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Trade and Human Capital Accumulation - Evidence from U.S. Immigrants

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Abstract

This study provides empirical evidence that trade increases on-the-job human capital accumulation by estimating the effect of home country openness on estimated returns to home country experience of U.S. immigrants. The positive effect of trade on on-the-job human capital accumulation remains significant when controlling for GDP, educational attainment and institutional quality. It is not the result of self-selection, heterogeneity in returns to experience, English speaking origin or cultural background. The effect persists when restricting the sample to non-OECD countries, thereby resolving the theoretical ambiguity whether trade increases or decreases learning-by-doing. The role of trade in generating economic growth is therefore likely to be more important than generally considered.

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"Human capital accumulation takes place in school, in research organizations and in the course of producing goods and engaging in trade." Robert Lucas (1993)

1 Introduction

Theory identifies the effect of trade on on-the-job human capital accumulation as an important channel through which trade may enhance economic growth. But whether trade increases or decreases on-the-job human capital accumulation is ambiguous from a theoretical point of view. Trade may foster the acquisition of human capital by facilitating the transfer of ideas and technology from technologically more advanced countries to less advanced economies. Technology transfer affects human capital accumulation through two channels. First, implementing and working with a new technology increases the knowledge of workers. On-the-job learning is hence a by-product of trade. Second, trade may lead to an increase in wages of skilled relative to unskilled workers inducing workers to invest more in human capital (e.g. Hall and Jones (1999), Pissarides (1997) and Goh and Olivier (2002)).

Opening up to trade may also theoretically reduce on-the-job human capital accumulation. If some productive activities carry a higher rate of skill acquisition than others, moving from autarchy to free trade may depress learning-by-doing. This happens if trade induces countries to import high-quality goods rather than to produce them (Stokey (1991) and Young (1991)).[1]

Approaching the question whether trade increases of decreases on-the-job human capital accumulation empirically requires a measure of on-the-job accumulation of human capital, such as the return to experience. Cross-country data on returns to experience is not well suited to estimate the effect of trade on human capital accumulation since the return to experience is determined by the price of on-the-job human capital, as well as its quantity and quality. The identification of cross-country differences in human capital accumulation requires to hold this price constant across countries. But the price of on-the-job human capital is a function of country-specific variables such as technology, supply of human capital, labor market institutions and governmental quality.

If all these country-specific variables were constant across time, panel data would be a solution to this problem. But panel data on cross-country

[1] Routine or traditional production techniques, for example, are likely to be associated with less learning than more complex, technology-intensive tasks (Lucas (1988, 1993)).

returns to experience is generally not available. Moreover panel data could not solve another fundamental problem. Opening up to trade does not only change commodity prices, it also affects relative factor prices and hence the price of human capital.[2] As a consequence, observing higher returns to experience in more open economies does not allow to conclude that trade increases on-the-job human capital accumulation.

These problems are likely to explain why there exist very few empirical studies about cross-country differences in on-the-job human capital accumulation. The empirical strategy pursued in this paper overcomes these issues as it does not rely on cross-country data. Instead, it uses data on US immigrants from different source countries to estimate US returns to home country experience. These returns are measured within the same labor market and are therefore not affected by cross-country differences in the price of on-the-job human capital. Furthermore, the US labor market is characterized by a relatively low level of labor market regulation which assures that wages and hence estimated returns to experience are related to productivity.

I provide evidence of a positive and significant effect of home country trade on returns to home country experience of US immigrants, indicating that trade enhances the accumulation of on-the-job human capital. High investment rates per worker, which can be considered a precondition for technology adoption, and strong governments and institutions have a positive and significant effect on returns to home country experience. The positive effect of trade on returns to home country experience persists when restricting the sample to developing countries, providing empirical evidence for the hypothesis that trade increases learning-by-doing through technology transfer even in less developed countries. It is robust to the issues of self-selection, heterogeneity in returns to experience and English speaking origin and is unlikely to be the result of unobserved cultural background.

The remaining part of this paper is organized as follows. The next section provides a short summary of the related literature. Section 3 summarizes the empirical strategy. Section 4 discusses data and provides a preliminary data analysis. The main results are presented and discussed in section 5. Section 6 performs a series of robustness checks. The final section concludes.

[2] According to the Stolper-Samuelson theorem the relative reward of a factor that is more intensively used in the production of a good increases as the price of the good rises.

2 Related Literature

Human capital accumulation on the job, either through learning by doing or formal training does not come for free. Individuals have to invest time, effort and monetary costs in terms of direct training costs and foregone earnings in order to increase their human capital. How does trade influence this individual investment decision?

A standard model which provides basic insights into the human capital investment decision is the Ben Porath Model (Ben Porath (1967)). This model predicts that the optimal amount of human capital investment depends on the wage rate per unit of human capital, the cost of training and the rate of obsolence. Bartel and Sicherman (1998) show that in the Ben Porath Model an increase in the wage rate per unit of human capital unambiguously increases investment in each period. Raising the productivity of human capital may reduce the cost of training and/or increase the value of time in training relative to work. Both changes enhance investment in training. On the other hand, the introduction of new work processes may make existing human capital obsolete. A higher rate of obsolence of human capital may lower investment in human capital.

If opening up to trade induces countries to specialize in the production of goods whose production technology carries a low rate of learning, then human capital accumulation is likely to decrease. But if trade leads to technology transfer then opening up to trade may speed up learning in technologically less advanced countries because implementing and working with the new technology increases the knowledge of workers. This positive effect of trade on human capital accumulation is reinforced if the transferred technology is skill biased by raising the demand for skilled workers relative to unskilled workers permanently. A higher relative demand for skilled workers leads to an increase in the wage rate per unit of human capital, triggering human capital investment. At the same time the transfer of skill-biased technologies may depress investment in human capital if, for example, the introduction of new products or production technologies makes existing skills obsolete at a faster rate.[3]

Consistent with the idea that trade increases the demand for skilled labor, there exists empirical evidence of a positive association between trade and relative wages of skilled workers. Using cross-country data, Denny,

[3] The transfer of new technologies may not only affect the optimal amount of human capital investment, but also the types of skills which workers would like to acquire. Workers may, for example, be more likely to invest in the accumulation of skills that are more highly valued at the world technology frontier.

Harmon and Lydon (2001) identify higher returns to education in more open countries. Several country studies that analyze the effect of trade on relative wages of skilled and unskilled workers conclude that technology transfer is the most likely reason for the increase in wage inequality (e.g. Robbins (1994, 1995), Hanson and Harrison (1994)).

Still, observing higher relative wages in more open economies does not allow to conclude that trade enhances human capital accumulation since relative wages are likely to be affected by country specific factors, such as technology, supply of human capital or labor market regulations. Direct evidence on the relation between trade and human capital accumulation is far from conclusive. Using a cointegration analysis, Chuang (2000) finds a bidirectional Granger causality between exports and the share of individuals who have attained higher education in Taiwan. Alcala and Ciccone (2001) conclude that trade increases productivity in the cross-country context, but find no statistically significant association between openness and the average level of human capital, as measured by years of education. None of these studies analyzes the effect of trade on on-the-job human capital accumulation.

This is not the first study using data on US immigrants in order to deduce information about their country of origin. Hanushek and Kim (1999) and Bratsberg and Terrel (2002), for example, analyze the effect of home country school quality on earnings of US immigrants. Hanushek and Kim (1999) find a strong and positive effect of international math and science test scores on earnings and returns to education of US immigrants. Bratsberg and Terrel (2002) conclude that holding per-capita GDP constant, immigrants from countries with lower pupil-teacher ratios and greater expenditures per pupil earn higher returns to education in the US. Borjas (1998) provides empirical evidence about the effect of source country characteristics on US immigrant quality. This is the only study to my knowledge that relates openness to earnings of US immigrants. He finds no significant effect of openness on the log entry wage of US immigrants when controlling for country fixed effect and/or educational attainment. None of these studies analyzes the effect of home country characteristics on on-the-job human capital accumulation of US immigrants.

3 Estimating the effect of trade on returns to experience

This paper addresses the question whether trade increases or decreases on-the-job human capital accumulation by relating US returns to home country experience of immigrants to home country openness. The methodology used is similar to the two-step procedure proposed by Card and Krueger (1992). The first step consists of estimating a Mincerian earnings equation to obtain estimates of country-specific returns to home country experience. In the second step, these estimated returns to home country experience are regressed on a measure of home-country openness and other control variables.

In the first step, a Mincerian earnings equation is estimated for each country separately. This equation relates log of earnings to years of schooling, potential labor market experience and its square. Labor market experience of immigrant i from country j can be decomposed into pre-migration experience (H_{ij}) and post-migration experience (U_{ij}). Assuming that the effect of experience in a country is linear in experience and its square, the earnings function of immigrants who completed their education in their source country can be written as

$$\ln y_{ij} = \alpha_j + \beta_j S_{ij} + \theta_{1j} H_{ij} + \theta_{2j} H_{ij}^2 + \gamma_{1j} U_{ij} + \gamma_{2j} U_{ij}^2 + \eta_{ij}. \tag{1}$$

The return to home country experience equals $\frac{\partial \ln y_{ij}}{\partial H_{ij}} = \theta_{1j} + 2\theta_{2j} H$. θ_{1j} is the slope of the log earnings experience profile. θ_{2j} captures the curvature and is usually negative, leading to the familiar concave experience earnings profile. H is the number of years at which returns to home country experience are evaluated.

The coefficients in equation (1) are not held constant across countries since there exists convincing evidence that the intercept as well as returns to individual characteristics of US immigrants, such as education or time spent in the US, are likely to vary across countries of origin. Borjas (1998), for example shows, that the log entry wage varies with source country characteristics. Hanushek and Kim (1999) and Bratsberg and Ragan (2002) provide evidence that returns to education vary substantially across countries, reflecting both differences in quality of education and transferability of skills.

The question whether trade increases or decreases on-the-job human capital accumulation is addressed in this study by relating home country openness of US immigrants to their returns to home country experience. Assuming a linear relation between openness and return to experience, this question translates into

$$\theta_{1_j} + 2\theta_{2j}H = a_H + b_H Open_j. \tag{2}$$

where $Open_j$ is some measure of openness in country j. A positive (negative) sign of the estimator of the coefficient b_H indicates that trade increases (decreases) on-the-job human capital accumulation. The marginal effect of openness on returns to home country experience is restricted to be constant across countries in specification (2). This assumption will be relaxed during the empirical analysis for some specifications and b_H will be allowed to vary for sub-groups of countries.[4]

Relying on the fact that the return to experience captures productive capabilities attributable to on-the-job human capital investment, this estimation strategy requires to exclude that factors that are not related to on-the-job human capital investment may generate the upward slope of the experience earnings profile at the beginning of a worker's career. In a search environment, for example, wages may grow with labor market experience because workers may improve the quality of their jobs by means of job search (see for example, Jovanovich (1979)). Moving to the United States is likely to imply for immigrants that the search capital is lost. Employer schemes to economize on costs of monitoring (Lazear (1981)) and turnover costs (Salop and Salop (1976)) may also generate an upward sloping experience earnings profile but are unlikely to explain positive returns to home country experience of US immigrants.[5] It is therefore reasonable to assume that returns to home country experience of US immigrants are related to on-the-job human capital investment.

To obtain an estimate of the return to home country experience, I substitute potential experience $E_{ij} \equiv H_{ij} + U_{ij}$ for home country experience H_{ij},

[4] Openness does not only vary across countries but also over time t, that is

$$\theta_{1jt} + 2\theta_{2jt}H = a_{jH} + g_{tH} + bHOpen_{jt}. \tag{3}$$

Identifying the home country fixed effect (a_{jH}) and the time effect (g_{tH}) requires to construct a panel data set on returns to experience. This is severely constrained by the limited amount of observations available for a large number of countries in the US Censuses.

