two economies. The share of salaried employees employed in Israel started off at 22% in 1970, climbed to around 50% three years later, and then fluctuated between 49% and 61%, starting to fall off in the late 1980s. Hence, a key employment decision of the Palestinian male worker was the choice of employment location — Israel or the local economy. This location decision bears much similarity to the decision faced by low-skilled migrants elsewhere. The difference is also clear: the Palestinian worker faced travel costs rather than migration costs. But in other respects — such as language proficiency, knowledge of labor market practices, skill adaptability, etc. — Palestinian employment in Israel was akin to migrant employment.\footnote{See Dustmann (1999) for a discussion of immigrants whose duration in the host country is limited.}

This classification is further evidenced by the substitution that took place in migrant employment in Israel in the course of the 1990s.\footnote{For accounts of migration to Israel see Friedberg (2001) and Cohen and Eckstein (2004).} In 1990, Palestinian workers constituted 8.8% of business sector employment in Israel, while only 0.1% were non-Palestinians. Since then — for reasons elaborated below — the Palestinian share has fallen, reaching a low of 1.5% in 2002; concurrently the share of non-Palestinian migrant workers, coming from Eastern Europe, East Asia and West Africa, rose, reaching 12.6% in 2002 [Bank of Israel (2003, page 141)]. The non-Palestinian migrant workers — all of them low-skilled — entered the same industries in which the Palestinians had previously worked. This substitution is evident also at the micro level: in the construction sector, which is a major industry for migrant workers in Israel, Palestinians constituted 43% of employment in 1992 with no other migrant workers; by 1996 the Palestinian share fell to 12% while...
the non-Palestinian share stood at 26%; these new migrant workers were employed in the same occupations as the Palestinians within the industry [Amir (1999)].

Beginning in December 1987 the labor links between the Israeli and the Palestinian economies underwent a series of severe shocks: at the latter date a popular uprising (the first ‘intifada’) broke out against the occupation, leading to strikes, curfews and new security regulations, such as occasional closures of the territories. In 1993, following peace negotiations, the Oslo accords were signed, giving the Palestinians autonomous control over parts of the West Bank and the Gaza Strip. In September 2000 a second uprising broke out, with even greater ensuing turbulence. Following the August 2005 Israeli withdrawal from the Gaza Strip there have been more violent confrontations. Consequently Palestinian employment in Israel since the end of 1987 was much more volatile and, generally, on a declining trend. In this paper I use data on Palestinian workers from 1987, a period of high Palestinian labor market involvement in Israel, pre-dating the events cited above. I elaborate more on the sample period choice and on the data properties in the next section.

In order to place the Palestinian migrant workers in broader context, it is useful to note three key facts on migrant workers in developed economies:

(i) **The share of foreign residents in developed economies has generally increased in the post-war period and in particular in the 1990s.** Zlotnik (1998, Table 1) reports that foreign-born population as a share of total population in developed countries has increased from 3.1% in 1965 to 4.5% in 1990. In Western Europe the rise in that period was from 3.6% to 6.1%; in Northern America from 6.0% to 8.6%. From 1988 to 1998 the share of foreign or foreign born population in 20 OECD economies (OECD (2001, Table 2)) has further risen from 5.7% to 6.9%.

(ii) **Migration into developed economies has seen a big increase in the share of migrants from developing economies.** Zlotnik (1998, Tables 3 and 4) reports that the share of migrants from developing economies in the total migration annual flow, going from the 1960s to the 1990s, has risen from 42% to 80% in the U.S.,\(^{10}\) from 12% to 78% in Canada, from 25% to 31% in Germany, and from 46% to 79% in the Netherlands.

(iii) **The share of low-skill migrant workers in developed economies is substantial.** OECD

\(^{10}\)Specifically in the U.S. almost 48% of immigrants came from Hispanic countries in the period 1991-1999 compared to less than 25% in 1951-1960 [see INS (1999, Table 2)].
(2003, page 45) reports that the percentage of the population with lower secondary education is typically higher among foreigners than among natives; thus, for example, it is 30.1% among foreigners in the U.S. as compared to 9.3% among natives (in 2000-2001); the numbers for France are 66.7% vs 34.9%, for Germany 48.5% vs 15.1%, and for the U.K. 30.1% vs. 18.8%.

Palestinian employment in Israel can be seen as a case of phenomena (ii) and (iii): low skill migrant workers (as shown below) from a developing economy working in a developed one.

4 Data, Methodology, and Results

In this section I estimate the selection and wage equations for Palestinians working in Israel and East Jerusalem as one sector and working locally (in the West Bank and Gaza) as the other sector. In what follows I discuss the data (4.1), the econometric methodology (4.2), and identification and specification issues (4.3). I then report the results (4.4). The analysis and interpretation are left to the subsequent sections.

4.1 The Data

The data are taken from the Territories Labor Force Survey (TLFS) conducted by the Israeli Central Bureau of Statistics [see the CBS annual report; for detailed descriptions of this data set, see CBS (1996) and Angrist (1996)].\textsuperscript{11} Its principles are similar to the Israeli Labor Force Survey done by the CBS, which is akin to other such surveys, such as the U.S. Current Population Survey. The survey used a 1967 CBS-conducted Census as the sampling frame, with a major update in 1987. It was conducted quarterly and included 6,500 households in the West Bank and 2,000 in Gaza, surveyed by local Palestinian enumerators employed by the Israeli Civil Administration in the Territories. The TLFS included questions on demographics, schooling and labor market experience.

In this paper I use observations on Palestinian men\textsuperscript{12} aged 18-64 from the TLFS in the year 1987. This year represents the time of highest data quality (following the sample frame revision) and, as mentioned, a high share of Palestinian employment in Israel. It was the last one before the

\textsuperscript{11}I am grateful to Joshua Angrist for the use of his processed version of the TLFS data set.

\textsuperscript{12}As mentioned, women had very low participation rates, and when working in the market economy, did so locally, not in Israel.
uprising and the ensuing turbulence.

Table 1 presents sample statistics for the variables used in the empirical analysis.

**Table 1**

The table shows that, on average, local workers (stayers) earned lower wages and were more educated and more experienced than workers in Israel (migrants). Average schooling levels are consistent with the features of a developing economy. Decomposing each group into types of residence, it can be seen that rural residence was the main type for migrants. For stayers, rural and urban residence had similar employment shares. I provide further information on the employment characteristics (industries and occupations) of these workers and on workers skill levels, when discussing the relevant estimation results below.

4.2 Econometric Methodology

Estimation of equations (7) for workers employed locally and employed in Israel will yield estimates of all the key elements of the model, i.e., $\ln \pi_i, \mu_i$ and the elements of $\Sigma$. To do that the following procedure is used:

(i) I posit that $\ln t_i = c_i S$ where $S$ is decomposed into observed and unobserved variables $S_o$ and $S_u$, and $c_i$ their associated coefficients, are $c_{io}$ and $c_{iu}$, respectively. Thus equations (7) become:

$$
\ln w_i = \ln \pi_i + \beta_i X + u_i, \quad i = 1, 2
$$

(12)

where $\beta_i = c_{io}, X = S_o$ and $c_{iu} S_u = u_i$.

