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The fiscal impact of high-skilled emigration: Flows of Indians to the U.S. ★

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Abstract

What are the fiscal consequences of high-skilled emigration for source countries? This paper develops methodologies for inferring these consequences and applies them to the recent sizable emigration of high-skilled workers from India to the U.S. This wave of emigration from India to the U.S. is shown to be unusually concentrated amongst the prime-age work force, the highly educated and high earners. In order to calculate the fiscal losses associated with these emigrants, estimates of their counterfactual earnings distributions are generated using two distinct methods and integrated with a model of the Indian fiscal system to calculate fiscal consequences. Conservative estimates indicate that the annual net fiscal impact to India of high-skilled emigration to the U.S. is one-half of 1% of gross national income (or 2.5% of total fiscal revenues). The sensitivity of these results to the method of predicting counterfactual incomes and the implications of these estimates for other developing countries is discussed in detail.

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1. Introduction

It is widely acknowledged that demographic changes in the developed world, resulting from aging and declining fertility, will have significant economic repercussions. A broad range of policy changes will be required to meet these challenges, including changes in immigration policies. In turn, these likely changes in immigration policies have the potential to have significant impacts on the developing world where highly

skilled individuals have, heretofore, been constrained in their emigration decisions by the restrictive immigration policies of developed countries. The increased mobility of these highly skilled individuals is likely to represent a major innovation in factor flows in the twenty first century, with potentially large consequences on source and destination countries.¹

The last decade of flows of human capital from India to the U.S. may portend what the scope, magnitude and consequences of those worldwide flows will look like over the decades to come. In response to tremendous demand for skilled workers, the U.S. implemented a selective, temporary immigration policy for skilled workers during the 1990s that resulted in a significant change in the flows of human capital from India to the U.S.

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¹ Desai, Kapur, and McHale (2004) discuss the various arguments for why greater mobility will characterize the next half century and the possible responses by developing countries. See Storesletten (2000) for a specific proposal of greater skilled immigration as a solution to fiscal pressures from demographic shifts in the developed world.

As of March 2006, almost 1.5 million Indian-born individuals were resident in the United States—a more than tripling of this population since 1990. Of these, more than half were in the 25 to 44 year old group, and more than three quarters of the working-age population had a bachelor's degree or better. Indeed, an estimated 43% of this age group had a masters, professional, or doctorate degree, compared to just 10% with better than a bachelor's degree in the native-born population.

Human capital outflows of this magnitude will influence a developing country in myriad ways—many beneficial. A prosperous diaspora can be a source and facilitator of trade, investment and ideas; a rich vein of remittances; and a potential stock of high human capital returnee emigrants. However, losing a substantial fraction of its “best and brightest” may have substantial negative effects on a country as well. The loss of skilled workers may harm cooperating factors—complementary skilled workers, less-skilled workers, entrepreneurs, and capital providers. The outflow of talent may also make the country less attractive as a destination for foreign direct investment and may stunt the development the needed critical mass for successful high technology clusters. This outflow may also have deeply inimical consequences on a country's institutions, particularly universities, thereby affecting its long-term development.²

This paper emphasizes one additional dimension of these human capital flows for developing countries and, specifically, the Indian economy—the direct fiscal impact of losing a key component of the tax base. Given their human capital characteristics, U.S. resident Indians would typically have been substantial net contributors to the Indian tax base if they had not emigrated. Thus, their absence imposes a fiscal burden of higher taxes and lower spending on “those left behind” (TLBs).³ The implication of the “brain drain” for fiscal policies is the subject of a large theoretical literature (see, for example, the papers collected in [Bhagwati and Wilson \(1989\)](#)). The major focus of this literature is the implications of international labor mobility on the *ex ante* design of fiscal policy, typically in an optimal taxation framework.