[5] In these models wages grow because firms defer compensation in order to prevent workers from shirking (Lazear (1981)) or in order to induce a self-selection of heterogeneous workers that enhances productivity (Salop and Salop (1976)).

$$\ln y_{ij} = \alpha_j + \beta_j S_{ij} + \theta_{1j} E_{ij} + \theta_{2j} E_{ij}^2 \\ + (\gamma_{1j} - \theta_{1j}) U_{ij} + (\gamma_{2j} + \theta_{2j}) U_{ij}^2 - (2\theta_{2j}) E_{ij} U_{ij} + \eta_{ij} \tag{4}$$

where $\ln y_{ij}$ is the log of annual earnings for immigrant i from source country j. S_{ij} is a series of dummy variables for different degrees of schooling. U_{ij} is measured as the difference between the census year and the year at the midpoint of the year of immigration bracket.[6] As can be seen from equation (4), the coefficient on U_{ij} consists of the difference between the return to post-migration and pre-migration experience. Potential experience E_{ij} is defined as *age* minus *years of education* minus *six*.

The second step of the two-step procedure consists of regressing the estimated returns to experience on a measure of openness, that is

$$\widehat{\theta_{1j}} + 2\widehat{\theta_{2j}} H = \alpha_H + \beta_H Open_j + \gamma_H X_j + u_j \tag{5}$$

X_j is a set of observed country-specific characteristics, such as GDP per capita, investment per worker, average years of education in the home country and governmental quality. These variables will be discussed in detail when presenting the results. Unobserved country-specific characteristics are captured by u_j.

Under the assumption that openness affects only the slope of the earnings-experience profile but not its curvature, the efficiency of the estimator of β_H could be improved by estimating the effect of openness in one step. The two-step procedure, however, has several important advantages. First, it provides a straight-forward interpretation of the results by allowing to estimate the effect of openness on returns to home country experience and not only on the slope of the earnings-experience profile. Second, being computationally less burdensome it facilitates the estimation of extremely flexible forms of the first stage regression. In one of the specifications presented below returns to experience are, for example, allowed to vary with level of education. Third, it allows to illustrate the diversity in returns to experience across countries.

A special case of (2) is to assume that with the exception of θ_{1j} the coefficients on the Mincerian equation do not vary across countries. This implies that openness can only affect the slope of the experience-earnings profile but not its curvature.

[6] Data on US immigrants is taken from the 1980 and 1990 US Censuses.

Under this assumption, equation (4) may be written as

$$\begin{aligned}\ln y_{ij} &= \alpha + \beta S_{ij} + a_0 E_{ij} + b_0 E_{ij} Open_j + \theta_2 E_{ij}^2 - 2\theta_2 E_{ij} U_{ij} \\ &\quad +(\gamma_1 - a_0)U - b_0 U_{ij} Open_j + \eta_{ij}\end{aligned} \tag{6}$$

This equation forms the starting point of my empirical analysis. The results will be presented in the following section.

4 Data Analysis

My empirical analysis uses data from the 1980 and 1990 US Censuses.[7] The dependent variable of the Mincerian earnings equation is the natural logarithm of the annual wage or salary income in the year preceding the census. The set of control variables includes potential experience, dummies for each year of schooling, years spent in the US and its square, married with spouse present and dummy variables indicating whether the respondent speaks only English or speaks English very well, health limiting work, residence in SMSA, eight census divisions and year of immigration. To control for changes in labor market conditions a dummy indicating Census year 1980 is added to the regression and interacted with regional and educational dummies. Interaction terms with the Census year dummy and other explanatory variables are not statistically significant and are therefore excluded from the specifications. Descriptive statistics are provided in Table 1.[8]

The summary statistics of trade used in this analysis is the natural logarithm of the mean of Open, where the mean is calculated from 1970 to 1980. I will refer to this measure as log Open.[9] Using the logarithm of this summary measure of trade implies that the effect of a one percentage point increase in Open on the dependent variable is larger the lower the level of openness.

Table 2 presents the results of the Mincerian earnings equation for the two censuses. As can be seen in the last column of Table 2, which combines the 1980 and 1990 Census, the estimated return to home country experience

[7] The data are available online at http://www.ipums.org. For more information on the data, see Ruggles and Sobek (1997).

[8] A detailed description of the data can be found in the data appendix.

[9] Open is defined as the ratio of imports plus exports in exchange rate US$ relative to GDP in purchasing-power-parity US$. Other studies that use this measure are Alcala and Ciccone (2001) and Dollar and Kraay (2002).

evaluated at five year experience is 1.8 percent a year and declines to 1.4 percent when evaluated at ten years of experience. It is a well documented fact that returns to home country experience of immigrants are on average low compared to returns to experience of native born US citizens. Using data from the 1970 Census, Chiswick (1978), for example, reports returns to experience of 1.4 percent for immigrants and 2.1 percent for US natives.

Adding openness to the regression and estimating equation (6) leads to the estimates presented in Table 3. The estimated return to home country experience amounts to 2.1 percent evaluated at 5 years of labor market experience and the mean of log Open. Imposing the constraints on b_0 and θ_2 implied by equation (6) reduces the estimated return to home country experience to 1.6 percent. The coefficient on the interaction term between log Open and experience has a positive sign and is significant.[10] Increasing Open from 0.2 to 0.3 raises the return to home country experience by 0.2 percentage points if coefficients are unconstrained.[11] Taking a country from the 10th percentile to the 90th percentile of log Open raises the estimated return to home country experience by 1.2 percentage points and increases to 1.3 percentage points in the constrained regression.

Based on the results, Figure 1 displays the predicted log earnings-experience profiles for two US immigrants. Both immigrants are assumed to have the same individual characteristics, but the source countries of the immigrants differ in their degree of openness. As equation (6) imposes that neither the intercept of the Mincerian earnings equation nor the return to individuals characteristics vary with country of origin, the intercept of the log earnings-experience profile is the same for both immigrants. Moreover, since equation (6) assumes that openness affects only the slope but not the curvature of the profile, the difference in returns to experience among the two immigrants remains constant throughout their work life.

Restricting the intercept of the Mincerian earnings equation to be constant across countries may lead to a biased estimate of the effect of openness on the slope of the log earnings-experience profile.[12] If initial wages of US immigrants from more open economies are higher, then the effect of open-

[10] The calculation of the standard errors takes into account heteroscedasticity and clustering. Not controlling for clustering may lead to a serious downward bias in the OLS standard errors when adding aggregate market variable to micro units. (see Moulton (1986, 1990))

[11] The change in Open from 0.2 to 0.3 corresponds approximately to an increase from the 20th percentile to the median value. To give an example, this change corresponds to South Korea (Open equals 0.20) as compared to Taiwan (0.32) or Australia (0.20) as compared to Canada (0.33).

[12] It may also lead to a biased curvature of the profile.

ness on returns to experience is likely to be overstated.[13] Controlling for country fixed effects in the last column of Table 3 allows for cross-country variation in the intercept and leads to an estimated return to home country experience of 1.9 percent evaluated at 5 years of labor market experience and the mean of log Open. When controlling for country fixed effects, the coefficient on the interaction term between experience and openness remains significant, but drops from 0.006 to 0.002. This implies that raising Open from 0.2 to 0.3 leads to an increase in the annual return to experience by 1 percentage point.

As pointed out above empirical evidence suggests that not only the intercept of the Mincerian earnings equation, but also the returns to individual characteristics, such as education or post-migration experience, are likely to vary across source countries of US immigrants. This issue can be addressed by estimating the effect of openness on returns to experience by means of the two-step method.

5 Openness and Returns to Experience

The first step of the two-step method consists in estimating the Mincerian earnings equation for each country separately, yielding estimates of the country-specific returns to home country experience.[14] Differences in returns to home country experience across countries of origin of US immigrants are substantial. Evaluated at 5 (10) years of labor market experience statistically significant returns range from 7.8 (6.6) percent for immigrants proceeding from Norway, Finland and Japan to 1.4 (1) percent for Philippines, Mexicans and Guatemalans (see Table 4). The relatively low average return to home country experience of US immigrants identified in previous

[13] Immigrants from more open economies may not only have higher returns to experience, but also higher entry wages. As pointed out above, Borjas (1998) finds no significant effect of openness on the entry wage level of US immigrants as soon as he controls for country fixed effects and/or initial educational attainment. However, he finds a positive and significant effect of GDP per capita on log entry wages. Given that GDP per capita and openness are positively correlated, trade is likely to affect log entry wages as long as GDP per capita is not controlled for.

[14] Returns to experience are only estimated for countries with at least 50 US immigrants that satisfy the election criteria, using data from the 1980 and 1990 census jointly. An alternative strategy would have been to estimate country-specific returns to experience per census year. However, variation in returns to experience across census years is not significant, inducing me to stack the 1980 and 1990 census. This increases the number of observations used for estimating the country-specific returns to experience and therefore the precision of the estimates.

studies is henceforth likely to be determined by the fact that immigrants from Mexico form a large share of the overall US immigrant population. Nearly 32 percent of immigrants in my sample are Mexicans. Taking the unweighted average across the 93 countries in the sample leads to a return to home country experience of 3.1 percent with a standard deviation of 3.7.

Returns to home country experience change with years of experience. If a country with a higher log earnings experience slope θ_{1j} has a larger coefficient on the curvature of the log earnings experience profile in absolute value then the ranking in returns to experience of two countries may be reversed when evaluating returns at different years of experience.[15] Illustrating this fact figure 2 shows that the difference between returns to experience of immigrants from Korea and Taiwan, for example, increases with years of home country experience, while the contrary holds for Belgium and Portugal. For the analysis below, I use five years of labor market experience as the year at which to evaluate returns to home country experience experience. [16]

The second step of the estimation strategy consists of regressing estimated returns to home country experience of US immigrants on home country openness in order to understand how trade relates to on-the-job accumulation of human capital. Table 5 presents the results for three different samples: all countries, non-Oil countries and non-OECD/non-Oil countries. The dependent variable is the estimated return to home country experience evaluated at five years of labor market experience in percent. As in section 4, the statistic of openness is the natural logarith of the mean of Open, where the mean is calculated from 1970 to 1980 in order to control for short-term fluctuation.[17]

Regressing estimated returns to home country experience on openness yields a positive and significant coefficient, as shown in specification (I) of Table 5. The coefficient amounts to 1.290 when using the entire sample and reduces slightly, when dropping the oil exporting countries. Increasing Open from 0.2 to 0.3 raises the annual return to home country experience by 0.5 percentage points in the non-Oil sample. Given the low returns to home country experience of US immigrants, this effect is quite large.

Restricting the sample to non-OECD countries depresses the effect of openness on returns to experience. Still it remains positive and significant.[18]

[15] This may arise, for example, if the introduction of new technologies in a country induces young workers to invest more in on-the-job learning, but makes knowledge of older workers obsolete at a faster rate.

[16] Results for other years of experience are available upon request.

[17] A detailed description of variables can be found in the Data Appendix.

[18] Standard errors are calculated using the White estimator in order to correct for het-

Controlling for regional dummies in specification (III) approximately doubles the R-square, but does not alter the sign and the significance level of the coefficients on log Open.[19]

These findings indicate a positive and significant effect of trade on returns to home country experience of US immigrants. They do not imply that US immigrants proceeding from more open countries receive more training in their home country. Human capital is not completely transferable across countries. Some part of it evaporates as immigrants cross the border since an immigrant may bring skills which are not marketable in the US. A share of human capital accumulated on the job is firm-specific and many general skills are tied to a particular product market or technology. As a consequence, higher returns to home country experience do not necessarily indicate that an immigrant accumulated a higher quantity of human capital during his working life. But they show that he accumulated more skills that are valued by the US labor market.

This interpretation of returns to experience is not inconsistent with the story underlying the theoretical link between openness and human capital accumulation, arguing that immigrants accumulate skills because they are in contact with production technologies developed in countries which are closer to the world technology frontier. But it is exactly skills related to more advanced technologies that are likely to be valued by the US labor market.