(ii) When estimating (12), I take into account sample selection, which is inherent in the model. Thus define the variable $z^*$:

$$
z^* = \ln w_1 + \ln (1 - k_1(L)) - \ln w_2 - \ln (1 - k_2(L))
$$

(13)

$$
= \ln \pi_1 + \ln(1 - k_1(L)) + \ln (1 - k_2(L)) + \beta_1 X - \beta_2 X + u_1 - u_2
$$

and the indicator variable $z$:
\[ z = 1 \text{ if } z^* > 0 \]  
\[ z = 0 \text{ otherwise} \]  

According to the model one observes \( \ln w_1 \) only if \( z^* > 0 \) i.e., when \( z = 1 \). Paralleling (8) we have:

\[
\begin{align*}
\Pr(z = 1) &= \Phi(\ln \frac{\pi_1}{\pi_2} + \ln (1 - k_1(L)) + \beta_1 X - \beta_2 X + u_1 - u_2) \\
\Pr(z = 0) &= 1 - \Phi(\ln \frac{\pi_1}{\pi_2} + \ln (1 - k_1(L)) + \beta_1 X - \beta_2 X + u_1 - u_2)
\end{align*}
\]  

Based on equations (10) - (11) we know that the observed \( \ln w_1 \) is thus given by:

\[
\ln w_1 \mid (z = 1) = \ln \pi_1 + \beta_1 X + \frac{\sigma_{11} - \sigma_{12}}{\sigma^*} \lambda(c_1) + u_1
\]  

This may also be written as follows:

\[
\ln w_1 \mid (z = 1) = \ln \pi_1 + \beta_1 X + \rho_1 \sqrt{\sigma_{11}} \lambda(c_1) + u_1
\]  

A similar equation holds true for the other sector. Note that while the \( X \) vector appears in both (15) and (17), the \( L \) vector appears only in the selection equation (15).

I estimate the model using Full Maximum Likelihood. Following Heckman (1979) one can interpret the selection bias in (12) as an omitted variable bias. If \( \lambda(c_i) \) is not included in the equation, the estimates of the vector of coefficients \( \beta_i \) may be biased. The intuition is as follows: not including \( \lambda(c_i) \) as a regressor ignores the influence of all the variables in question on the dependent variable – which is the conditional wage – through the self-selection process. This influence comes in addition to the direct effect expressed by \( \beta_i \). Thus the uncorrected OLS estimate does not take into account the co-variation between the variable \( x_k \) in question (education, for example) and the selectivity variable \( \lambda \). The sign of the bias depends on the effect of \( x_k \) on selection and on the effect of selectivity on the dependent variable, i.e., on wages in this case. The following equation expresses this bias formally. For any variable \( x_k \) in \( X \):
\[
\frac{\partial E(\ln w_i \mid z = 1)}{\partial x_k} = \beta_{ik} + \left[ \frac{\sigma_{ii} - \sigma_{ij}}{\sigma^*} \right] \frac{\partial \lambda}{\partial c_i} \frac{\partial c_i}{\partial x_k}
\]  

(18)

There are three components to the selectivity bias term (the second term on the RHS):

(i) \[ \frac{\sigma_{ii} - \sigma_{ij}}{\sigma^*} \] — this is the term determining the type of selection taking place (based on unobservables) as discussed above. Note that it can be negative (in one sector of case i above) or positive (the other sector of case i and in cases ii and iii). This term expresses the effect of selectivity on wages.

(ii) \( \frac{\partial \lambda}{\partial c_i} < 0 \) — this negative term expresses the relation between the selectivity regressor \( \lambda \) and the proportion \( c_i \) of the workers in the sector or the probability that an observation be included in the sample; as this proportion (or probability) increases, the bias diminishes.

(iii) \( \frac{\partial c_i}{\partial x_k} \) — this term expresses the influence of the variable in question on selection. Note that \( \Pr(z = 1) = \Phi(\sigma^* c_i) \). Thus the sign of this component is determined by estimates of the selection equations (15).

The sign of the bias depends on the type of selection process (point i) and on the direction of influence of the relevant variable on the sectorial selection (point iii). The magnitude depends on these factors as well as on the \( \frac{\partial \lambda}{\partial c_i} \) term.

4.3 Identification and Specification

The identification problems of selection models have been much explored. Moffitt (1999) offers a discussion of the key issues and their possible resolution. The prevalent method is the use of exclusion restrictions. The way the model here can be estimated using exclusion restrictions is by postulating variables that affect travel costs, and hence selection, but not wages. Three such variables in this data set that would be plausible are:

(i) Geographical regions or localities. This is a useful measure of the determinants of travel costs because workers are located in different distances from the locations of employers and therefore face different costs in terms of travel time and the actual payment for travel.

(ii) Type of residence. The type of residence variable includes rural areas, urban areas, and refugee camps. These may serve to indicate travel costs as rural residents are likely to be more

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13 The results of the selection equations (19) reported below demonstrate that these variables are indeed significant.
spread out and refugee camps residents are likely to be more concentrated. In camps there are likely to be organized, common means of transport.

(iii) Marital status. This variable is not directly related to travel costs but may serve to indicate costs that pertain to the economic life of the household; for example, a migrant worker has less time to engage in home production or to take care of the children, and so working in Israel is more costly for a married worker as opposed to an unmarried person.

The data sample does not contain other variables relating to the household that could provide additional exclusion restrictions. Hence, for the travel cost function \( k_i(L) \), included in the selection equation only, I postulate the following:

\[
k_i(L) = \sum_p \theta_p \cdot l_p^i + \sum_n \gamma_n Y_n^i
\]

where \( l \) is the region of the worker’s residence, \( p \) is an index of regions, \( \theta_p \) is a coefficient to be estimated; the \( Y_n \) variables are additional variables affecting travel costs and \( \gamma_n \) are their coefficients to be estimated; as before, sector \( i \) indicates the local or host economy. The \( \theta \)s and the \( \gamma \)s are estimated in the selection equations (15). The \( l_p \) variables are the dummy variables for geographical regions or localities discussed above. The \( Y_n \) variables are the type of residence and martial status variables. Summary statistics of these variables appear in Table 1 above.

For the task function variables \( X \), included in both the selection and wage equations, I use education and a linear-quadratic formulation for experience\(^{14}\). I also use indicator variables for the quarters within 1987, which I do not report.