This paper attempts to complement this line of inquiry by developing and implementing methodologies for calculating the fiscal consequences to TLBs from the accumulated emigrant stock given existing fiscal policies. While implemented with respect to the Indian-born population in the U.S., these results indicate the scope of analogous consequences for countries characterized by the emigration of their more educated workers. In order to consider the fiscal consequences of this emigration, the paper develops methods that can be applied more broadly. First, we determine a range of estimates for the counterfactual income distribution of the emigrants if they were living in India. We do this by estimating a joint model of earnings and employment participation using data from the Indian National Sample Survey (NSS). The observed human capital characteristics of the Indian emigrants in the U.S. are used to determine the counterfactual

² See [Kapur and McHale \(2005\)](#) and [Solimano \(2001\)](#) for an elaboration of these varied effects.

³ In the short run, the loss of net fiscal contributors may also show up in higher budget deficits, as governments are slow to adjust taxes and spending on TLBs.

income distribution. Second, we then run the counterfactual distribution through a model of the Indian fiscal system to determine tax losses, expenditure savings, and ultimately the net fiscal impact of emigration.⁴

Two variants of the procedure for generating the counterfactual income distribution are investigated. The first method uses the expected earnings and expected participation conditional on the observed human capital characteristics of the emigrants. This method suffers from the problem that Indian emigrants appear to be positively selected based on unobserved human capital characteristics (e.g. the quality of the university where they studied). The second method attempts to correct for positive selection by assuming that selection on the unobserved characteristics mirrors selection on the characteristics that are observed. Essentially, if an emigrant's observed human capital characteristics would put them at a given percentile of the Indian earnings or participation distribution, we assume that they are at the same percentile in the relevant error distribution as well. This method for generating the counterfactual incomes provides an estimate of an annual net fiscal loss for India in 2005 equal to roughly one-half of one percentage point of gross national income.

The remainder of the paper is structured as follows. Section 2 provides a brief overview of existing work on the impact of high-skilled emigration on source countries. Section 3 describes the evolution of the Indian-born population using data from U.S. Decennial Censuses and Current Population Surveys (CPS) between 1994 and 2006. In particular, this analysis emphasizes the distinctive nature of the Indian-born population on age, education and income dimensions. Section 4 then develops our methodology for estimating the net fiscal impact of emigration. Section 5 presents and discusses the results of applying this model using data from the Indian NSS and the U.S. CPS. Section 6 concludes with a discussion of the implications of this analysis for fiscal policy in India and developing countries more generally.

2. Related literature

This paper contributes to a small but growing literature on the effects of skilled emigration on the welfare of home-country residents. This literature can be framed in terms of four channels associated with migration: prospect, absence, diaspora, and return. The first channel captures how the prospect of emigration affects the expected return on human capital (see e.g., [Beine et al. \(2001, 2007\)](#); [Stark and Wang, \(2002\)](#)). The central idea is that the prospect of emigration increases human capital investments, but a fraction of the additional human capital chooses not to leave or does not qualify to leave.⁵

Research on the absence channel has the longest pedigree (see e.g., [Grubel and Scott \(1966\)](#), [Johnson, \(1967\)](#)). The focus

⁴ This is a calculation of the direct fiscal impact of the absence of given individuals from the Indian economy. Our analysis abstracts from a range of possible indirect fiscal impacts, such the impact of the spending of remittances on indirect tax revenues or the impact of emigrants returning with enhanced human and financial capital.

⁵ [Beine et al. \(in press\)](#) provide empirical support for the idea that the prospect of emigration can raise human capital and growth, though they readily admit their data is imperfect.