Confusion about the causal effect of trade on returns to experience can arise from omitting variables that are correlated with both returns to experience and openness. As long as neglected elements are fixed within regions this is of no concern as differences in unobservables are absorbed by regional dummies. But if a positive correlation of unmeasured determinants of returns to experience and openness persists even after controlling for regions, the estimated coefficient on openness does not reveal the causal effect of openness on returns to experience. This issue can be solved by including country-specific variables in the set of explanatory variables that affect returns to experience and are correlated with log Open. Prime candidates are GDP per capita and average years and quality of schooling.

The correlation coefficient between estimated returns to home country

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eroscedasticity. Disturbances are likely to be heteroscedastic as the dependent variable in the second stage regression is itself an estimated regression coefficient.

[19] To control for region-specific effects, I keep regional dummies in the specification if they are at least statistical significant at the 10-percent level. There is one exception to this rule. If the deletion of a statistical insignificant regional dummy increases the Akaike criterion, the regional dummy is kept.

experience and log of real GDP in the entire sample is 0.295.[20] This positive association between log of real GDP and returns to experience is not surprising. Resources devoted to schooling and training tend to be higher in richer countries. But even after controlling for school and training resources a significant positive effect of GDP per capita on returns to experience is likely to persist, as countries with a higher GDP per capita are more likely to have production technologies similar to the US. This implies that the types of skills immigrants from richer countries learn on the job are more valued by the US labor market than skills obtained in less developed countries.

At the same time a large empirical literature provides evidence of a positive association between GDP per capita and trade. The positive correlation coefficient of 0.475 between log of real GDP and log Open in the data is consistent with these findings and indicates that not controlling for GDP per capita is likely to lead to an overestimation of the effect of openness on returns to experience.

As expected, regressing returns to home country experience on GDP per capita yields a significantly positive coefficient on GDP per capita and reduces the coefficient on log Open in all three samples. Specification (IV) in Table 5 reveals that once GDP per capita and regional dummies are controlled for, the coefficient on log Open falls to approximately 0.830, but remains significant at the 5 percent significance level in all three samples.

Average years of schooling as well as quality of schooling are likely to be positively associated with returns to experience. According to the Ben-Porath Model, individuals with more schooling and better schooling tend to invest more in human capital on the job. This arises from the fact that individuals with a higher level of education are likely to be more able and/or face lower discount rates. Higher average years of schooling may further reflect a higher demand for human capital, increasing both the profitability of investing in schooling and on-the-job training. A higher level and better quality of average schooling may also lead to lower costs of post-school investment and/or increase its benefits for two reasons. First, in the presence of human capital externalities working hand in hand with skilled workers may enhance the individual's learning on the job. Second, a higher level of average education is likely to be positively correlated with the level of human capital of the training staff.

A higher average level and better quality of schooling is also likely to be positively correlated with openness since it may increase the demand for

[20] Consistent with log Open, the log of real GDP per capita is defined as the log of its mean calculated from 1970 to 1980.

high technology goods. Evidence on this channel is, for example, provided by Caselli and Coleman (2001). They show that high levels of educational attainment are important determinants of adopting computer technology. Given the positive correlation between schooling and returns to experience as well as schooling and openness, controlling for the average level and the quality of schooling in the second stage regression is likely to reduce the coefficient on openness.

Information on average years of schooling in the home country is taken from Barro and Lee (1993). This variable is only available for a subset of the sample. Regressing log Open on estimated returns to home country experience in the sample for which data on average years of schooling is available does not substantially alter the coefficient on log Open, as can be seen in specification (I) of Table 6.

As expected, returns to experience are higher in countries that have a higher level of average schooling. Controlling additionally for average years of schooling reduces the coefficient on log Open. The coefficient on average years of schooling is, however, only significant when using the entire sample and as long as GDP per capita is not added to the set of explanatory variables. Similarly, other measures of the quantity of schooling, e.g. the log of average years of schooling and the percentage of the population with primary and secondary school completed, are not significantly associated with estimated returns to experience when controlling for openness and GDP per capita. Average years of schooling is the variable that maximizes the R-square. Measures of school quality, such as the quality indices from Hanushek and Kim (1999) and measures such as the pupil-teacher ratio and real expenditure per pupil from Barro and Lee (1993) do not yield statistically significant results. Since the coefficients on measures of quality and quantity of schooling turn insignificant once GDP per capita and openness are controlled for and since adding them to the regression has only a negligible effect on the R-square, the following results will be presented without controlling for measures of schooling.[21]

Not only GDP per capita and educational attainment are likely to affect the return to home country experience. On-the-job accumulation of human capital occurring in the manufacturing sector is likely to be more highly valued by the US labor market than skills acquired in the agricultural sector. Conditional on regional dummies, the partial correlation coefficient between

[21] The R-square of a regression of returns to experience on log Open, log of GDP per Capita and regional dummies in the sample that provides information on average years of schooling is 0.303 for all countries, 0.295 for the non-Oil countries and 0.133 for the non-OECD/non-Oil Countries.

the share of manufacturing and returns to home country experience equals 0.25 and is significant at the 5 percent level. The share of agriculture is - as expected- negatively correlated with these returns.

Estimation results presented in Table 7 show that independent of the sample the coefficient on the share of manufacturing is positive. Apart from non-OECD sample, this effect is significant, when controlling for GDP and regional dummies, indicating that on average returns to home country experience are higher for immigrants proceeding from countries with a higher share of manufacturing. The effect of an increase in the share of manufacturing is small compared to the effect of an increase in openness. Raising the share of manufacturing by 0.1, which is equal to one standard deviation, increases the predicted return to home country experience by 0.005 percentage points. An increase in Open from 0.2 to 0.3, on the other hand, raises these returns by 0.41 percentage points. The marginal effect of Open on returns to experience declines as openness increases. Still, raising the trade to GDP share from 0.8 to 0.9 implies that the return to home country experience is predicted to be 0.11 percentage points higher. Amounting to 0.24 the standard deviation of openness exceeds substantially the standard deviation of the share of manufacturing. Increasing openness from 0.2 by one standard deviation raises predicted returns to home country experience by 0.8 percentage points. In none of the specifications presented in Table 7 the coefficient on the share of agriculture is significant.

Institutions and government may provide an environment to individuals and firms that encourages the accumulation of skills and the investment in new technologies (Hall and Jones (1999)). To capture this notion of governmental and institutional quality, I follow Hall and Jones (1999) in using an index of government antidiversion policy (GADP). The index is described in detail in section $A.2.2.$ of the Data Appendix. It assumes values between zero to one and increases in value with the effectiveness of government policies in supporting an environment favorable to productive activities. Among the countries with the highest GADP figure Switzerland (GADP of 1), Netherlands (0.988), Sweden (0.987) and New Zealand (0.986). GADP is lowest for Liberia (0.197), Iraq (0.226) and Haiti (0.236).

The results of specification (IV) in Table 7 confirm a positive effect of governmental quality on returns to experience. The effect is sizeable. An increase of GADP by one standard deviation (0.2) raises returns by 1.6 percentage points in the entire sample and by 2.1 percentage points for US immigrants proceeding from non-OECD countries. The strong effect of GADP on returns to experience is in line with the results of Alcala and Ciccone (2004). They find that institutional quality is a highly significant determinant of human capital. Adding GADP to the set of explanatory variable leads to a drop in the coefficient on log Open. The coefficient of 0.512 in the sub-sample of non-OECD/non-Oil countries (specification IV) indicates that an increase in Open from 0.2 to 0.3 raises returns to experience of US immigrants by 0.2 percentage points. When additionally controlling for the share of manufacturing, the coefficients on GDP per capita and the share of manufacturing become insignificant. The same holds for all regional dummies. The coefficient on openness, however, remains marginally significant for non-Oil countries and non-OECD/non-Oil countries.

High investment rates are a precondition for technology adoption and hence learning by doing.[22] It is henceforth not surprising that investment rates per worker have a significantly positive effect on returns to experience of US immigrants as shown in Table 8. Adding investment rates per worker to the regression, renders the coefficient on GDP per capita insignificant and negative as can be seen in specifications (III) and (IV). This is likely to be the result of a strong collinearity between GDP per capita and investment per worker. The correlation coefficient between GDP per capita and investment per worker amounts to 0.925 for both the entire sample and the sample of non-oil exporting countries. Regressing log of investment per worker on log of Open, log of GDP per capita and regional dummies leads to an R-square of 0.88. Only 12 percent of the variation in log investment per worker is independent of the included explanatory variables. The positive correlation of both GDP per capita and investment per workers with returns to experience combined with the high correlation among the two variables may explain the negative sign of the partial regression coefficient of GDP per capita in this specification.

Since investment per worker is likely to be related to institutional and governmental quality, GADP is added to the regressions in the last two columns of Table 8. Log investment per workers turns insignificant once GADP is controlled for, as can be seen by comparing column (III) with (V).

These results indicate a positive and significant effect of openness on returns to home country experience of US immigrants, even when restricting the sample to immigrants from non-OECD countries. This is consistent with the hypothesis that trade increases human capital accumulation in less developed countries through technology transfer. Technology transfer may affect human capital accumulation if implementing and working with new

[22] See literature on embodied technological progress, for example, Greenwood et al. (1997).

technologies increases the knowledge of workers.

The hypothesis that openness leads to on-the-job learning by doing through technology transfer, may be tested by relating measures of technology transfer to estimated return to experience. Technology transfer takes place either through the production of goods in less developed countries which were already produced in more developed economies, through the importation of intermediate goods or R&D spillover. R&D spillover are likely to work through imported goods from more developed countries.[23] This suggests to use technologically intensive imports from more developed economies as a proxy for technology transfer. But technology transfer may not only be related to imports, but also to exports. Exporting to more developed countries may require to implement strategies that increase firm-level efficiency. In addition, contact with foreign customers is likely to create an environment of learning opportunities.

If trade leads to on-the-job human capital accumulation through technology transfer, then for less developed countries imports from or exports to non-OECD countries can be expected to have a positive effect on returns to experience. The same applies to imports of technology intensive goods. Regressing the estimated returns to experience on various measures of imports and exports, such as exports and imports by trading partner (OECD versus non OECD) and imports of computers per worker yields the coefficients presented in Table 9.[24] Two specifications are displayed in this table. Specification (I) controls for a measure of openness and regional dummies. GDP, the share of manufacturing and GADP are added in specification (II). The effect on returns to home-country experience remains positive independent of the trade measure used. The coefficient on computer imports is statistically highly significant in both samples in specification (I). The same applies to manufacturing exports.

Summarizing, these results indicate a positive and significant effect of openness in the home country on returns to home country experience of US immigrants. High investment rates are a significant determinant of on-the-job human capital accumulation as well as governmental and institutional

[23] For example, Coe, Helpman and Hoffmaister (1995) find that total factor productivity in developing countries is positively associated with R&D expenditure abroad and that the spillover from an industrial country to a developing country are proportional to the share of the industrial country's imports in the developing countries' gross domestic product.

[24] Trade measures are taken from Caselli and Coleman (2001) who construct the data using information provided by Feenstra, Lipsey and Bowen (1997). For a detailed description of the data see Caselli and Coleman (2001). With the exception of log Open all variables are defined in per worker terms.

quality. The effect of trade on on-the-job human capital accumulation remains positive when restricting the sample to immigrants from non-OECD countries. This finding supports those theories that claim that opening up to trade leads to technology transfer, thereby creating learning opportunities in less developed countries.

6 Robustness Checks

6.1 Self-Selection

The result that US immigrants proceeding from more open countries have a higher return to home country experience, does not necessarily allow to conclude that trade increases on-the-job human capital accumulation of the average home country resident. US immigrants do not form a random sample of the home country population. The decision to migrate is, among other things, determined by a comparison of earnings opportunities across home and destination country. As a consequence, the same covariates that affect earnings, such as home country experience, schooling and ability do also affect the probability to migrate. The US return to home country experience of US immigrants does therefore not necessarily have any predictive value about the US return to home country experience of the average home country resident.