Approximating I get:

\[
\ln(1 - k_i(L)) = \ln(1 - \sum_p \theta_p \cdot l_p^i + \sum_n \gamma_n Y_n^i)
\]

\[
\approx - \sum_p \theta_p \cdot l_p^i - \sum_n \gamma_n Y_n^i
\]

The selection equations are thus:

\(^{14}\)Experience being defined as age minus education minus 5.
Pr(\(z = 1\)) = \Phi(\ln \pi_1/\pi_2 + \sum_p \theta_p \cdot t_{p}^2 - \sum_p \theta_p \cdot t_{p}^1 + \sum_n \gamma_n Y_n^2 - \sum_n \gamma_n Y_n^1 + \beta_1 X - \beta_2 X + u_1 - u_2)(19)

Pr(\(z = 0\)) = 1 - \Phi(\ln \pi_1/\pi_2 + \sum_p \theta_p \cdot t_{p}^2 - \sum_p \theta_p \cdot t_{p}^1 + \sum_n \gamma_n Y_n^2 - \sum_n \gamma_n Y_n^1 + \beta_1 X - \beta_2 X + u_1 - u_2)

The estimated wage equation is the following:

\[
\ln w_i \mid \text{sector } i = \ln \pi_i + \beta_0 + \beta_1 \text{educ} + \beta_2 \text{exp} + \beta_2 \text{exp}^2 + \sum_{m=2}^4 \gamma_m Q_m + \left[\frac{\sigma_{ii} - \sigma_{ij}}{\sigma^*}\right] \lambda(c_i) + u_i
\]

where \(i, j\) denote sectors, \(Q\) is an indicator variable for the quarter, and \(m\) denotes the quarter number. The dependent variable in the wage equation is the log of real hourly wages (\(\ln w_i\)), defined as the nominal monthly wage divided by hours worked and deflated by the CPI.\(^{15}\) The use of hourly wages is designed to avoid confounding the choice of work place with the choice of work time (hours or days).\(^{16}\) Education (educ) and experience (exp) are defined in years.

The benchmark specification reported below [column (1) of Tables 2 and 3] has no exclusion restrictions. The alternative, specification 2, includes all the variables discussed above contained in \(L\), so there are three exclusion restrictions. Specification (3) uses OLS to test for the effect of selection correction (running only the wage equation).

### 4.4 Results

Tables 2 and 3 report the results. Table 2 reports the estimates of the selection equation and Table 3 reports the estimates of the wage equation for the specifications discussed above. In each case I report the point estimates with standard errors in parentheses; in the wage regressions I also report the implied second moments (\(\rho_i, \sigma_{ii}\) and \(\rho_{12}\)), and two test statistics: the Wald test and the \(\rho_i = 0\) test (both using \(\chi^2\) test statistics, with P-values in parentheses).

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\(^{15}\) Real, rather than nominal, wages are used as inflation was relatively high (16.1%) in the course of 1987.

\(^{16}\) I delete observations of nominal hourly wages less than 0.1 NIS and higher than 11.5 NIS. These are the lowest 1% and highest 0.2% of the wage distribution. For these observations wages are either extremely low or unreasonably high, indicating that they are either measured with error or that they reflect very few hours of monthly work. A similar procedure was employed by Heckman and Sedlacek (1985).
Tables 2 and 3

The following results emerge:

(i) Migration selection is negatively related to education, experience, refugee camp and urban residence, and is positively related to being married.

(ii) The constant of the equation is substantially higher in Israel.

(iii) While education and experience premia are fairly standard in local employment, they are very low in Israel employment. Consistent with this finding are the afore-cited selection equation results, whereby education and experience decrease the probability of choosing employment in Israel.

(iv) Estimates of the second moments indicate higher variance of the local unobserved skills distribution. The ratio of standard deviations $\sqrt{\sigma_{israel}} / \sqrt{\sigma_{local}}$ is around 0.85.

(v) The correlation between the unobserved skill distributions is close to zero and is much lower than the ratio of standard deviations, i.e., $\rho_{israel,local} < \frac{\sqrt{\sigma_{israel}}}{\sqrt{\sigma_{local}}}$.

(vi) While the point estimates are similar across columns 1 and 2, the use of exclusion restrictions in column 2 substantially lowers the standard errors of the estimates.

I turn now to examine the implications of these results. In what follows I use the results of column (1) of Tables 2 and 3 as the benchmark results (but column 2 delivers essentially the same implications).

5 Selection Patterns

In this section I examine the implications of the results reported in Tables 2 and 3. First, I look at the premia: the constants of the wage equation, reflecting the baseline wage differential (‘migration premium’), and the premia to education and experience (5.1). Then I look at the estimates of the elements of the $\Sigma$ matrix and discuss the implications with respect to selection patterns (5.2).

5.1 Migration Premium and Returns to Observed Skills

The wage equation’s intercept – reflecting the task price $\pi_i$ and the constant $\mu_i$ in the task function – is substantially higher in Israel. Note that this difference in baseline wages, or ‘migration pre-
mium,‘ is much higher than the difference in mean wages between Israel and local employment: the difference in the constant of the equation between Israel and local employment is 0.58 log points while the difference in average wages is 0.08 log points (both in terms of log real hourly wage). I analyze this difference in more detail in sub-section 6.1 below.

The following picture emerges with respect to the skill premia:

(i) Locally, the schooling premium is around 4%; in Israel it is estimated to be about 1%.
(ii) Locally the experience premia profile of earnings has the familiar hump-shape while in Israel it is relatively flat and low.

Figure 1 illustrates these results.

\textbf{Figure 1}

Thus while local premia for education and experience behave in a standard way, employment in Israel offers low rewards for these attributes. Less educated and less experienced workers therefore chose to work in Israel; those with better skills chose to work locally and were compensated for the baseline wage differential by the local returns given to their skills. This represents negative selection on observed skills.

This sorting pattern, implied by the results of estimation, is borne out by the actual, observed locational distributions by education and age. Table 1 above has presented key moments for education and experience. The following table offers additional evidence by describing the distribution of workers across work locations by education and age:

\textbf{Table 4}

The table confirms that it is indeed the less educated and younger workers who worked relatively more in Israel. Locally, mean schooling and age are higher. Particularly striking are the results for the high schooling group, where the share of workers is substantially higher in local employment.

There are a number of implications to these patterns:

First, the returns to the same skills differ markedly for migrant and stayers. The local economy rewarded education and experience substantially more. This phenomenon can be explained
by looking more closely at the types of jobs in each economy. Table 5 shows the distribution of employment across industries and occupations.

Table 5

Local employment was characterized by industries and occupations that presumably require the performance of more complex tasks. In particular, government, personal, and financial services are about 40% of local employment. In contrast, in Israel employment was highly concentrated (over 80%) in three industries – construction, manufacturing and agriculture. In terms of occupations, 21% of local workers were employed in high-skilled occupations (the top three in the table) vs. 2% in such occupations in Israel. Hence it is not surprising that local employment offered higher rewards for education and experience.

Second, the very low returns to schooling in the Israeli economy are consistent with the findings of Borjas (1995), whereby schooling acquired in the source country has lower value than schooling acquired in the host country. The low returns to experience are consistent with the results of Dustmann and Meghir (2005), who studied returns to experience (on several dimensions) for young German workers. They found that much of the return to unskilled workers is due to such workers finding good matches and remaining with them. The case of unskilled Palestinians in Israel is likely to violate both requirements – there is no search process for good matches and the employment relationship is not of long duration.

Third, the results imply that aggregation in these circumstances produces a misleading picture. Running regular OLS regressions for the entire Palestinian labor market, including both local workers and migrant workers in Israel, yields a return to education of 3.5% in the aggregate economy. According to the selectivity corrected estimates reported in Table 3 these were around 4% locally and 1% in Israel. The return to experience, evaluated at the mean experience level, is 0.35 overall in the simple aggregate OLS regressions. Using the corrected regressions of Table 3 it is 0.36 locally and 0.17 in the Israeli economy. Thus simple OLS regressions of the entire economy obscure the diversity of returns. The corrected regressions yields estimates that are higher for workers employed in the local economy and much lower for workers in the host (Israeli) economy.