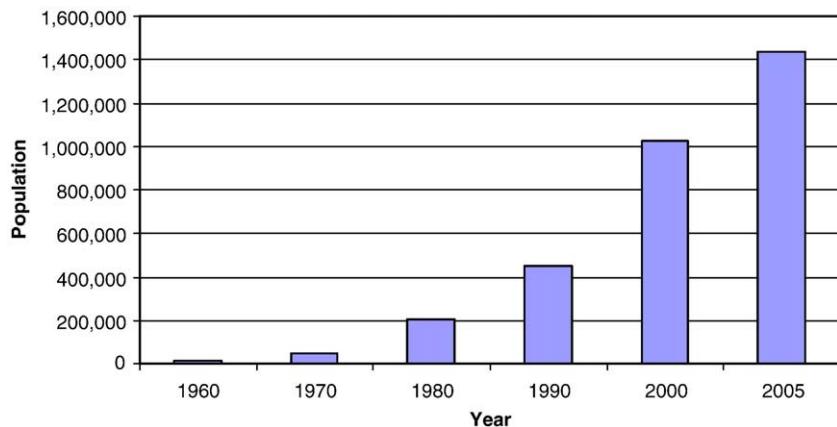


Fig. 1. Indian-born population in the United States.

is on how the absence of part of a country's skilled nationals affects the domestic economy. Since some of the emigration effects parallel the effects of immigration, the richest source of information on the direct effects of mobile human capital is from the much larger immigration literature. A key controversy is the impact of migration on the wages of substitute workers (for surveys see [Borjas \(1994\)](#), [Friedberg and Hunt \(1995\)](#), and [National Research Council \(1997\)](#)).⁶ Work on the absence-related effects of emigration on poorer countries is becoming more prevalent. [Mishra \(2007\)](#) provides recent evidence of substantial wage and welfare effects of Mexican emigration. Also using Mexican data, [Chiquiar and Hanson \(2005\)](#) find evidence that challenges the conventional wisdom that emigrants from Mexico are negatively selected.

We generally consider fiscal effects as a subset of the absence channel.⁷ The papers collected in [Bhagwati and Wilson \(1989\)](#) provide a rich treatment of outwardly mobile human capital on optimal taxation policies, but there appears to be no systemic attempt to estimate actual fiscal losses from high-skilled emigration.⁸ By comparison, the fiscal effect chapters on [National Research Council \(1997\)](#) give detailed estimates of the long- and short-run effects of immigration to the United States, finding, for example, that the average long-term net fiscal benefit of an immigrant with more than a high school education is almost \$200,000 (1996 dollars).

The third channel focuses on the role of the diaspora as a source and facilitator of international business and remittances. This burgeoning literature includes survey work on diasporic networks (e.g., [Saxenian \(2002\)](#)), empirical estimation of the effect

⁶ So called "area studies" look for wage effects by examining the relationship between the number of immigrants (or change in the number of immigrants) in an area and the wage level (or change in wage level) in that area (see [Altonji and Card, 1991](#)). These studies tend not to find significant wage effects. Others have argued that immigrant inflows lead to native outflows, dispersing the wage effect throughout the economy (see e.g., [Borjas et al., 1996](#)).

⁷ Fiscal effects are possible of course through the other channels as well. For example, remittances from the diaspora can affect expenditure tax revenues, and returning emigrants can bring back entitlements to foreign social insurance benefits.

⁸ For related theoretical analyses of these questions, see [Bhagwati and Rodriguez \(1976\)](#), [Bhagwati \(1998\)](#), [Mirrlees \(1982\)](#), and [Wilson \(1982a, 1982b\)](#).

of diasporas and trade (e.g., [Gould \(1994\)](#)), and theoretical exploration of the intermediation function ([Rauch \(2001\)](#) provides an excellent survey). The general finding is that diasporic networks have a significant effect on international business. Finally, work on the return channel has concentrated on the determinants and selectivity of return (e.g., [Kwok and Leland \(1982\)](#), [Borjas and Bratsberg \(1996\)](#)), and the impact of emigration on returnees human capital and earnings (e.g., [Barrett and O'Connell \(2001\)](#)).⁹

3. Characteristics of the Indian population in the U.S.

[Fig. 1](#) illustrates the evolution of the Indian-born population in the U.S. over the last half-century.¹⁰ The figures document the continuous, rapid growth of this population since 1960 when only 12,296 Indian-born individuals were resident in the U.S. This growth has resulted in an Indian-born population of 450,406 in 1990 and a subsequent more than doubling to more than one million by 2000. The population was close to 1.5 million by the middle of this decade, suggesting that it is on track to double again before decade's end.