A short sketch of the Roy Model along the lines of Borjas (1987, 1998) illustrates this nicely. Suppose that earnings of residents in country j are given by w_{0j}. If the entire home country population were to move to the United States, their earnings distribution in the US would be given by w_{1j}. w_{0j} and w_{1j} may be written as

$$\begin{aligned} \ln w_{0j} &= \mu_{0j} + \theta_{0j} X_j + v_{0j} \\ \ln w_{1j} &= \mu_{1j} + \theta_{1j} X_j + v_{1j} \end{aligned}$$

For the simplicity of the exposition, let's refer to X_j as home country experience. Assume that the return to home country experience does not vary with years of experience. θ_{0j} is the return to home country experience in the home country, while θ_{1j} is the US return to home country experience of the average home country resident.

Residents of source country j decide to migrate, i.e. $I > 0$, if wages in the US net of migration costs c_j exceed wages in the home country.[25] This

[25] Not only the differences between US and source country earnings opportunities as

migration condition may be written as

$$\begin{aligned}\Pr ob(I &> 0) = \Pr ob(\ln w_{1j} - c_j - \ln w_{0j} > 0) \\ &= \Pr ob(\mu_{1j} - \mu_{0j} + (\theta_{1j} - \theta_{0j})X_j - c_j + v_{1j} - v_{0j} > 0)\end{aligned}$$

Conditional on a given level of home country experience, the probability to migrate increases the higher the US return to home country experience relative to the home country return, holding all other wage determinants constant. Under the assumption that v_{0j} and v_{1j} have a bivariate normal distribution with zero mean, standard deviations σ_0 and σ_1 and correlation coefficient ρ, the substitution of the migration condition into the wage equation yields

$$E(\ln w_{1j}|X_j, I_j > 0) = \mu_{1_j} + \theta_{1j}X_j + \frac{\sigma_{0j}\sigma_{1j}}{\sigma_{vj}}(\frac{\sigma_{1j}}{\sigma_{0j}} - \rho_j)\lambda_j$$

where $\lambda_j = E(v_j|v_j > z_j) = \phi(z_j)/(1 - \Phi(z_j)$, $v_j = (v_{1j} - v_{0j})/\sigma_{vj}$, $z_{j=}(\mu_{0j} - \mu_{1j} + c_j - (\theta_{1j} - \theta_{0j})X_j)/\sigma_{vj}$ and $\sigma_{vj} = \sqrt{\sigma^2_{vj-}\sigma_{0j}\sigma_{1j}}$. λ_j is called the inverse Mills ratio. $1 - \Phi(z_j)$ is the probability to migrate. (Heckman (1979))

The fact that the truncation of the error term depends on X_j implies that the expected value of the estimated return to home country experience of US immigrants differs from the US return to home country experience of the average home country resident if λ_j is not controlled for, as

$$E(\widehat{\theta_j}) = \theta_{1j} + \sigma_j Cov(\lambda_j, X_j)/Var(\lambda_j) \tag{7}$$

where $\sigma_j = \frac{\sigma_{0j}\sigma_{1j}}{\sigma_{vj}}(\frac{\sigma_{1j}}{\sigma_{0j}} - \rho_j)$.

Equation (7) shows that the expected value of the return to home country experience estimated using the sample of US immigrants $E(\widehat{\theta_j})$ is composed of two terms. There is a direct effect of home country experience on log

well as migration costs determine the decision to migrate. US immigration laws matter as well. Furthermore, the decision to migrate to the US is not exclusively based on economic gains, but also on family ties and political reasons. Census data does not allow to control for these factors as it neither provides information about the legal status of the immigrant nor the reason for immigration. The Roy model further assumes that migration decisions are irreversible and hence ignores the issue of self-selection induced by selective return migration. Last, self-selection may also occur when immigrants decide in which US division to reside. The regional variation in demand for skills, however, seems to be a less important determinant for the settlement of immigrants across regions than it is for native borns (see Bratsberg and Terrell (2000)).

earnings which is given by θ_{1j}, the parameter of interest. The second term captures the fact that home country experience affects the probability to migrate. Not controlling for this term implies that the expected value of returns to home country experience estimated on the sample of US immigrants does not allow to identify the US return to home country experience of the average home country resident.

What is the direction of this bias and more importantly how does it relate to the estimated effect of openness on returns to experience?[26] Migration theory proposes and the empirical literature provides evidence that immigrants are positively self-selected. Given positive self-selection,

$$E(lnw_{1j}|X_j, I_j > 0) > E(lnw_{1j}|X_j)$$

and hence $\sigma_j > 0$.

According to the Roy model the sign of the covariance between the inverse Mills ratio and home country experience $Cov(\lambda_j, X_j)$ depends on whether the US return to home country experience exceeds or falls short of the home country return to home country experience. If the US return to home country experience exceeds the home country return, then the gain from migrating increases with home country experience and immigrants with more home country experience are likely to be drawn from a wider distribution of unobservable skills. Therefore, the truncation point and λ_j decreases as X_j rises and given positive selection, the return to home country experience estimated on a sample of US immigrants is lower then θ_{1j}.

But this is not the whole story. Experience of US immigrants is composed of home country experience and experience obtained when living in the US. The return to labor market experience varies according to whether the experience was acquired before or after migrating to the US. While in my sample the estimated return to home country experience evaluated at ten years of experience is 1.4 percent, the return to time spent in the US is 2.1 percent. It is a well documented fact that the return to home country experience is lower than the return to US experience of US immigrants (e.g. Chiswick and Miller (2000) and Borjas (1998)).[27]

[26] Throughout this section I refer to the term bias as the difference between the expected value of returns to home country experience estimated on the sample of US immigrants and the US return to home country experience in the home country population.

[27] The relatively low return to pre-migration experience leads to an earnings disadvantage for immigrants relative to natives with similar labor market experience at arrival to the US. However, the fact the post-migration returns to experience tend to exceed returns to experience of US natives implies that with time spent in the US the relative earnings position of immigrants improves.

Since the decision to migrate is a function of the expected discounted life-time gain from migration, the difference between pre and post-migration returns to experience determines the age at immigration. The fact that the return to post-migration experience exceeds the return to pre-migration experience may lead to a decrease in the probability to immigrate to the US as home country experience increases even if US returns to home country experience exceed home country returns. This would induce a positive correlation between λ_j and X_j and an upward bias of the return to home country experience estimated on the subsample of US immigrants.

US immigrants from a given country are on average younger than potential immigrants defined as home country residents who are between 15 and 64 years old. When arriving to the US, immigrants are on average 30 years old which compares to a mean age of 34 in the potential immigrant population.[28] US immigrants from all countries in the sample, with the exception of South Korea and South Africa, are younger at arrival then the potential immigrant population in the home country. Cross-country variation in mean age at arrival for immigrants is substantial, ranging from 26 year for Mexico and Saudi Arabia to 34 year for South Korea.

The probability to migrate for immigrants who completed their education in the home country is hump-shaped with respect to age. Constructing migration rates conditional on age and male gender for eleven five-year age brackets reveals that for 67 out of 81 countries in the sample on migration rates the probability to migrate is highest for immigrants who are between 25 and 29 years old.[29] Immigrants proceeding from Bahamas, Costa Rica, El Salvador, Guatemala, Mexico, Puerto Rico, Yemen, Saudi Arabia, Ireland, Sierra Leone and Saudi Arabia are most likely to immigrate between the age of 20 and 24. For immigrants from Sri Lanka, Bulgaria and Poland the probability to migrate is highest when they are between 30 and 34 years old. The cross-country difference in the age that maximizes the probability to migrate may reflect differences in the level of education across immigrant groups. The average Bulgarian and Sri Lankan immigrant, for example, is far more educated then the average US immigrant, while immigrants from El Salvador, Guatemala, Mexico, Puerto Rico and Yemen fall within the

[28] Data on population within given age brackets is taken from the International Data Base of the US Census.

[29] These migration rates are constructed by estimating the number of immigrants at different age brackets living in the United States based on data of the 1980 and 1990 Census. By combining these estimates with data on the population within the same age bracket. Data on the population within age brackets is taken from World Development Indicators of the World Bank.

group with the lowest average educational attainment.

Controlling for the bias of the estimated return to home country experience induced by self-selection in the first-stage regression requires to account for the truncation of the error term. Adding a selection correction term in the form of the inverse Mills ratio to the Mincerian earnings equation in the first step may solve this issue if the unobservables have a joint normal distribution. This Mills ratio can be constructed by using the estimated migration rates conditional on age and male gender. Since education determines potential experience as well as age at arrival, I also use migration rates of male immigrants for three levels of schooling: less then seven years, seven to twelve years and more than twelve. These migration rates have been taken from Bratsberg and Terrell (2002).[30]

Controlling for selection does not change the effect of openness on returns to experience when controlling for log Open, log GDP per capita and significant regional dummies. This can be seen by comparing specification (I) of Table 10 with specification (IV) of Table 5. Once GADP and the share of manufacture are added to the regression in specification (II) the coefficient on log Open decreases by about 10 percent in the entire sample and by 30 percent in the non-OECD sample relative to the uncorrected coefficients if migration rates conditional on age are used to control for self-selection. Migration rates conditional on schooling are only available for a subset of countries. Adding them to the first step regressions reduces the sample size significantly as can be seen in the last two columns of Table 10. Despite the change in the sample, the coefficients on log Open are similar in specification (I) independent on whether migrations rates conditional on age or conditional on education are added to the first step regression.

6.2 Returns to Experience and Schooling

Log earnings experience profiles tend to be steeper for better schooled workers. An OECD study, for example, suggests that participation in job-related training programs is correlated with educational attainment (OECD

[30] Relaxing the assumption of joint normality in order to identify the US return to home country experience in the home country population requires to satisfy an exclusion restriction,i.e. a regressor that affects the migration probability of immigrants from a given country differently, but does not determine earnings. As age at arrival does not only determine the probability to migrate but also earnings, the exclusion restriction is not satisfied. Immigrants may leave their country for political reasons. Wars or political turmoil are likely to affect the decision to migrate, but not wages. If these variables affect immigrants who immigrate at different years of immigration in a different way, they may be used in order to control for selection.

(1997)). Similarly, Bartel and Sicherman (1998) provide empirical evidence that the probability of receiving training increases monotonically with education. Psacharopolous and Layard (1979) show that experience profiles are steeper for individuals with higher educational attainment. Using US panel data, Altonji and Pierret (1997) reach a similar conclusion. Based on data of 11 European countries, Brunello and Comi (2000) find that employees with tertiary education have steeper experience profiles then employees with upper secondary or compulsory education.

The same applies to US immigrants. Returns to home country experience of US immigrants are higher for immigrants with more years of education. Table 11 shows that the slope of the home country experience profile is steeper for US immigrants with at least a high school degree as compared to immigrants with a lower level of schooling. At the same time the coefficient on the square of experience is higher for better schooled immigrants indicating a faster decrease in returns to experience. The largest gap between skilled and less skilled US immigrants is reached after approximately ten years of labor market experience. Controlling for fixed effects decreases the slope of the log earnings profile slightly. It leaves the fact unchanged that the log earnings profile is steeper for younger workers with higher educational attainment.

If returns to home country experience vary with education then the OLS estimator of the homogenous US return to home country experience may be written as a variance weighted average of the returns to home country experience of the different educational categories. As US immigrants are on average better educated then home country residents, heterogeneity in returns to experience implies that the average US return to home country experience estimated on a sample of US immigrants exceeds the average US return to home country experience in the home country population.[31]

If education affects returns to experience and if educational differences between home country and immigrants population are related to source country characteristics, then the estimated effect of openness on returns to experience will differ from the effect of openness on US returns to home country experience of the average source country resident. Consider, for ex-

[31] The concavity of the log earnings-experience profiles implies that the return to experience decreases with years of experience. There exists empirical evidence that this decrease is more pronounced for workers with a higher level of schooling (see for example, Brunello and Comi (2000)). Workers with a long labor market experience and a high level of schooling may therefore have lower returns to experience then comparable less schooled workers. Consequently, the claim that returns to experience are higher for more schooled workers refers in what follows to workers with few years of labor market experience.

ample, that openness affects the decision to migrate by reducing migration costs because it familiarizes residents in the home country with the institutional, cultural and social environment in the United States. The decrease in migration costs is likely to be larger for workers with a high level of schooling relative to workers with a low level of schooling because of differences in literacy, language and technological skills. Openness may then have a larger effect of the migration probability of better schooled workers relative to less schooled workers. Given that returns to experience are higher for immigrants with more schooling, we would observe a positive correlation between openness and returns to experience because openness induces more skilled workers to leave the country, and not because openness induces more accumulation of on-the-job human capital.