How important is the selection bias for the coefficient estimates? Table 3 has reported the
education and experience coefficients for the wage equations using OLS not corrected for sample selection bias (column 3), which can be compared to the coefficients of the corrected equation (column 1 or 2). There is a certain downward bias for the local economy and a certain upward bias for the Israeli economy. This is consistent with the afore-cited selection patterns. In terms of equation (18) the term $\frac{\partial c_i}{\partial x_k}$ is positive locally, negative in Israel. Hence, experience and education premia are overstated in the Israeli economy and understated in the local economy if one does not control for selection bias. As a result, the difference between migrants and stayers is understated in the uncorrected regressions. This is akin to the underestimation of the college premium when the two sectors are college graduates and high-school graduates and when selection is positive in each sector (see Willis and Rosen (1979)). Note that this coefficient bias is given by

$$\frac{\sigma_{ii} - \sigma_{ij}}{\sigma_{*}} \frac{\partial \lambda}{\partial c_i} \frac{\partial c_i}{\partial x_k}$$

[see equation (18)], and is not to be confused with the mean wage premium due to selection, given by $\frac{\sigma_{ii} - \sigma_{ij}}{\sigma_{*}} \lambda(c_i)$ [see equation (10)].

5.2 Self-Selection and the Unobserved Skills Distributions

Tables 2 and 3 above report estimates of the unobserved skills variance-co-variance matrix ($\Sigma$). These allow for the analysis of the self-selection process. As discussed in sub-section 2.2. above, a key issue is the relationship between the correlation of the unobserved skill distributions in the two sectors ($\rho_{12}$) and the relative skill standard deviations $\sqrt{\sigma_{11}/\sigma_{22}}$. The results indicate that:

(i) The correlation $\rho_{\text{israel,local}}$ is around zero. It is much lower than the ratio of standard deviations $\sqrt{\sigma_{\text{israel}}/\sigma_{\text{local}}}$.

(ii) The variance in local employment is higher than that of employment in Israel ($\sigma_{\text{local}} > \sigma_{\text{israel}}$).

These results are reasonable: the low correlation is probably due to the fact that local and Israeli occupational tasks differed, as discussed above. In particular, government employment was predominant locally and required very different skills than those needed for the occupations that dominated employment in Israel – construction, manufacturing and agriculture. The latter require skills that are less dispersed than those in the more high-skilled occupations of local employment – an “anybody can do it” effect – hence the lower variance in Israel employment.

As a consequence selection was positive in each sector. This corresponds to case (ii) dis-
discussed in sub-section 2.2 above, with positive selection. It constitutes a “refugee sorting” case in the Borjas (1987) terminology.

Willis and Rosen (1979) discuss the nature of the correlation $\rho_{12}$. They point out that there is a difference between a one-dimensional approach, whereby skills reflect one factor such as IQ, and a multi-dimensional approach, whereby there are different abilities that have differential importance in different tasks. Examples would be strength, agility, dexterity, creativity, intelligence, visual acuity, etc. They define case (i), discussed in sub-section 2.2 above, as “hierarchical sorting” – those in the high-wage sector are drawn from the upper portion of the potential earnings distribution while those in the low-wage sector are drawn from the lower portion of the potential earnings distribution, and cases (ii) and (iii) as “non-hierarchical sorting.” These terms relate to Roy’s (1951) notion of a hierarchy of occupations that is affected by the ability variances. They examine the earnings of U.S. college graduates vs. high-school graduates and find positive selection in both groups. They interpret this result as a rejection of the one factor model for skills and of the ability bias findings in previous literature. Instead, they argue that the results point to a multiple factor model and non-hierarchical sorting via self-selection. This interpretation is reinforced by the recent findings of Heckman, Stixrud, and Urzua (2006), who show that non-cognitive skills are as important as cognitive skills for labor market outcomes. More specifically, they mention skills like dependability, persistence, consistency, industriousness, and perseverance as important in certain occupations, particularly in blue-collar jobs.

I get similar results. The similarity of the Willis and Rosen findings and the results here pertains not only to the finding of positive self-selection in both sectors, but also to the identity of the sectors in terms of the type of jobs offered. One sector – in their case the college graduate jobs sector, here the local one – offers jobs that require relatively high education. The other sector – high school graduate jobs in their case, employment in Israel here – offers jobs that require relatively low levels of education. Hence, the more educated workers self select in both cases to the former sector and the less educated to the latter sector, implying negative self-selection on observed skills. However, conditional on observed skills, unobserved skills distributions are such that there is positive self-selection.\footnote{Note that the difference found here between self selection on observables (negative) and on unobservables (pos-}

\footnote{Note that the difference found here between self selection on observables (negative) and on unobservables (positive) is explained by the fact that the former is due to the observed skills distribution, while the latter is due to the unobserved skills distribution, which is positively correlated with the observed skills.}
6 Quantifying Self Selection

I turn to look at the magnitudes involved in the processes of self-selection described above. In sub-section 6.1 I look at the components of mean wages in each sector and at the mean wage differential between migrants and stayers. In sub-section 6.2 I offer a diagrammatical exposition of the estimates of the second moments, which are pertinent to the self-selection processes.

6.1 First Moments

I quantify the relative role played by the different elements of the model – task prices, skill premia, skill levels, and selectivity effects. I do so using actual data and the point estimates of column (1) from Table 3.

In panel (a) of Table 6 I report the elements of mean wages in each of the sectors, using the following equations:

\[
\ln w_{\text{local}} = \hat{k}_{\text{local}} + \hat{\beta}_{\text{local}} \bar{X}_{\text{local}} + \hat{p}_{\text{local}} \sqrt{\sigma_{\text{local}}^2} \hat{\lambda}_{\text{local}}
\]

\[
\ln w_{\text{Israel}} = \hat{k}_{\text{Israel}} + \hat{\beta}_{\text{Israel}} \bar{X}_{\text{Israel}} + \hat{p}_{\text{Israel}} \sqrt{\sigma_{\text{Israel}}^2} \hat{\lambda}_{\text{Israel}}
\]

where \(\ln w_{i}\) is the mean log hourly wage in economy \(i\), \(\hat{k}_{i} = \ln \bar{\pi}_0 + \hat{\beta}_0\) for economy \(i\) using the point estimates of the wage equation’s constant, \(\hat{\beta}_i\) is a vector of the point estimates of the coefficients in economy \(i\), \(\bar{X}_i\) is a vector of the mean values of the independent variables in economy \(i\), and \(\hat{p}_i \sqrt{\sigma_{ii}^2} \hat{\lambda}_i\) are the estimates of the second moments times the average of the estimated inverse of Mills’ ratio.

In panel (b) of Table 6 I look at the mean wage differential between migrants and stayers. I follow the methodology proposed by Oaxaca and Ransom (1994) and decompose the mean wage differential between Palestinian workers in the Israeli economy and in the local economy into components: a part due to task prices plus the intercept of the task function (i.e., the constant in the wage equation); a part due to differences in skill premia across the two sectors; a part due to
differences in skill levels across the two sectors; and a part due to differences in selection effects. This is done in two ways, elaborated in the table.