[Table 1](#) uses data from the 1990 and 2000 censuses to record the evolution of the stock of immigrants in the U.S. from selected countries over the 1990s. We focus on the population 25 and over since this group is likely to have completed their formal education. The table shows that the large absolute and proportionate increases (533 thousand and 175% respectively) in the stock of Indians were not unique phenomena. For example, the stock of Chinese in this age group increased by just over 442 thousand or

⁹ [Borjas and Bratsberg \(1996\)](#) find that return migration from the U.S. is positively related to income per capita in the home country and negatively related to distance from the U.S. They also find that return migration tends to augment initial selection effects: for countries that sent more skilled migrants the returnees tended to be the less skilled of the initial emigrants; for countries that sent less skilled migrants the returnees tended to be the more skilled of the initial emigrants. [Barrett and O'Connell \(2001\)](#) find that returning emigrants to Ireland in the late 1990s earned a significant wage premium over workers with identical characteristics who never left.

¹⁰ The observation for 1990 is from the 1990 U.S. census, whereas the observations for 1994 to 2001 are from the annual U.S. CPS (1994 was the first year when the CPS began asking respondents about their country of birth). Details of these data sources are provided in the data appendix.

Table 1

Emigration rates to the U.S. by education level, population 25 and over

Country of birth	U.S. resident population (≥ 25)				Emigration rate, 2000			
	1990	2000	Change	% Change	Total	Primary	Secondary	Tertiary
Mexico	2,743,638	6,374,825	3,631,187	132	11.7	9.7	14.7	14.2
Philippines	728,454	1,163,555	435,101	60	3.5	0.6	2.2	10.5
India	304,030	836,780	532,750	175	0.2	0.1	0.2	2.7
China	404,579	846,780	442,201	109	0.1	0.1	0.2	2.2
El Salvador	263,625	619,185	355,560	135	19.5	11.0	53.4	28.3
Dom. Republic	187,871	527,520	339,649	181	11.4	5.0	29.8	19.9
Jamaica	159,913	449,795	289,882	181	25.0	4.5	29.0	78.6
Colombia	162,739	402,935	240,196	148	2.1	0.4	3.8	9.0
Guatemala	127,346	341,590	214,244	168	7.1	3.7	23.0	20.5
Peru	86,323	220,815	134,492	156	1.8	0.3	2.4	4.0
Pakistan	52,717	165,425	112,708	214	0.3	0.1	0.5	6.0
Brazil	53,904	154,250	100,346	186	0.2	0.1	0.5	1.1
Egypt	53,261	96,660	43,399	81	0.3	0.1	0.2	2.2
Bangladesh	12,385	69,180	56,795	459	0.1	0.1	0.3	2.2
Turkey	43,605	64,780	21,175	49	0.2	0.1	0.4	1.3
Indonesia	32,172	53,170	20,998	65	0.1	0.1	0.1	0.7
Sri Lanka	8,715	21,820	13,105	150	0.2	0.1	0.1	5.3
Sudan	2,496	12,730	10,234	410	0.1	0.1	0.3	3.3
Tunisia	2,816	5,555	2,739	97	0.1	0.1	0.2	1.3

Note: For each education category, the emigration rate equals the ratio of the number of emigrants to the sum of the domestic population and the number of emigrants. Sources: Carrington and Detragiache (1998) for 1990 and Adams (2003) for 2000. Both sources combine U.S. census data with Barro-Lee human capital stock data.

109%. The table also shows the size of the emigrant stock by education level relative to the total size of the country's stock at that education level (domestic residents and emigrants). This can be viewed as a crude measure of the emigration rate to the U.S. Here we see that even at the tertiary level India has a comparatively low emigration rate, with 2.7% of its total tertiary-educated stock residing in the U.S. in 2000. In comparison, the emigration rate for Jamaica is a staggering 79%. Docquier and Marfouk (2006) have recently used a similar methodology to calculate emigration rates to the entire OECD. They find that the emigration rate for the tertiary-educated Indians is 4.2% to all industrialized countries, which shows that the U.S. is the destination of choice for highly educated Indians.