But opening up to trade may also induce a decrease in the relative migration rate of skilled workers. As pointed out above, there exists empirical evidence that trade increases the demand for skilled workers. If openness raises the return to schooling or returns to home country experience in the home country relative to the respective return in the United States, openness may actually lead to a decrease in the immigration rate of highly skilled workers. In this case, the effect of openness on returns to home country experience would be underestimated.[32]

The positive effect of openness on returns to home country experience is not determined by the skill distribution of the US immigrant population. This is demonstrated by regressing returns to home country experience of highly skilled and low skilled workers separately on log Open and other control variables in the first and second column of Table 12.[33] Comparing these coefficients with column (VI) in Table 5 reveals that the coefficient

[32] Difference in educational attainment between US immigrants and home country population varies substantially across countries, ranging from 2 to 18 years. It is largest for immigrants proceeding from Africa. US immigrants, for example, from Namibia and Mali form the group with the highest educational attainment of US immigrants with on average 18 years of schooling. At the same time educational attainment in these countries is among the lowest in the world. On the other hand, educational attainment of Mexican, Canadian, Italian, Greek and Portuguese US immigrants mimics rather well average educational attainment in their home country population.

[33] Highly skilled workers are defined as workers with at least a high school degree. The average return to experience of low skilled workers in this sample amounts to 2.18 percent (with a standard deviation of 2.587), while the corresponding return of highly skilled workers equals 2.965 percent (4.893).

Estimations presented in Table 12 exclude countries with less then 100 observations in order to increases the precision of the estimates which are obtained in the first step. This implies that Algeria, Liberia, Malta, Saudi Arabia, Sierra Leone, Singapore, Switzerland, Tanzania, Tunisia, Uganda and Yemen drop out of the sample.

on log Open does not change significantly in the entire sample as well as the sample of non-oil countries. But the effect of openness on returns to experience of highly skilled US immigrants - as shown in column (II) - is not significant in any of the three samples. Apart from GADP, no explanatory variables is significant in this specification arising from the fact that the cross-country variance in returns to experience is substantially higher for more skilled workers. Since the variance of the returns to experience among highly skilled is relatively large, the mean square error of specification (II) is about four times higher than in specification (I), scaling up the standard errors of the coefficients.

Using the average estimated return to home country experience evaluated at the skill distribution in the home country does also not alter the principal findings. Column (III) of Table 12 uses average estimated returns to home country experience evaluated at the skill distribution in the home country as dependent variable. The results are very similar to the estimates presented in Table 7 for the entire sample and the sample of non-Oil countries. Increasing the share of trade in GDP from 0.2 to 0.3, raises the average return to home country experience in the non-Oil economies by about 0.35 percent. However, when restricting the sample to non-OECD economies the coefficient on Open is about 50 percent lower than the respective coefficient of Table 7. The coefficient on log Open does also not change significantly when evaluating returns to experience at the skill distribution of US immigrants as can be seen in the last column of Table 12.

Summarizing, these findings reveal that the effect of openness on returns to experience is not driven by cross-country differences in the educational attainment differential between home country residents and US immigrants. Controlling for heterogeneity in returns, however, decreases the coefficient on openness in the non-OECD sample and renders it insignificant.

6.3 English Speaking Origin

Returns to home country experience depend on whether the immigrant can transfer his knowledge and skills to the US economy. Transferability of human capital to the US is largely determined by English proficiency. Since countries where English is an official language tend to be more open, the estimated coefficient on openness may overestimate the effect of openness on returns to home country experience.

The finding of a positive and significant effect of openness on returns to experience applies to immigrants from English speaking and non English speaking countries alike. The results presented in Table 13 provide evidence that the positive effect of openness on returns to home country experience is independent on whether the immigrant originates from a country where English is widely spoken or not. English speaking countries subsume all countries were English is an official language or widely used in certain population groups.[34] Columns (I) and (II) of table 13 display the estimation results for non-English speaking and English speaking countries, respectively. The coefficient on openness is positive and significant for both specifications. The difference in the coefficients is not statistically significant, which is likely to reflect the fact that English proficiency is already controlled for in the first step regression.

6.4 Cultural Background

The question remains to be answered whether the effect of openness on home country experience may capture cultural differences among US immigrants. Re-estimating the first step Mincerian equation for the sample of immigrants who completed their education, but had no labor market experience in their home country allows to address this issue. If the effect of openness on returns to home country experience is determined by cultural differences, openness can be expected to exert a significant and positive effect on returns to US experience of US immigrants who had at least some exposure to the culture of their home country.

Controlling only for openness leads to coefficients close to zero independent of the sample, as can be seen in column (I) of Table 14. Adding significant regional dummies in column (II) and GDP per capita in column (III) increases the coefficients on log Open in the different samples. Still they remain insignificant. Once GADP and the share of manufacturing are added to the regression the coefficient on openness falls to zero again. Cultural background is therefore unlikely to explain the effect of openness on returns to home country experience.

7 Conclusion

This paper provides empirical evidence that trade increases on-the-job human capital accumulation. This finding is not the result of self-selection, heterogeneity in returns to experience, English speaking origin or cultural background. The effect of trade on on-the-job human capital accumulation remains positive when restricting the sample to immigrants from non-

[34] The set of English speaking countries is described in the Data Appendix.

OECD countries, supporting the claim that trade leads to technology transfer, thereby creating learning opportunities in less developed countries.

Human capital accumulation is considered an important determinant of economic growth. While a considerable amount of research has been dedicated in explaining cross-country differences in the accumulation of human capital in school and research organizations, less is known about on-the-job accumulation of human capital.

But on-the-job human capital accumulation is likely to contribute considerably to economic growth. Historically, the acquisition of human capital mainly took place on-the-job. The extended schooling system and the consequent late entry into the labor market are a phenomenon of the last decades. Moreover, high educational attainment is a characteristic of rich countries. For many less developed economies, the main bulk of human capital accumulation is still likely to occur on-the-job. If trade increases on-the job human capital accumulation, its role in generating growth is likely to be more important than generally considered.

A Data Appendix

A.1 Sample Selection Criteria

The analysis is based on a sample drawn from the 5/100 public-use micro data files of the US Censuses of Population of 1980 and 1990.[35] The sample is restricted to male US immigrants who are between 25 and 64 years old, worked and earned at least $1000 wage or salary income in the year preceding the census and were not enrolled in school at the time of the census. Furthermore, immigrants in the sample arrived to the US after 1959 and completed their education in their home country. The latter restriction is motivated by the fact that both censuses provides only information on the highest educational degree obtained. It is hence impossible to identify years of experience in the home country for immigrants who acquired US schooling.

The censuses provides information on the year of immigration only within brackets of varying width. Following Bratsberg and Ragan (2002), Bratsberg and Terrell (2002) and Chiswick and Miller (2002) an immigrant is included in the sample if (6+ $years\ of\ education$) is lower than his age at the lower bound of the year of immigration bracket. This restriction ensures that no immigrant who acquired US schooling enters the sample. These sample selection criteria leave a total sample of 173137 observations, of which 58695 belong to the 1980 census and 114442 to the 1990 census. Descriptive statistics of the full sample are presented in Table 1.

The sample size reduces to 171445 observations when matching the census data with the Penn World Tables Mark 5.6 as some countries do not report information on openness.

A.2 Variable Description

A.2.1 Census Variables

The dependent variable of the wage regression is the natural logarithm of the annual wage or salary income in 1979 or 1989. Years of schooling in the 1980 census are based on the "Highest Year of Schooling Attended". If the respondent did not complete the highest grade attended, one year is subtracted. The rule used to convert educational attainment to years of schooling in the 1990 census is the same as in Bratsberg and Terrell (2002).

[35] The data are available online at http://www.ipums.org. For more information on the data, see Ruggles and Sobek (1997).

Experience is defined as $(age - years\ of\ schooling - 6)$. Experience in the US is calculated with respect to the middle of the year of immigration bracket.

A.2.2 Macroeconomic Variables

Variables necessary to calculate the measure of GDP per capita, investment per worker and Open are taken from the Penn World Tables Mark 5.6 revision of Summers and Heston (1991). The measure of GDP is RGDPL, which is per capita GDP expressed in constant year international prices. Open is defined as imports plus exports in exchange rate US$ relative to GDP in purchasing-power-parity US$ and deflated by international export prices. This measure of openness has been proposed by Ciccone and Alcala (2004). Average educational attainment is measured for the population aged 25 and over, as reported by Barro and Lee (2000). Data on pupil-teacher ratio and real public spending per student are from Lee and Barro (2001). Measures of cognitive skills are taken from Hanushek and Kim (1999).

The index of government antidiversion (GADP) is taken from Hall and Jones (1999). It is based on data from the International Country Risk Guide which rates 130 countries according to 24 categories. The GADP is defined as the equal-weighted average of five of these categories (law and order, bureaucratic quality, corruption, risk of expropriation and government repudiation of contracts) for the years 1986-1995. The index is measured from zero to one. The value of the index increases with the effectiveness of government policies in supporting an environment favorable to productive activities.

Data on the share of agriculture and manufacturing in GDP are taken from Caselli and Coleman (2001) and are based on data from the World Bank. Data on imports and exports are from Caselli and Coleman (2001), who take the original data from Feenstra, Lipsey and Bowen (1997).

A.2.3 Regional Dummies

Regional Dummies are defined for Africa, Asia, Latin America, Transition Economies and Island. Island includes the Caribbean and Pacific Island States, the African Island States in the Indian Ocean as well as Cape Verde, Malta and Cyprus. Hongkong, Taiwan and Singapore are added to the Asian dummy. Oil exporting countries are Iran, Iraq, Jordania, Saudi Arabia, Syria and Yemen. The base dummy consists of the OECD member countries as of 1990 plus Turkey and Israel.

A.2.4 English Speaking Countries

According to the World Factbook 2001 English is an official language in Australia, Bahamas, Barbados, Belize, Canada, Fiji, Ghana, Guyana, Hong Kong, Ireland, Jamaica, Kenya, Liberia, Malta, New Zealand, Nigeria, Philippines, Singapore, South Africa, Tanzania, Trinidad and Tobago, Uganda and the UK. Countries were English is an official language but used by a limited minority are Sierra Leone, India and Pakistan. Countries were English is not an official language but widely used within certain population groups applies to Jordania, Panama, South Korea and Western Samoa.