Table 6

The table indicates the following:

a. The average actual difference in wages is 0.08 log points in favor of migrant workers. In terms of observable skills this difference is 0.11 log points \((\hat{k} + \hat{\beta}X)\)

b. What are these differences due to? The reward to skills is substantially higher locally i.e. for stayers; wages are higher by 0.46 log points in terms of observable skills \((\hat{\beta}X)\) and 0.04 log points in terms of the selection premium on unobservable skills. Why, then, are migrant workers wages higher? This is due to a much higher baseline value, reflected in the 0.57 log points difference in the constants of the equation \((\hat{k})\), which can be thought of as a migration premium.

c. The skill premium differential is mostly due to the difference in premia \((\hat{\beta}_{local} - \hat{\beta}_{Israel})\) rather than to the difference in skill levels \((X_{local} - X_{Israel})\).

There are two key results here: one is that the actual mean wage differential (in real hourly wage terms) for Palestinian workers in the two economies is relatively small, only 0.08 log points. The other is that this latter finding masks big disparities: there is a big baseline wage differential in favor of workers employed in the Israeli economy (0.57 log points) offset by all the other terms in the decomposition. The main offset comes from the skill premia differential \((\hat{\beta}_{local} - \hat{\beta}_{Israel})\) in favor of local employment (around 0.45 log points). The offset due to skill levels differences \((X_{local} - X_{Israel})\) or to differences in the (positive) selection effect is much smaller. The key implication is that wage equalization across economies (i.e., the Israeli economy and the local economy, with both cases pertaining to Palestinian workers) is attained through the assignment of workers by the self-selection process. While clear disparities exist between the two economies – the baseline wage differential, or migration premium, and the wage skill premia – they almost cancel out through self-selection.
6.2 Second Moments

To see the role of the second moments in the self-selection process, as well as the role of the first moments, consider the following regression equation:\(^{18}\)

\[
\ln t_2 = \mu_2 + \frac{\sigma_{12}}{\sigma_{11}}(\ln t_1 - \mu_1) + \varepsilon_2
\]

\[
= \left( \mu_2 - \frac{\sigma_{12}}{\sigma_{11}}\mu_1 \right) + \frac{\sigma_{12}}{\sigma_{11}}\ln t_1 + \varepsilon_2
\]

where:

\[
\text{var } \varepsilon_2 = \sigma_{22}\left[1 - \frac{\sigma_{12}^2}{\sigma_{11}\sigma_{22}}\right]
\]

In log tasks (\(\ln t_2 - \ln t_1\)) space this regression is shown in the following figure (based on the discussion in Heckman and Sedlacek (1985, Figures 1 and 2)):

**Figure 2**

To understand the figure note the following elements:

(i) For any given worker, the log task value (\(\ln t_{\text{local}}\)) in the local sector is given by a value on the horizontal axis.

(ii) The regression line gives the linearly predicted log task value in the Israel sector, i.e., predicted \(\ln t_{\text{Israel}}\). It has the intercept given by \(\mu_{\text{Israel}} - \frac{\sigma_{\text{local,Israel}}}{\sigma_{\text{local}}}\mu_{\text{local}}\),\(^{19}\) and the slope given by \(\frac{\sigma_{\text{local,Israel}}}{\sigma_{\text{local}}}\).

Actual values lie along the normal distribution around the regression line, as shown in two places in the figure; note that the distributions plotted relate to the vertical \(\ln t_{\text{Israel}}\) values. The data points are distributed – conditional on the \(\ln t_{\text{local}}\) value – with \(\text{var } \varepsilon_{\text{Israel}}\).

The regression line and the normal distribution are plotted using the point estimates of the parameters and second moments reported in column 1 of Table 3.

\(^{18}\) Derived from multiplying both sides of the equation \(\ln t_1 = \mu_1 + u_1\) by \(\frac{1}{\sigma_{11}}\) and subtracting from \(\ln t_2\).

\(^{19}\) I use the point estimates of the coefficients, and the sample means of the \(X\) variables, to generate \(\mu_{\text{local}}\) and \(\mu_{\text{Israel}}\). I adopt the normalization of \(\beta_0 = 0\).
(iii) The other line in the figure is the 45 degree line serving as the line of equal income 
\(w_{\text{local}} = w_{\text{Israel}}\).\(^{20}\) It starts from a negative intercept as \(\pi_{\text{Israel}} > \pi_{\text{local}}\).

This last line is key for selection: when the worker has a value below this line he chooses the local sector; above it, he chooses to work in Israel. Hence, the fraction of workers choosing to migrate is the part of the normal distribution above the line, while the part below it is the fraction of stayers.

Using the actual estimates from column (1) of Table 3, the figure illustrates the positive selection in each sector.\(^{21}\) Graphically this is seen by noting that when individuals are classified according to their task value, the fraction of people working locally increases as the local task level increases. In other words, as one moves up the \(\ln t_{\text{local}}\) axis, the fraction of workers selecting the local sector rises. A similar graph with \(\ln t_{\text{israel}}\) on the horizontal axis (not shown) would show a similar selection effect in the Israeli economy.

The figure shows the role of the migration premium through the position of the \(w_{\text{local}} = w_{\text{Israel}}\) line, the role of observable skill premia through the intercept term of the regression line, and the role of unobservable skills through the intercept and slope of the regression line and through the variance of the distribution at each point. To see where the role of the second moments comes in, note that with estimates of the first moments but not of the second moments, there is no information on the slope of the regression line, insufficient information on its position, and no information on the variance of the distribution around the line.

Three major features of the actual estimates are manifested in the figure: (i) \(\mu_{\text{Israel}} < \mu_{\text{local}}\) so the intercept of the regression line is relatively low; (ii) \(\frac{\sigma_{\text{local,Israel}}}{\sigma_{\text{local}}}\) is negative so the regression slope is negative; and (iii) \(\pi_{\text{Israel}} > \pi_{\text{local}}\) so the line of equal income starts from below 0. All of these features are reasonable: \(\mu_{\text{Israel}} < \mu_{\text{local}}\) as the host (Israeli) economy has low rewards for skills (education and experience) in the low-skill occupations offered; there is low, negative correlation between the unobserved skills required in these occupations, as discussed above; and

Equal income means \(\ln w_1 = \ln w_2\) or \(\ln \pi_1 + \ln t_1 = \ln \pi_2 + \ln t_2\). Hence it is given by \(\ln t_2 = \ln \pi_1 - \ln \pi_2 + \ln t_1\).

In terms of equation (10) this means that in each sector

\[E(\ln w_i | \{\ln w_i + \ln [1 - k_j(L)] > \ln w_j + \ln [1 - k_j(L)]\}) > E(\ln w_i).\]
the host economy, being richer and presumably more productive, has a higher task price i.e., \( \pi_{Israel} > \pi_{local} \).