While the fraction of the population emigrating from India is not high relative to many developing countries, the very high human capital content of the U.S.-resident emigrant stock is striking. The 2000 census reveals that 80% of Indians in America who are 25 and older had a tertiary education, compared, for example, to 45% of Jamaicans or just 14% of Mexicans. Table 2 shows the average age, education, and income characteristics of the Indian-born population over the period from 1994 to 2006 in comparison with the native-born and also the other foreign-born residents of the U.S. While the median ages for the Indian-born do not appear to be significantly different from the native-born or other foreign-born, the age distributions presented in Table 2 demonstrate some marked differences in the populations. The Indian-born are much more concentrated in the prime working-age population. More than half of the Indian-born are in the 25 to 44 year old age group compared to 28% of the native-born and 43% of the other foreign-born. It is also notable that dependents (under-18 or over-64) are just 14% of the Indian-born population, but roughly

40% for the native-born population. While this compression of the age distribution might be expected for immigrants relative to the native-born, the Indian-born differ markedly from the other foreign-born as well.

Turning to educational achievement, the second panel in Table 2 shows that the Indian-born population is distinct in terms of its education distribution. The average share between 1994 and 2006 of the native-born population with a bachelor's degree or better was 27%—compared with 73% for the Indian-born. In contrast, the share of other foreign-born was similar to the native-born with an average share of 25%. The share of the Indian-born with post-bachelor's degrees—master's degrees, professional degrees, and doctorates—is also high at 38% compared to 8% and 9% for the native-born and other foreign-born, respectively. Finally, the highly educated nature of the Indian-born population appears to be accelerating through the period in contrast to the relatively stable trends for the native-born and other foreign-born. The third panel in Table 2 demonstrates how these distinctive age and education distributions for the Indian-born translate into a distinctive income distribution relative to the native-born and other foreign-born. While an average of 6% of the native-born earned an income more than four-times the native-born median over the period from 1994 to 2006, an average of 15% of the Indian-born earned an income above this same high-income cut-off. There has also been substantial growth in the aggregate income earned by the Indian-born, with the total income of the working-age population rising from \$18 billion in 1994 to \$63 billion by 2006 when measured in constant 2006 dollars. Taken together, these descriptive statistics suggest that this high-skilled emigration from India to the U.S. has the potential for sizable fiscal consequences to India. In the aggregate, a population that was roughly 0.1% of the population of India in 2005 had an aggregate income equal to

Table 2

A comparison of Indian-born with natives and other foreign-born

A. Age distribution

	Median	Average population shares, 1994–2006				
		<18	18–24	25–44	45–64	65+
Native-born	34	28	9	28	22	13
Indian-born	35	8	9	53	25	6
Other foreign-born	37	11	11	43	24	12

B. Educational distribution (population 25–64)

	Average population shares, 1994–2006						
	<High School	High School Graduate	Some College	Bachelor's	Masters	Professional	PhD
Native-born	10	34	28	19	6	1	1
Indian-born	6	11	10	35	26	7	5
Other foreign-born	32	25	18	16	5	2	2

C. Income distribution (income ranges based on native-born median income, population 18–64)

	Average population shares, 1994–2006				
	0 to 0.5*Med	0 to 0.5*Med to Med	Med to *2Med	2*Med to 4*Med	>4*Med
Native-born	36	13	25	20	6
Indian-born	36	9	17	24	15
Other foreign-born	42	19	23	13	4

Source: CPS, March Supplement, 1994–2006.

10.5% of Indian gross national income when converted at the market exchange rate.