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Tables

Table 1 Descriptive Sample Statistics

	1980 Census		1990 Census	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Log of Annual Earnings	9.346	0.754	9.757	0.852
Experience	23.736	10.377	24.656	10.678
Experience US	8.884	5.220	11.493	7.406
Education				
Years of Education	10.108	5.180	10.022	5.362
Grade less than 5	0.150	0.357	0.174	0.379
Grade 5 to 8	0.258	0.438	0.194	0.395
Grade 9	0.040	0.196	0.044	0.206
Grade 10 to 11	0.070	0.256	0.100	0.300
Grade 12 and GED	0.195	0.396	0.153	0.360
Some College	0.024	0.154	0.096	0.294
Associate Degree	0.073	0.260	0.042	0.200
Bachelor's Degree	0.109	0.312	0.106	0.308
Master's Degree	0.025	0.156	0.048	0.214
Professional/Doctoral	0.055	0.227	0.043	0.202
Region				
Pacific	0.348	0.476	0.384	0.486
Mid Atlantic	0.260	0.438	0.213	0.410
East North Central	0.115	0.319	0.078	0.268
West North Central	0.013	0.114	0.010	0.101
South Atlantic	0.079	0.269	0.118	0.323
East South Central	0.005	0.072	0.005	0.071
West South Central	0.084	0.278	0.101	0.301
Mountain	0.031	0.173	0.036	0.187
New England	0.065	0.247	0.054	0.226
Year of Immigration				
1960-64	0.142	0.349	0.052	0.222
1965-69	0.224	0.417	0.090	0.286
1970-74	0.304	0.460	0.141	0.348
1975-80	0.330	0.470	0.185	0.389
1980-81	0.000	0.000	0.137	0.343
1982-84	0.000	0.000	0.126	0.332
1985-86	0.000	0.000	0.120	0.325
1987-90	0.000	0.000	0.149	0.356
Others				
Married (Spouse Present)	0.776	0.417	0.685	0.464
English (Only or Very well)	0.379	0.485	0.396	0.489
Disability	0.023	0.148	0.025	0.155
SMSA	0.913	0.282	0.910	0.286
# Observations	58695		114442	

Base dummies are Grade 12 and GED for education, Pacific for region and 1960-64 for year of immigration. For variable description, see Data Appendix.

Table 2 Earnings Regression

Census	1980		1990		1980/1990	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Grade less than 5	-0.288***	0.051	-0.351***	0.033	-0.351***	0.033
Grade 5 to 8	-0.172***	0.033	-0.270***	0.02	-0.270***	0.02
Grade 9	-0.147***	0.021	-0.211***	0.023	-0.212***	0.023
Grade 10 to 11	-0.059***	0.016	-0.134***	0.014	-0.134***	0.014
Some College	0.091***	0.025	0.129***	0.017	0.129***	0.017
Associate Degree	0.156***	0.023	0.240***	0.026	0.241***	0.026
Bachelor's Degree	0.375***	0.059	0.444***	0.074	0.444***	0.074
Master's Degree	0.471***	0.04	0.624***	0.042	0.624***	0.041
Profess./Doctoral	0.617***	0.025	0.777***	0.027	0.777***	0.027
Exp	0.024***	0.004	0.022***	0.004	0.023***	0.004
Exp2 / 100	-0.046***	0.007	-0.041***	0.007	-0.043***	0.007
ExpUS	0.041***	0.009	0.036***	0.009	0.036***	0.008
ExpUS2/100	-0.102***	0.027	-0.073***	0.016	-0.075***	0.014
Exp*ExpUS	0.018	0.013	0.017	0.013	0.018	0.013
Married	0.252***	0.013	0.272***	0.016	0.272***	0.015
English	0.203***	0.046	0.199**	0.044	0.199***	0.044
Disabled	-0.245***	0.033	-0.277**	0.031	-0.277***	0.031
SMSA	0.045	0.036	0.077**	0.019	0.077***	0.019
Mid Atlantic	0.002	0.036	0.129***	0.039	0.129***	0.039
East North Central	0.192***	0.022	0.113***	0.024	0.113***	0.024
West North Central	0.134***	0.046	-0.010	0.035	-0.010	0.034
South Atlantic	0.001	0.024	-0.021	0.033	-0.022	0.032
East South Central	0.140**	0.059	0.076	0.057	0.076	0.057
West South Central	-0.007	0.021	-0.173***	0.017	-0.173***	0.017
Mountain	-0.004	0.031	-0.114***	0.016	-0.114***	0.016
New England	0.118***	0.037	0.224***	0.05	0.224***	0.05
1980					-0.447	0.092
Constant	8.435***	0.052	8.835***	0.067	8.826***	0.059
Adjusted R-Square	0.253		0.313		0.333	
# Observations	58695		114442		173137	

Dependent variable is the log of annual earnings. Regression using 1980 and 1990 Censuses includes interaction terms between the 1980 dummy and all other dummies. Standard errors account for heteroscedasticity and clustering within country of origin. Double asterisk denotes statistical significance at the 5-percent level and triple at the 1-percent level.

Table 3 Earnings Regression and Openness

	OLS	Fixed Effect	Constrained
Exp	0.034***	0.025***	0.024***
	(0.004)	(0.001)	(0.001)
Exp2 / 100	-0.039***	-0.039***	-0.027***
	(0.007)	(0.002)	(0.001)
ExpUS	0.028***	0.027***	0.02***
	(0.008)	(0.001)	(0.001)
ExpUS2/100	-0.059***	-0.046****	-0.100***
	(0.012)	(0.005)	(0.005)
Exp*ExpUS/100	0.005	-0.014***	0.053***
	(0.011)	(0.004)	(0.003)
Exp*log RealOpen	0.006***	0.002***	0.006***
	(0.001)	(0,000)	(0,000)
ExpUS*log RealOpen	-0.004***	-0.006***	-0.006***
	(0.001)	(0,000)	(0,000)
Constant	8.833***	8.814***	8.975***
	(0.057)	(0.014)	(0.012)
R-Square	0.344	0.313	
# Observations	171445	171445	171445

Dependent variable is the log of annual earnings. Regressions include dummies for year of education, marital status English speaking status, health status, SMSA, census division, 1980 and year of immigration, as well as interaction terms between the 1980 dummy and all other dummies. Standard errors are in parentheses. They account for heteroscedasticity and clustering within country of origin. Single asterisk denotes statistical significance at the 10-percent, double at the 5-percent, triple at the 1-percent level.

Table 4 Estimated Returns to Home Country Experience

Country	Exp.	Std. Err.	Exp.^2	Std. Err.	# Obs.
Tunisia	0.173	0.255	-0.00433	0.00738	51
Singapore	0.101	0.069	-0.00213	0.00153	67
Norway	0.09***	0.026	-0.0012*	0.00067	198
Finland	0.089***	0.034	-0.00142**	0.00070	134
Japan	0.086***	0.007	-0.00132***	0.00021	2884
South Africa	0.085***	0.019	-0.0018***	0.00048	419
Tanzania	0.085	0.058	-0.00102	0.00134	78
Uganda	0.082	0.071	-0.00406	0.00245	80
Germany. West	0.082***	0.010	-0.00164***	0.00027	1750
Cyprus	0.082**	0.032	-0.00121*	0.00066	105
Malaysia	0.076***	0.025	-0.00112**	0.00050	205
Netherlands	0.075***	0.015	-0.0011***	0.00038	661
Denmark	0.074***	0.028	-0.00144**	0.00070	232
Saudi Arabia	0.068	0.056	0.00016	0.00132	84
Switzerland	0.067***	0.023	-0.00165***	0.00060	387
Canada	0.067***	0.006	-0.00121***	0.00013	4588
Belgium	0.066**	0.029	-0.00182**	0.00078	225
United Kingdom	0.066***	0.005	-0.00122***	0.00012	5866
Western Samoa	0.066*	0.035	-0.00146*	0.00079	141
Sweden	0.065***	0.023	-0.00113*	0.00068	300
Australia	0.062***	0.022	-0.00106**	0.00054	426
Ethiopia	0.052**	0.024	-0.00114*	0.00064	282
Sri Lanka	0.048	0.032	-0.00127*	0.00076	184
Israel	0.047***	0.014	-0.00077**	0.00032	953
Brazil	0.046***	0.012	-0.00066**	0.00030	782
Bulgaria	0.043	0.046	-0.00028	0.00099	130
Hungary	0.042**	0.019	-0.00046	0.00044	634
Malta	0.042	0.047	0.00005	0.00096	83
Ireland	0.041***	0.012	-0.00084***	0.00029	1164
Kenya	0.041	0.055	-0.00015	0.00147	129
France	0.039***	0.015	-0.00039	0.00044	864
Czechoslovakia	0.039**	0.017	-0.00075*	0.00039	608
Indonesia	0.039**	0.017	-0.0008*	0.00040	473
Egypt	0.039***	0.012	-0.00081***	0.00031	1178
Algeria	0.037	0.103	0.0009	0.00280	66
Italy	0.037***	0.005	-0.00061***	0.00009	5373
Nigeria	0.035	0.027	-0.00007	0.00080	385

Exp. is the estimated coefficient on experience and Exp2. on experience squared. Std. Err. refers to Standard Errors. The dependent variable is the log of annual earnings. The specification of the regression is described in the text. Single asterisk denotes statistical significance at the 10-percent, double at the 5-percent and triple at the 1-percent level.

Table 4 Estimated Returns to Home Country Experience continued

Country	Exp.	Std. Err.	Exp.^2	Std. Err.	# Obs.
Czechoslovakia	0.039**	0.017	-0.00075*	0.00039	608
Indonesia	0.039**	0.017	-0.0008*	0.00040	473
Egypt	0.039***	0.012	-0.00081***	0.00031	1178
Algeria	0.037	0.103	0.0009	0.00280	66
Italy	0.037***	0.005	-0.00061***	0.00009	5373
Nigeria	0.035	0.027	-0.00007	0.00080	385
Morocco	0.034	0.038	-0.00007	0.00101	207
Turkey	0.034***	0.012	-0.00065****	0.00025	575
Taiwan	0.034***	0.009	-0.00046**	0.00021	1728
Iran	0.032***	0.010	-0.0005**	0.00021	1644
Bolivia	0.032*	0.019	-0.00066	0.00044	298
Argentina	0.031***	0.010	-0.00048**	0.00022	1383
Thailand	0.030*	0.016	-0.00088**	0.00040	609
New Zealand	0.027	0.032	-0.00037	0.00085	216
Hong Kong	0.027**	0.012	-0.00069**	0.00028	742
Greece	0.027***	0.007	-0.00045***	0.00014	2695
Korea. Rep.	0.027*	0.016	-0.00054	0.00035	640
Dominican Rep.	0.022***	0.005	-0.00041***	0.00010	3150
Bahamas	0.021	0.040	0.00005	0.00090	108
Portugal	0.021***	0.004	-0.00046***	0.00008	3985
Peru	0.021***	0.008	-0.00047***	0.00017	1661
Chile	0.021	0.013	-0.00038	0.00030	769
India	0.020***	0.005	-0.0005***	0.00011	5871
Belize	0.019	0.022	-0.00036	0.00040	241
Ecuador	0.018**	0.007	-0.0003**	0.00015	1750
Colombia	0.018***	0.005	-0.00035***	0.00011	3258
Barbados	0.018	0.014	-0.00058**	0.00029	509
Haiti	0.017***	0.006	-0.00028**	0.00012	2484
China	0.017***	0.004	-0.00031***	0.00007	5960
Yugoslavia	0.017**	0.008	-0.00026	0.00016	1873
Puerto Rico	0.016***	0.005	-0.00026**	0.00012	3877

Exp. is the estimated coefficient on experience and Exp2. on experience squared. Std. Err. refers to Standard Errors. The dependent variable is the log of annual earnings. The specification of the regression is described in the text. Single asterisk denotes statistical significance at the 10-percent, double at the 5-percent and triple at the 1-percent level.