One question of interest is to consider how migration would change following changes in the observed skill premia and in the unobserved skills distributions. The model is able to predict the size of migration when key parameters (\( \pi, \mu \)), determining first moments, change. But changes in second moments (\( \sigma_{ii}, \sigma_{ij} \)) lead to ambiguous outcomes, as contradictory effects are at play. These results can be seen in the graphical framework of Figure 2 as follows:

Migration unambiguously rises when:

a. The migration premium rises, i.e., when \( \frac{\pi_{host}}{\pi_{local}} \) rises. The line of equal income shifts downwards. Fewer workers choose the local economy and more migrate.

b. When skill premia in the host economy (\( \mu_{host} \)) rises or skill premia in the local economy (\( \mu_{local} \)) fall. This raises the intercept, shifting the regression line upwards. Now more workers choose foreign employment.

The change in migration is ambiguous when the following changes in the unobserved skills distributions take place:

a. When the local (source economy) distribution becomes more dispersed, i.e., \( \sigma_{local} \) rises, the intercept rises and the slope declines (in absolute value) so the regression line rises and flattens. In addition, the variance of the normal distribution around the line rises. The overall effect is ambiguous.

b. When the co-variance of the skills across the two economies declines, i.e., \( \sigma_{local,host} \) falls, the same happens: the regression line shifts up and flattens and the normal distribution becomes more dispersed. Again, the overall effect is ambiguous.

c. When the host country distribution becomes less dispersed, i.e., \( \sigma_{host} \) falls, the variance of the normal distribution falls. The overall effect is once more ambiguous.

This analysis implies that government policy generates unambiguous migration changes if it affects task prices, for example through taxation. Any policy which affects skills, such as education policy, has more complex outcomes. In particular, policy influencing \( \sum \) has ambiguous migration outcomes.

22 According to (3), higher aggregate productivity \( \frac{\partial F}{\partial T_i} \) implies higher \( \pi_i \).
7 Conclusions

The analysis has depicted a picture of migrant self selection that can shed some light on the ongoing debate about the identity of low-skill migrants. Evidently, the analysis does not pertain to the data sets often considered in this debate, such as data on Mexican migrants in the U.S., and therefore cannot illuminate these migration episodes directly. But it provides a reasonable picture of migrant self-selection based on full estimation of the Borjas (1987) model. As will be further shown below, the findings are consistent with the key facts of other cases of low-skill migration from developing economies to developed ones.

The following pattern has emerged: a substantial baseline wage differential (migration premium) coupled with low skill premia led workers to sort themselves. The relatively highly-skilled workers selected local, more complex tasks, while the low-skilled workers chose to work in Israel, performing relatively simple tasks. There were low returns in the host economy to key observed skills, such as education and experience, probably due to the nature of the job tasks in question. This resulted in negative selection on observed skills. A significant baseline wage differential (migration premium) was in place, due to the host economy being more developed than the source economy, luring migrant workers. In terms of the model this is expressed by a higher task price. This migration premium offset the negative effect of low skill premia. Conditional on observed skills, selection on unobservable skills was positive. This was due to the low correlation between the distributions of these skills in the two economies. The low correlation can be explained by the different nature of occupations in the two economies and by the idea that unobserved skills are multi-dimensional. Hence the different nature of jobs offered to migrants and stayers account for both the observed skill premia patterns and the relationship between the unobserved skill distributions. Taken together, these estimates appear quite reasonable, and are fully consistent with the distributions of education, experience, occupations, and industries of migrants and stayers.\(^2^3\)

Many, if not all, patterns of the data here are in accord with what has been reported else-

\(^{23}\)Another application of the concept of self-selection to questions of immigration was suggested by Berman and Rzakhanov (2000). Their analysis pertains to fertility decisions combined with migration decisions. While this kind of analysis is not empirically relevant here, in a more general context their ideas can serve to strengthen the argument made here about a migration premium.

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where. These include migrants (from developing economies) being employed in low-skill occupations in more developed host economies. Workers migrate as they get higher wages in the host economies than in their source economies. The data set used here permitted the estimation of the relevant second moments determining self-selection. Thus it was able to explain these patterns in a more nuanced way than much of the literature. In particular, the findings suggest that there is negative selection on observed skills but positive selection on unobserved skills (conditional on observed skills). In terms of unobservables and in the formal terminology of the model, both the literature and this paper find that \( \frac{\sigma_{\text{local}}}{\sigma_{\text{host}}} > 1 \). The condition for negative selection is \( \frac{\sigma_{\text{host}}}{\sigma_{\text{local}}} > \rho_{\text{local,host}} \). However, often there is no direct evidence on \( \rho_{\text{local,host}} \). A related problem is the assumption, often made, that in the host economy, natives and migrants have the same task distribution; this may have led to erroneous conclusions (i.e., mostly with respect to \( \rho_{\text{local,host}} \)). The results here\(^\text{24}\) indicate that \( \frac{\sigma_{\text{local}}}{\sigma_{\text{host}}} > \frac{\sigma_{\text{host}}}{\sigma_{\text{local}}} > \rho_{\text{local,host}} \), hence positive self-selection on unobservables. This also implies that uncorrected migrant skill premia are overestimated, a finding which has important implications for the study of the economic performance of immigrants.

The results indicate that one needs to give the appropriate attention to the differential role played by (i) the baseline wage differential (migration premium) due to the difference between developed and developing economies, (ii) selection on observable skills, driven by skill premia differentials, and (iii) selection on unobservable skills, related to the differences in job requirements.

The results also imply that skill premia in the source economy (inclusive of migrant workers) suffer from an aggregation bias. The analysis of wage differentials shows that wage differences between migrants and stayers were substantially narrowed down due to self-selection, by the offsetting effects of the migration premium and skill premia.

The approach implemented and tested in this paper may have wider applications and implications. One example is that it suggests a way of dealing with the increasingly important phenomenon of job outsourcing. The workers choosing to work in such jobs (usually high-skilled) could be characterized by (i) a developed vs. developing country difference, akin to the migration premium; (ii) selection on observable skills; and (iii) selection on unobservable skills.

\(^{24}\)Based on estimates of these second moments.
References


Table 1  
Sample Statistics 1987  

<table>
<thead>
<tr>
<th>variable</th>
<th>Working in the Local Economy</th>
<th>Working in Israel</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>7,053</td>
<td>11,522</td>
</tr>
<tr>
<td>wage (hourly, in logs)</td>
<td>-2.83 (0.39)</td>
<td>-2.75 (0.33)</td>
</tr>
<tr>
<td>education (in years)</td>
<td>8.8 (4.4)</td>
<td>7.7 (3.9)</td>
</tr>
<tr>
<td>experience (in years)</td>
<td>18.9 (13.1)</td>
<td>18.0 (13.2)</td>
</tr>
<tr>
<td>regions of residence</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jenin</td>
<td>7.5 %</td>
<td>9.3%</td>
</tr>
<tr>
<td>Nablus</td>
<td>16.7%</td>
<td>6.1%</td>
</tr>
<tr>
<td>Tulkarm</td>
<td>7.1 %</td>
<td>13.7 %</td>
</tr>
<tr>
<td>Ramallah</td>
<td>16.9%</td>
<td>13.1%</td>
</tr>
<tr>
<td>Jordan valley</td>
<td>2.3 %</td>
<td>0.8 %</td>
</tr>
<tr>
<td>Bethlehem</td>
<td>10.8%</td>
<td>11.7%</td>
</tr>
<tr>
<td>Hebron</td>
<td>20.2%</td>
<td>17.3%</td>
</tr>
<tr>
<td>Rafiah</td>
<td>1.9%</td>
<td>3.5 %</td>
</tr>
<tr>
<td>Gaza</td>
<td>12.7%</td>
<td>15.1%</td>
</tr>
<tr>
<td>Khan Yunis</td>
<td>3.9%</td>
<td>9.3%</td>
</tr>
<tr>
<td>rural residence</td>
<td>41%</td>
<td>61 %</td>
</tr>
<tr>
<td>urban residence</td>
<td>47%</td>
<td>22 %</td>
</tr>
<tr>
<td>refugee camp residence</td>
<td>12 %</td>
<td>17 %</td>
</tr>
<tr>
<td>married</td>
<td>68%</td>
<td>67 %</td>
</tr>
</tbody>
</table>
Notes:

1. For log wages, years of education and years of experience, the table reports mean of variables with standard deviations in parentheses.