4. Methodology for estimating fiscal impacts

4.1. Basic framework

In order to motivate the calculations that follow, we first outline a simple framework that underlies the subsequent fiscal impact estimates. The framework centers on the Indian market for skilled workers and corresponds to Fig. 2. We assume all factors of production are in fixed supply; factors are paid their marginal products; and there are no factor-related spillovers.¹¹

w is the skilled wage; and skilled workers face an income tax rate, t , and receive per capita government benefits equal to b . For any given number of skilled workers, S , national income is given by the area under the skilled worker marginal product curve. National income can be divided into the incomes of non-skilled workers, the incomes of skilled workers after fiscal adjustments, $[(1-t)w+b]S$, and the net fiscal contribution of skilled workers, $[tw-b]S$.

Emigration is represented by E and reduces the number of skilled workers from S_0 to S_1 . The change in the national income of TLBs due to emigration is given by the sum of the shaded areas in Fig. 4. This total loss can be divided into the net fiscal loss (NFL),

$$L_f^{\text{TBL}} = \text{NFL} = (tw_0 + b)E. \quad (1)$$

and the non-fiscal losses to cooperating factors.¹²

The size of the net fiscal loss depends on the tax rate, the pre-emigration skilled wage, the benefit level, and the number of emigrants. The next two subsections explain how we estimate an expanded version of this equation by producing counterfactual estimates of the distribution of w for emigrant Indians, and then combining these income estimates with details of the Indian fiscal system to produce estimates of direct net fiscal losses. We stress that these direct net fiscal losses do not capture the total effect on the Indian budget. In addition to the direct effect of losing a portion of the tax base, skilled emigration will

¹¹ While we think it is the natural assumption to make, setting the wage equal to marginal (social) product is not an innocuous assumption. If the Indian labor market is characterized by surplus labor, for example, the lost output from an emigrant is zero. In this case, although an individual's emigration causes no output loss, the incomes of TLBs rise by the amount the emigrant was being paid. Even though this surplus labor model might be appropriate in some circumstances—e.g., subsistence agriculture or pervasive overstaffing in state enterprises—we think that it is unlikely to apply to the types of skilled workers that emigrated to the U.S. during the 1990s. In other words, it is unlikely that the kinds of workers who emigrated, many of whom were highly educated and skilled in information technology, were not adding value in India. Of course, adding value is not the same thing as having wages exactly equal to marginal product. Union wage setting or efficiency wages could lead to wages that are in excess of marginal product; it is also possible that wages are set below marginal product (e.g., a talented civil servant facing a rigid civil service pay structure). It should be noted that India's IT sector is the least unionized of the formal sectors of the economy. Moreover, the specific human capital characteristics of most of the emigrants of 1990s cohort were much in demand since the IT sector grew at greater than 50% annually during the decade.

¹² The non-fiscal loss can be approximated by the formula, $L_{nf}^{\text{TBL}} \approx \frac{1}{2} \frac{\varepsilon}{S_0} w_0 E^2$ where ε is the elasticity of skilled wage with respect to the number of skilled workers.

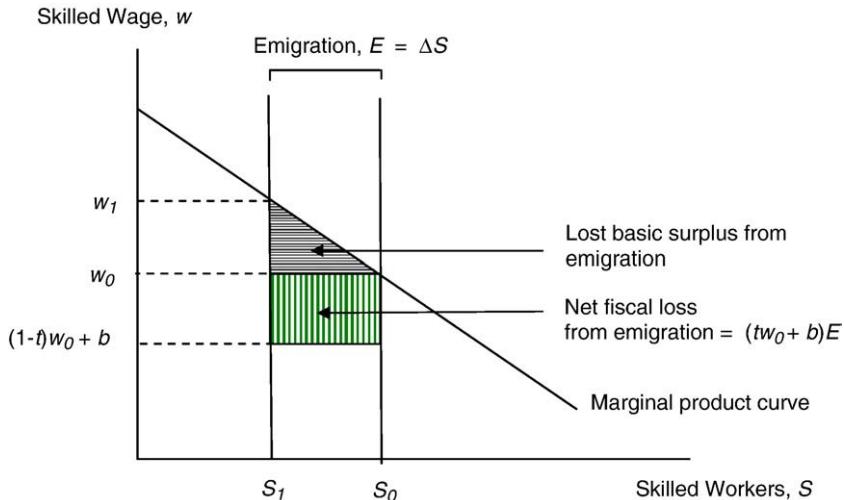


Fig. 2. The fiscal impact of emigration on "TLBs".