Table 4 Estimated Returns to Home Country Experience continued

Country	Exp.	Std. Err.	Exp.^2	Std. Err.	# Obs.
Mexico	0.016***	0.001	-0.00028***	0.00003	54610
Guatemala	0.015**	0.007	-0.00012	0.00013	2313
Poland	0.014**	0.006	-0.00026**	0.00012	3322
Romania	0.014	0.011	-0.00042*	0.00024	938
Costa Rica	0.013	0.015	-0.00011	0.00032	422
Jamaica	0.012**	0.006	-0.00022**	0.00011	3355
Syria	0.011	0.017	-0.00028	0.00032	429
Philippines	0.010***	0.003	-0.00036***	0.00006	10085
Uruguay	0.010	0.019	-0.00021	0.00040	381
Ghana	0.009	0.035	-0.00088	0.00087	252
Guyana	0.008	0.010	-0.00015	0.00019	1075
Jordan	0.006	0.024	-0.00016	0.00053	300
El Salvador	0.006	0.005	-0.00013	0.00009	4419
Austria	0.006	0.028	0.00037	0.00082	309
Trinidad & Tobago	0.005	0.010	-0.00001	0.00022	1183
Pakistan	0.004	0.011	0.00013	0.00028	1150
Spain	0.004	0.011	-0.00032	0.00024	986
Cape Verde Islands	0.004	0.022	-0.00007	0.00038	173
Iraq	0.003	0.015	0.00042	0.00031	553
U.S.S.R.	0.003	0.008	0.0001	0.00017	2197
Honduras	0.003	0.012	0.00000	0.00026	861
Panama	0.002	0.015	-0.00017	0.00034	575
Myanmar	0.001	0.022	0.00008	0.00045	284
Nicaragua	-0.003	0.008	0.00006	0.00017	1272
Bangladesh	-0.004	0.023	0.00033	0.00051	289
Fiji	-0.004	0.020	0.00002	0.00038	239
Venezuela	-0.007	0.027	0.00036	0.00063	273
Paraguay	-0.032	0.062	0.00038	0.00160	75
Yemen	-0.037	0.045	-0.00004	0.00079	86
Liberia	-0.037	0.075	0.00172	0.00200	77
Sierra Leone	-0.132	0.127	0.00443	0.00375	55

Exp. is the estimated coefficient on experience and Exp2. on experience squared. Std. Err. refers to Standard Errors. The dependent variable is the log of annual earnings. The specification of the regression is described in the text. Single asterisk denotes statistical significance at the 10-percent, double at the 5-percent and triple at the 1-percent level.

Table 5 Standard Specification

	(I)	(II)	(III)	(IV)
		A. All Countries		
Log Open	1.290***	0.927**	1.262***	0.830**
	(0.292)	(0.357)	(0.290)	(0.362)
Log GDP per Capita		0.663		0.722*
		(0.408)		(0.388)
Regional Dummies	No	No	Yes	Yes
R-Square	0.120	0.153	0.239	0.276
# Observations	93	93	93	93
		B. Non-Oil Countries		
Log Open	1.222***	0.926**	1.189***	0.850**
	(0.287)	(0.363)	(0.286)	(0.372)
Log GDP per Capita		0.546		0.572
		(0.409)		(0.389)
Regional Dummies	No	No	Yes	Yes
R-Square	0.116	0.140	0.233	0.258
# Observations	87	87	87	87
		C. Non-OECD/Non-Oil Countries		
Log Open	0.838**	0.887**	0.729**	0.830**
	(0.333)	(0.395)	(0.329)	(0.415)
Log GDP per Capita				0.275
				(0.446)
Regional Dummies	No	No	Yes	Yes
R-Square	0.060	0.061	0.107	0.138
# Observations	67	67	67	67

Dependent variable is the estimated return to home country experience in percent. Estimation technique is OLS. Standard errors are in parentheses and are calculated using the White estimator. Single asterisk denotes statistical significance at the 10-percent level, double at the 5-percent and triple at the 1-percent level.

Table 6 Average Years of Schooling

	(I)	(II)	(III)	(IV)	(V)
			A. All Countries		
Log Open	1.262***	0.910**	0.788*	0.796*	0.647
	(0.290)	(0.428)	(0.427)	(0.437)	(0.425)
Av. Yrs Schooling		0.334*	0.335*	0.211	0.048
		(0.180)	(0.195)	(0.212)	(0.317)
Log GDP per Capita				0.517	0.911
				(0.472)	(0.610)
Regional Dummies	Yes	No	Yes	No	Yes
R-Square	0.239	0.206	0.277	0.213	0.303
# Observations	78	78	78	78	78
			B. Non-Oil Countries		
Log Open	1.189***	0.952**	0.853*	0.825*	0.677
	(0.286)	(0.447)	(0.446)	(0.437)	(0.430)
Av. Yrs Schooling		0.320	0.298	0.149	0.063
		(0.199)	(0.222)	(0.286)	(0.330)
Log GDP per Capita				0.647	0.854
				(0.623)	(0.658)
Regional Dummies	Yes	No	Yes	No	Yes
R-Square	0.233	0.202	0.28I	0.211	0.296
# Observations	74	74	74	74	74
			C. Non-OECD/Non-Oil Countries		
Log Open	0.729**	0.905*	0.788*	0.822*	0.540
	(0.329)	(0.504)	(0.472)	(0.484)	(0.429)
Av. Yrs Schooling		0.065	0.093	-0.042	-0.167
		(0.296)	(0.295)	(0.389)	(0.423)
Log GDP per Capita				0.456	1.147
				(0.738)	(0.933)
Regional Dummies	Yes	No	Yes	No	Yes
R-Square	0.107	0.080	0.118	0.081	0.144
# Observations	54	54	54	54	54

Dependent variable is the estimated return to home country experience in percent. Estimation technique is OLS. Standard errors are in parentheses and are calculated using the White estimator. Single asterisk denotes statistical significance at the 10-percent level, double at the 5-percent and triple at the 1-percent level.

Table 7 Share of Manufacturing and GADP

	(I)	(II)	(III)	(IV)	(V)
			A. All Countries		
Log Open	1.021**	0.821**	0.720**	0.465	0.833**
	(0.402)	(0.369)	(0.279)	(0.306)	(0.335)
Log GDP per Capita	0.783*	0.785*	-0.602	-0.055	-0.598
	(0.443)	(0.425)	(0.439)	(0.481)	(0.450)
Share Manufacture	0.054**	0.069**			0.028
	(0.027)	(0.028)			(0.026)
GADP			8.157***	7.747***	7.671***
			(1.624)	(1.714)	(1.468)
Regional Dummies	No	Yes	No	Yes	No
R-Square	0.222	0.291	0.300	0.343	0.333
# Observations	75	75	91	91	75
			B. Non-Oil Countries		
Log Open	0.988**	0.891**	0.740***	0.532*	0.897***
	(0.409)	(0.407)	(0.281)	(0.303)	(0.330)
Log GDP per Capita	0.821*	0.759*	-1.206***	-0.731	-1.026**
	(0.442)	(0.440)	(0.383)	(0.484)	(0.435)
Share Manufacture	0.048	0.063**			0.035
	(0.029)	(0.031)			(0.029)
GADP			10.325***	9.878***	9.374***
			(1.6434)	(1.841)	(1.623)
Regional Dummies	No	Yes	No	Yes	No
R-Square	0.218	0.315	0.334	0.363	0.346
# Observations	72	72	85	85	72
			C. Non-OECD/Non-Oil Countries		
Log Open	0.954**	0.771*	0.739**	0.512*	0.816**
	(0.451)	(0.428)	(0.291)	(0.312)	(0.331)
Log GDP per Capita	0.251	0.898*	-1.224***	-0.734	-0.980**
	(0.543)	(0.516)	(0.394)	(0.501)	(0.465)
Share Manufacture	0.048	0.064			0.012
	(0.039)	(0.040)			(0.036)
GADP			10.363	10.131***	10.196***
			(2.188)	(2.401)	(2.093)
Regional Dummies	No	Yes	No	Yes	No
R-Square	0.048	0.208		0.271	0.24
# Observations	53	53		65	53

Dependent variable is the estimated return to home country experience in percent. Estimation technique is OLS. Standard errors are in parentheses and are calculated using the White estimator. Single asterisk denotes statistical significance at the 10-percent level, double at the 5-percent and triple at the 1-percent level.

Table 8 Investment per Worker

	(I)	(II)	(III)	(IV)	(V)	(VI)
			A. All Countries			
Log Open	0.773*	0.310	0.819**	0.547	0.558*	0.187
	(0.402)	(0.384)	(0.399)	(0.402)	(0.332)	(0.351)
Log Inv. Per Worker	0.828**	1.506***	1.218	1.835	0.138	0.674
	(0.401)	(0.483)	(1.061)	(1.124)	(0.494)	(0.529)
Log GDP per Capita			-0.646	-1.430		
			(1.313)	(1.326)		
GADP					6.100***	4.558**
					(1.565)	(1.919)
Regional Dummies	No	Yes	No	Yes	No	Yes
R-Square	0.241	0.384	0.246	0.387	0.332	0.381
# Observations	82	82	82	82	82	82
			B. Non-Oil Countries			
Log Open	0.773*	0.330	0.829**	0.585	0.583*	0.340
	(0.407)	(0.390)	(0.405)	(0.408)	(0.335)	(0.339)
Log Inv. Per Worker	0.840**	1.493***	1.278	1.877*	0.099	0.907
	(0.405)	(0.484)	(1.074)	(1.131)	(0.535)	(0.717)
Log GDP per Capita			-0.727	-1.525		
			(1.341)	(1.349)		
GADP					6.303***	4.707*
					(1.917)	(2.430)
Regional Dummies	No	Yes	No	Yes	No	Yes
R-Square	0.250	0.377	0.256	0.384	0.330	0.399
# Observations	78	78	78	78	78	78
			C. Non-OECD/Non-Oil Countries			
Log Open	0.636	0.378	0.767*	0.471	0.542	0.381
	(0.431)	(0.437)	(0.445)	(0.442)	(0.354)	(0.409)
Log Inv. Per Worker	0.638	1.192**	1.831*	2.150*	0.131	0.899
	(0.492)	(0.576)	(1.071)	(1.192)	(0.559)	(0.748)
Log GDP per Capita			-2.345	-1.940		
			(1.424)	(1.485)		
GADP					6.772***	2.949
					(2.061)	(3.364)
Regional Dummies	No	Yes	No	Yes	No	Yes
R-Square	0.137	0.287	0.199	0.328	0.212	0.297
# Observations	58	58	58	58	58	58

Dependent variable is the estimated return to home country experience in percent. Estimation technique is OLS. Standard errors are in parentheses and calculated using the White estimator. Single asterisk denotes statistical significance at the 10-percent, double at the 5-percent and triple at the 1-percent level.

Table 9 Imports and Exports per Worker

	(I) 1970	1975	1980	(II) 1970	1975	1980
	A. Non-Oil Countries					
Log Open	1.157***	1.141***	1.141***	0.743**	0.755**	0.891***
	(0.413)	(0.363)	(0.363)	(0.353)	(0.330)	(0.331)
Log Imports per Worker	0.569*	0.601**	0.773**	0.301	0.587**	0.591
	(0.299)	(0.315)	(0.298)	(0.284)	(0.332)	(0.388)
Log MNF Imp from OECD	0.484	0.564**	0.637**	0.209	0.493	0.457
	(0.307)	(0.319)	(0.277)	(0.243)	(0.312)	(0.322)
Log MNF Imp from Non-OECD	0.506**	0.356	0.594**	0.069	0.066	0.318
	(0.232)	(0.260)	(0.297)	(0.315)	(0.255)	(0.337)
Log of Computer Imp per Worker	0.437***	0.399***	0.520***	0.273	0.088	0.115
	(0.165)	(0.150)	(0.136)	(0.242)	(0.250)	(0.256)
Log Exports per Worker	0.690***	0.776***	0.842***	0.296	0.573**	0.807**
	(0.250)	(0.233)	(0.228)	(0.309)	(0.312)	(0.333)
Log MNF Exp to OECD	0.522***	0.559**	0.623***	0.339**	0.23	0.323
	(0.135)	(0.223)	(0.220)	(0.143)	(0.340)	(0.324)
Log MNF Exp to Non-OECD	0.520***	0.578**	0.794***	0.222	0.412	0.344
	(0.176)	(0.223)	(0.214)	(0.198)	(0.252)	(0.341)
# Observations	71	74	74	65	69	72
	C. Non-OECD/Non-Oil Countries					
Log Open	1.006**	1.019**	1.019**	0.618*	0.653**	0.841**
	(0.467)	(0.404)	(0.404)	(0.358)	(0.312)	(0.335)
Log Imports per Worker	0.473	0.521	0.733**	0.191	0.538	0.65
	(0.335)	(0.339)	(0.330)	(0.287)	(0.346)	(0.420)
Log MNF Imp from OECD	0.430	0.547	0.654**	0.173	0.551	0.590*
	(0.349)	(0.347)	(0.308)	(0.253)	(0.340)	(0.350)
Log MNF Imp from Non-OECD	0.406	0.209	0.496	-0.104	-0.133	0.195
	(0.259)	(0.293)	(0.333)	(0.381)	(0.284)	(0.370)
Log of Computer Imp per Worker	0.430**	0.366**	0.497***	0.117	0.115	0.344*
	(0.187)	(0.174)	(0.149)	(0.259)	(0.256)	(0.201)
Log Exports per Worker	0.546*	0.683**	0.771***	0.083	0.422	0.762**
	(0.304)	(0.270)	(0.258)	(0.335)	(0.309)	(0.354)
Log MNF Exp to OECD	0.464***	0.492**	0.575**	0.334**	0.235	0.384
	(0.151)	(0.217)	(0.219)	(0.155)	(0.388)	(0.371)
Log MNF Exp to Non-OECD	0.457**	0.505**	0.719**	0.146	0.322	0.323
	(0.196)	(0.240)	(0.243)	(0.209)	(0.276)	(0.379)
# Observations	52	55	55	46	50	53

Dependent variable is the estimated return to home country experience. All specifications include significant regional dummies. (II) additionally controls for log of GDP per capita, share of manufacturing and government antidiversion policy (GADP). Estimation technique is OLS. Standard errors are in parentheses and are calculated using the White estimator. MNF refers to manufacturing. Single asterisk denotes statistical significance at the 10-percent, double at the 5-percent and triple at the 1-percent level.