2. The region of residence, type of residence and married numbers are percentage of workers out of total sample in the column.
Table 2: The Selection Equation

Probability of selection of employment in Israel

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
<td>1.29</td>
<td>1.53</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.098)</td>
</tr>
<tr>
<td>education</td>
<td>-0.074</td>
<td>-0.084</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>experience</td>
<td>-0.03</td>
<td>-0.040</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>experience&lt;sup&gt;2&lt;/sup&gt;/100</td>
<td>0.024</td>
<td>0.034</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Refugee camp</td>
<td>-0.335</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>-0.980</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>0.149</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td></td>
</tr>
<tr>
<td>Jenin</td>
<td>0.19</td>
<td></td>
</tr>
<tr>
<td>Nablus</td>
<td>-0.35*</td>
<td></td>
</tr>
<tr>
<td>Tulkarm</td>
<td>0.66*</td>
<td></td>
</tr>
<tr>
<td>Ramallah</td>
<td>-0.12</td>
<td></td>
</tr>
<tr>
<td>Bethlehem</td>
<td>0.20</td>
<td></td>
</tr>
<tr>
<td>Hebron</td>
<td>0.04</td>
<td></td>
</tr>
<tr>
<td>Rafiah</td>
<td>0.89*</td>
<td></td>
</tr>
<tr>
<td>Gaza</td>
<td>0.71*</td>
<td></td>
</tr>
<tr>
<td>Khan Yunis</td>
<td>1.03*</td>
<td></td>
</tr>
</tbody>
</table>
Notes:

1. The equation relates to the probability of selection of employment in Israel. The specifications are elaborated in Section 4.3; see, in particular, equation (19).

2. The sample includes all wage earners except those with hourly wages below 0.1 NIS and above 11.5 NIS (cutting lowest 1% and highest 0.2 %).

3. The number of observations is 11,670.

4. Standard errors of the coefficients are in parentheses, except for the region of residence variables where a star denotes significance at 1%.

5. The equations included dummy variables for quarters, which are not reported.

6. The baseline region of residence is the Jordan valley.
Table 3
The Wage Equation

Dependent variable: log real hourly wage

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Local</td>
<td>Israel</td>
<td>Local</td>
</tr>
<tr>
<td>constant</td>
<td>-3.64</td>
<td>-3.10</td>
<td>-3.67</td>
</tr>
<tr>
<td></td>
<td>(0.065)</td>
<td>(0.017)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>education</td>
<td>0.038</td>
<td>0.012</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>experience</td>
<td>0.037</td>
<td>0.017</td>
<td>0.036</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>experience$^2$/100</td>
<td>-0.048</td>
<td>-0.027</td>
<td>-0.047</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>$\rho_i$</td>
<td>0.054</td>
<td>0.048</td>
<td>0.157</td>
</tr>
<tr>
<td></td>
<td>(0.080)</td>
<td>(0.109)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>$\sqrt{\sigma_{ii}}$</td>
<td>0.405</td>
<td>0.343</td>
<td>0.407</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>$\sqrt{\sigma_{11}}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sqrt{\sigma_{22}}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\rho_{12}$</td>
<td>-0.17</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wald test ($\chi^2$)</td>
<td>705.2</td>
<td>576.8</td>
<td>1,311</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>$\rho_i = 0$ test ($\chi^2$)</td>
<td>0.37</td>
<td>0.13</td>
<td>4.6</td>
</tr>
<tr>
<td></td>
<td>(0.54)</td>
<td>(0.72)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>$n$</td>
<td>7,206</td>
<td>11,670</td>
<td>7,206</td>
</tr>
</tbody>
</table>
Notes:

1. The sample includes all wage earners except those with hourly wages below 0.1 NIS and above 11.5 NIS (cutting lowest 1% and highest 0.2%).

2. The specifications are discussed in Section 4.3; see in particular equation (20).

3. $n$ is the number of observations in the regression.

4. Standard errors of the coefficients are in parentheses.

5. The regressions included dummy variables for quarters, which are not reported.

6. The Wald test is distributed $\chi^2$. The $\rho_i = 0$ test using $\chi^2(1)$ is an LR test of the null hypothesis that $\rho_i = 0$. P-values appear in parentheses.

7. The second moment estimates use the relations:

$$
\rho_1 = \left[ \frac{\sqrt{\sigma_{11}}}{\sqrt{\sigma_{22}}} - \rho_{12} \right] \frac{\sqrt{\sigma_{22}}}{\sigma^*}
$$

$$
\rho_2 = \left[ \frac{\sqrt{\sigma_{22}}}{\sqrt{\sigma_{11}}} - \rho_{12} \right] \frac{\sqrt{\sigma_{11}}}{\sigma^*}
$$
## Table 4

### Education and Age Distributions by Work Locations

#### a. Schooling Groups

<table>
<thead>
<tr>
<th>Years</th>
<th>0</th>
<th>1-4</th>
<th>5-6</th>
<th>7-8</th>
<th>9-12</th>
<th>13+</th>
</tr>
</thead>
<tbody>
<tr>
<td>Israel</td>
<td>7%</td>
<td>9%</td>
<td>22%</td>
<td>17%</td>
<td>38%</td>
<td>7%</td>
</tr>
<tr>
<td>Local</td>
<td>6%</td>
<td>9%</td>
<td>19%</td>
<td>13%</td>
<td>31%</td>
<td>22%</td>
</tr>
</tbody>
</table>

#### b. Age Groups

<table>
<thead>
<tr>
<th>Years</th>
<th>18-24</th>
<th>25-34</th>
<th>35-44</th>
<th>45-54</th>
<th>55-64</th>
</tr>
</thead>
<tbody>
<tr>
<td>Israel</td>
<td>39%</td>
<td>33%</td>
<td>15%</td>
<td>8%</td>
<td>5%</td>
</tr>
<tr>
<td>Local</td>
<td>28%</td>
<td>33%</td>
<td>21%</td>
<td>12%</td>
<td>6%</td>
</tr>
</tbody>
</table>

**Note:**

Sample is the same as in Table 3.
Table 5
Industry and Occupation Distributions by Work Locations