Table 10 Self-Selection

	Migration rate conditional on:			
	age		education	
	(I)	(II)	(I)	(II)
A. All Countries				
Log Open	0.851**	0.742*	0.950**	0.473
	(0.424)	(0.453)	(0.416)	(0.314)
Log GDP per Capita	0.793**	-0.162	0.659	-0.655
	(0.375)	(0.406)	(0.596)	(0.482)
GADP		4.712***		8.767***
		(1.527)		(1.755)
Share Manufacture		0.047		0.044
		(0.032)		(0.032)
R-Square	0.388	0.458	0.226	0.438
# Observations	80	68	59	54
B. Non-Oil Countries				
Log Open	0.870**	0.651	0.963**	0.465
	(0.434)	(0.432)	(0.414)	(0.311)
Log GDP per Capita	0.670*	-0.956*	0.656	-0.688
	(0.383)	(0.505)	(0.591)	(0.486)
GADP		9.283***		8.935***
		(1.853)		(1.895)
Share Manufacture		0.040		0.045
		(0.032)		(0.033)
R-Square	0.371	0.437	0.223	0.432
# Observations	74	65	57	52
C. Non-OECD/Non-Oil Countries				
Log Open	0.800*	0.561	0.744*	0.224
	(0.470)	(0.465)	(0.428)	(0.305)
Log GDP per Capita	0.604	-0.924*	-0.152	-0.618
	(0.464)	(0.520)	(0.759)	(0.570)
GADP		9.402***		8.986***
		(2.477)		(2.595)
Share Manufacture		0.029		0.028
		(0.036)		(0.044)
R-Square	0.260	0.311	0.064	0.025
# Observations	55	47	38	34

Dependent variable is the estimated return to home country experience in percent. Estimation technique is OLS. Migration rates are added as regressors in the first step regression. Standard errors are in parentheses and are calculated using the White estimator. Single asterisk denotes statistical significance at the 10-percent, double at the 5-percent and triple a the 1-percent level.

Table 11 Returns to Experience, Education and English Proficiency

	OLS	Fixed Effects
Exp	0.022***	0.020***
	(0.003)	(0.001)
Interaction with Exp	0.019***	0.019***
	(0.005)	(0.002)
Exp2 / 100	-0.041***	-0.037***
	(0.006)	(0.002)
Interaction with Exp2/100	-0.046***	-0.042***
	(0.009)	(0.005)
R-square	0.688	0.320
# Observations	173137	173137

Dependent variable is the log of annual earnings. Regressions include dummies for year of education, marital status, English speaking status, health status, SMSA, census division, 1980 and year of immigration, as well as interaction terms between the 1980 dummy and all other dummies. All experience terms are interacted with a dummy that assumes value one if the individual has at least 12 years of education. Standard errors are in parentheses. They are robust and account for clustering within country of origin. Single asterisk asterisks denotes statistical significance at the 10-percent, double at the 5-percent, triple at the 1-percent level.

Table 12 Returns to Experience and Education

	Highly skilled (I)	Low skilled (II)	Home country skill distribution (III)	US immigrants skill distribution (IV)
		A. All Countries		
Log Open	0.929**	0.953	0.909**	0.855*
	(0.430)	(0.877)	(0.413)	(0.437)
Log GDP per Capita	-1.071*	-0.349	-1.123**	-0.895
	(0.562)	(1.035)	(0.532)	(0.586)
GADP	6.087***	7.068*	6.468***	5.874***
	(2.250)	(3.878)	(1.712)	(1.554)
Share Manufacture	0.069**	0.046	0.066**	0.074**
	(0.031)	(0.058)	(0.031)	(0.031)
R-Square	0.484	0.176	0.588	0.573
# Observations	66	66	66	66
		B. Non-Oil Countries		
Log Open	0.905**	1.159	0.867**	0.760*
	(0.444)	(0.884)	(0.413)	(0.433)
Log GDP per Capita	-1.104	-1.137	-1.280**	-0.931
	(0.711)	(1.186)	(0.631)	(0.736)
GADP	6.243*	9.999**	7.379***	7.234***
	(3.330)	(4.547)	(2.550)	(2.527)
Share Manufacture	0.073**	0.062	0.064**	0.063*
	(0.033)	(0.059)	(0.031)	(0.035)
R-Square	0.538	0.202	0.586	0.573
# Observations	63	63	63	63
		C. Non-OECD/Non-Oil Countries		
Log Open	0.281	0.427	0.443	0.199
	(0.437)	(0.974)	(0.390)	(0.402)
Log GDP per Capita	-0.840	-0.627	-8.779	-0.478
	(0.699)	(1.060)	(0.667)	(0.680)
GADP	9.305***	11.498*	5.694**	6.485**
	(2.206)	(5.837)	(2.295)	(2.448)
Share Manufacture	-0.038	-0.034	0.041	0.014
	(0.033)	(0.091)	(0.035)	(0.035)
R-Square	0.291	0.115	0.462	0.462
# Observations	44	44	44	44

Dependent variable is the estimated return to home country experience in percent. Estimation technique is OLS. Standard errors are in parentheses and are calculated using the White estimator. Single asterisk denotes statistical significance at the 10-percent, double at the 5-percent and triple a the 1-percent level.

Table 13 Returns to Experience and English speaking Origin

	English not widely spoken (I)	English widely spoken (II)
A. All Countries		
Log Open	1.180**	1.372**
	(0.533)	(0.510)
Log GDP per Capita	0.025	-2.094**
	(0.429)	(0.829)
GADP	2.718*	13.372***
	(1.602)	(2.666)
Share Manufacture	0.053	0.147**
	(0.037)	(0.070)
R-Square	0.536	0.524
# Observations	51	24
B. Non-Oil Countries		
Log Open	1.180**	1.372**
	(0.547)	(0.510)
Log GDP per Capita	0.333	-2.094**
	(0.636)	(0.829)
GADP	1.176	13.372***
	(2.907)	(2.666)
Share Manufacture	0.053	0.147**
	(0.039)	(0.070)
R-Square	0.530	0.524
# Observations	48	24
C. Non-OECD/Non-Oil Countries		
Log Open	1.209**	1.630**
	(0.549)	(0.634)
Log GDP per Capita	1.002	-2.578**
	(0.668)	(1.131)
GADP	-0.634	11.725***
	(3.232)	(2.715)
Share Manufacture	0.074*	0.185*
	(0.040)	(0.099)
R-Square	0.547	0.541
# Observations	34	19

Dependent variable is the estimated return to home country experience in percent. Estimation technique is OLS. All specifications include significant regional dummies. Standard errors are in parentheses and are calculated using the White estimator. Single asterisk denotes statistical significance at the 10-percent, double at the 5-percent and triple a the 1-percent level.

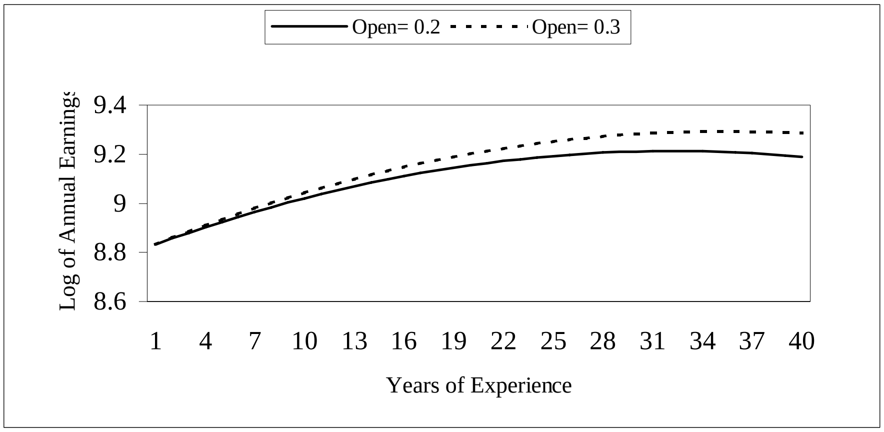
Table 14 Without Experience in Home Country

	(I)	(II)	(III)	(IV)
		A. All Countries		
Log Open	0.012	0.125	0.531	0.021
	(0.630)	(0.655)	(0.617)	(0.776)
Regional Dummies	No	Yes	Yes	Yes
R-Square	0.000	0.168	0.184	0.192
# Observations	70	70	70	58
		B. Non-Oil Countries		
Log Open	-0.014	0.932	0.475	0.0093
	(0.635)	(0.660)	(0.625)	(0.780)
Regional Dummies	No	Yes	Yes	Yes
R-Square	0.000	0.109	0.122	0.109
# Observations	66	66	66	58
		C. Non-OECD/Non-Oil Countries		
Log Open	0.080	0.192	0.574	-0.014
	(0.810)	(0.764)	(0.727)	(0.776)
Regional Dummies	No	Yes	Yes	Yes
R-Square	0.000	0.118	0.133	0.117
# Observations	50	50	50	40

Dependent variable is the estimated return to home country experience in percent. Estimation technique is OLS. All specifications include significant regional dummies. (III) controls additionally for GDP per capita and (IV) GADP and Share of Manufacturing. Standard errors are in parentheses and are calculated using the White estimator. Single asterisk denotes statistical significance at the 10-percent, double at the 5-percent and triple a the 1-percent level.

Figures

Figure 1 Log Earnings/Experience Profile



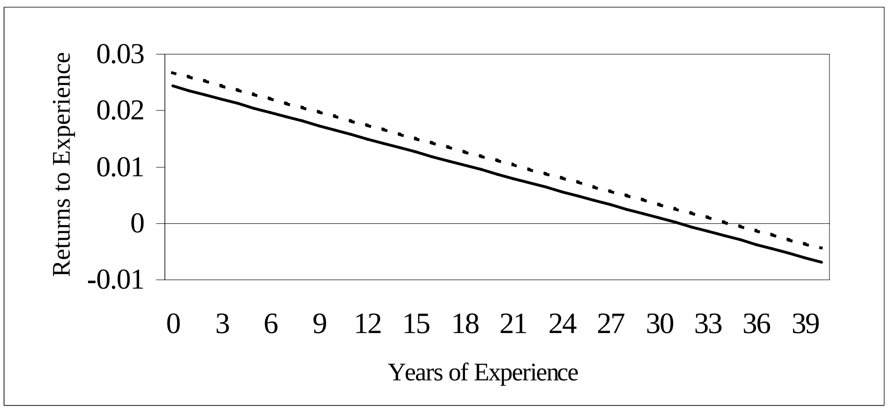


Figure 2 Returns to Experience and Years of Experience