### a. Industry Distributions

<table>
<thead>
<tr>
<th>Industry</th>
<th>Local</th>
<th>Israel</th>
</tr>
</thead>
<tbody>
<tr>
<td>agriculture</td>
<td>3%</td>
<td>11%</td>
</tr>
<tr>
<td>manufacturing</td>
<td>24%</td>
<td>20%</td>
</tr>
<tr>
<td>construction</td>
<td>22%</td>
<td>50%</td>
</tr>
<tr>
<td>commerce</td>
<td>5%</td>
<td>9%</td>
</tr>
<tr>
<td>government</td>
<td>34%</td>
<td>6%</td>
</tr>
<tr>
<td>transportation</td>
<td>6%</td>
<td>2%</td>
</tr>
<tr>
<td>personal services</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>finance</td>
<td>1%</td>
<td>0%</td>
</tr>
</tbody>
</table>

### b. Occupation Distributions

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Local</th>
<th>Israel</th>
</tr>
</thead>
<tbody>
<tr>
<td>academic</td>
<td>7%</td>
<td>0%</td>
</tr>
<tr>
<td>professionals</td>
<td>13%</td>
<td>1%</td>
</tr>
<tr>
<td>managers</td>
<td>1%</td>
<td>1%</td>
</tr>
<tr>
<td>clerical workers</td>
<td>9%</td>
<td>1%</td>
</tr>
<tr>
<td>agents, sales and service</td>
<td>3%</td>
<td>2%</td>
</tr>
<tr>
<td>skilled jobs in agriculture</td>
<td>8%</td>
<td>12%</td>
</tr>
<tr>
<td>manufacturing and construction skilled jobs</td>
<td>37%</td>
<td>42%</td>
</tr>
<tr>
<td>unskilled</td>
<td>22%</td>
<td>42%</td>
</tr>
</tbody>
</table>

**Note:**
Sample is the same as in Table 3.
Table 6
Decomposition of Mean Wages and of the Mean Wage Differential

a. Mean Log Wages

\[
\ln w_{\text{local}} = \hat{k}_{\text{local}} + \hat{\beta}_{\text{local}} \mathbf{X}_{\text{local}} + \hat{\rho}_{\text{local}} \sqrt{\sigma_{\text{local}} \lambda_{\text{local}}}
\]

\[
\ln w_{\text{Israel}} = \hat{k}_{\text{Israel}} + \hat{\beta}_{\text{Israel}} \mathbf{X}_{\text{Israel}} + \hat{\rho}_{\text{Israel}} \sqrt{\sigma_{\text{Israel}} \lambda_{\text{Israel}}}
\]

<table>
<thead>
<tr>
<th></th>
<th>local</th>
<th>Israel</th>
<th>difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean ln w actual</td>
<td>-2.816</td>
<td>-2.733</td>
<td>-0.083</td>
</tr>
<tr>
<td>(\hat{k})</td>
<td>-3.67</td>
<td>-3.09</td>
<td>-0.58</td>
</tr>
<tr>
<td>(\hat{\beta}\mathbf{X})</td>
<td>0.797</td>
<td>0.339</td>
<td>0.459</td>
</tr>
<tr>
<td>(\hat{\rho}\sqrt{\sigma\lambda})</td>
<td>0.068</td>
<td>0.028</td>
<td>0.039</td>
</tr>
</tbody>
</table>

b. The Mean Wage Differential I

\[
\ln w_{\text{local}} - \ln w_{\text{Israel}} = \hat{k}_{\text{local}} - \hat{k}_{\text{Israel}}
\]

\[+ \mathbf{X}_{\text{Israel}}(\hat{\beta}_{\text{local}} - \hat{\beta}_{\text{Israel}})
\]

\[+ \hat{\beta}_{\text{local}}(\mathbf{X}_{\text{local}} - \mathbf{X}_{\text{Israel}})
\]

\[+ \hat{\rho}_{\text{local}} \sqrt{\sigma_{\text{local}} \lambda_{\text{local}}} - \hat{\rho}_{\text{Israel}} \sqrt{\sigma_{\text{Israel}} \lambda_{\text{Israel}}}
\]

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(\ln w_{\text{local}} - \ln w_{\text{Israel}})</td>
<td>-0.083</td>
</tr>
<tr>
<td>(\hat{k}<em>{\text{local}} - \hat{k}</em>{\text{Israel}})</td>
<td>-0.58</td>
</tr>
<tr>
<td>(\mathbf{X}<em>{\text{Israel}}(\hat{\beta}</em>{\text{local}} - \hat{\beta}_{\text{Israel}}))</td>
<td>0.398</td>
</tr>
<tr>
<td>(\hat{\beta}<em>{\text{local}}(\mathbf{X}</em>{\text{local}} - \mathbf{X}_{\text{Israel}}))</td>
<td>0.061</td>
</tr>
<tr>
<td>(\hat{\rho}<em>{\text{local}} \sqrt{\sigma</em>{\text{local}} \lambda_{\text{local}}} - \hat{\rho}<em>{\text{Israel}} \sqrt{\sigma</em>{\text{Israel}} \lambda_{\text{Israel}}})</td>
<td>0.039</td>
</tr>
</tbody>
</table>
c. The Mean Wage Differential II

\[ \ln w_{\text{local}} - \ln w_{\text{Israel}} = \hat{k}_{\text{local}} - \hat{k}_{\text{Israel}} \]

\[ -\{ \bar{X}_{\text{local}} (\hat{\beta}_{\text{Israel}} - \hat{\beta}_{\text{local}}) + \hat{\beta}_{\text{Israel}} (\bar{X}_{\text{Israel}} - \bar{X}_{\text{local}}) \} \]

\[ + \rho_{\text{local}} \sqrt{\sigma_{\text{local}} \lambda_{\text{local}}} - \rho_{\text{Israel}} \sqrt{\sigma_{\text{Israel}} \lambda_{\text{Israel}}} \]

\[
\begin{array}{l|c}
\ln w_{\text{local}} - \ln w_{\text{Israel}} & -0.083 \\
\hline
\hat{k}_{\text{local}} - \hat{k}_{\text{Israel}} & -0.58 \\
\bar{X}_{\text{local}} (\hat{\beta}_{\text{Israel}} - \hat{\beta}_{\text{local}}) & -0.440 \\
\hat{\beta}_{\text{Israel}} (\bar{X}_{\text{Israel}} - \bar{X}_{\text{local}}) & -0.019 \\
\hat{\rho}_{\text{local}} \sqrt{\sigma_{\text{local}} \lambda_{\text{local}}} - \hat{\rho}_{\text{Israel}} \sqrt{\sigma_{\text{Israel}} \lambda_{\text{Israel}}} & 0.039 \\
\end{array}
\]

Notes:

1. Sample is the same as in Table 3.
2. Point estimates used are those of Table 3 column 1.
Figure 1
Premia Point Estimates

a. Education Premia

Local economy— top, red curve; host economy—bottom, dashed, blue curve
b. Experience Premia

Local economy— top, red curve; host economy—bottom, dashed, blue curve

Note:
The figures are based on the point estimates of Column 1, Table 3.
Figure 2: Second Moments Analysis

Regression – downward sloping; Equal income – 45 degree line