also affect the incomes of other factors and thus their net fiscal contributions. In addition, the emigrant stock may engage in economic actions that have fiscal consequences for the Indian government; e.g., trade, investment, and remittances.¹³ We also stress that our fiscal loss calculations take the fiscal parameters (t and b in our simple framework) as given. It is plausible that these parameters are themselves affected by the prospect or actuality of emigration. For example, the government might reduce top marginal tax rates to retain the most internationally mobile individuals, or cut back subsidies to higher education based on a prediction that many of the individuals to apply their subsidized educations elsewhere. Our calculations are designed to measure the direct fiscal impact given the parameters that are in place at a given point in time.

4.2. Counterfactual incomes

In order to determine the fiscal impact of the loss of the Indian-born resident in the U.S., it is necessary to consider first their counterfactual income distribution. This thought experiment involves considering the income that Indians in the U.S. would have earned if they were resident in India, and thus the potential loss to India from the accumulated emigrant stock.

Our counterfactual income distribution is based on a joint model of earnings and employment participation that we estimate using data on urban workers from the 50th round of the National Sample Survey.¹⁴ A standard incidental truncation model is employed given that earners are likely to be a self-selected subset of the working-age population. The model is a two-equation system consisting of an earnings equation (unconditional on

employment participation) and an employment participation equation:

$$\ln w_i = X_i\beta + \varepsilon_i. \quad (2)$$

$$\begin{aligned} p_i = 1 & \quad \text{if } w_i - w_i^r > 0 \\ p_i = 0 & \quad \text{if } w_i - w_i^r \leq 0 \\ \text{where } w_i - w_i^r & = Z_i\gamma + u_i. \end{aligned} \quad (3)$$

Log earnings ($\ln w_i$) are assumed to depend on human capital characteristics (notably educational attainment and experience). Participation (p_i) is assumed to depend on whether actual earnings (w_i) exceed reservation earnings (w_i^r), with the difference between the two assumed to be the sum of a linear function of human capital characteristics and a random draw from the standard normal distribution. The variables in Z include all the variables in X in addition to a dummy variable indicating the presence of capital income.¹⁵ The error terms in equations are assumed to be jointly normally distributed: $(\varepsilon_i, u_i) \sim N(0, 0, \sigma_\varepsilon, 1, \rho)$, where ρ measures the correlation between the two error terms.

An individual's counterfactual income is given by the product of predicted earnings conditional on employment participation and the probability employment participation. It is well known that in the context of incidental truncation that earnings conditional on employment is given by,

$$\ln w_i | (p_i = 1) = X_i\beta + \rho\sigma_\varepsilon\lambda_i + \nu_i \quad \text{where } \lambda_i = \frac{\phi(Z_i\gamma)}{\Phi(Z_i\gamma)}. \quad (4)$$

λ_i is the inverse Mills ratio. Although the disturbance term ν_i is uncorrelated with u_i , it does not have constant conditional variance. The conditional variance is given by,

$$\sigma_i^2 = \sigma_\varepsilon^2(1 - \rho\delta_i) \quad \text{where } \delta_i = \lambda_i(\lambda_i - Z_i\gamma). \quad (5)$$

¹³ See Kapur (2007).

¹⁴ This round was undertaken in 1993/94, which is prior to the mid- to late-1990s surge in U.S. bound emigration. Emigration-related market-wage effects should therefore be limited. The round does ask about the presence of capital income, but does not record the amount of such income. We therefore focus only on labor income.

¹⁵ The presence of capital income is used as an identifier in the participation equation.

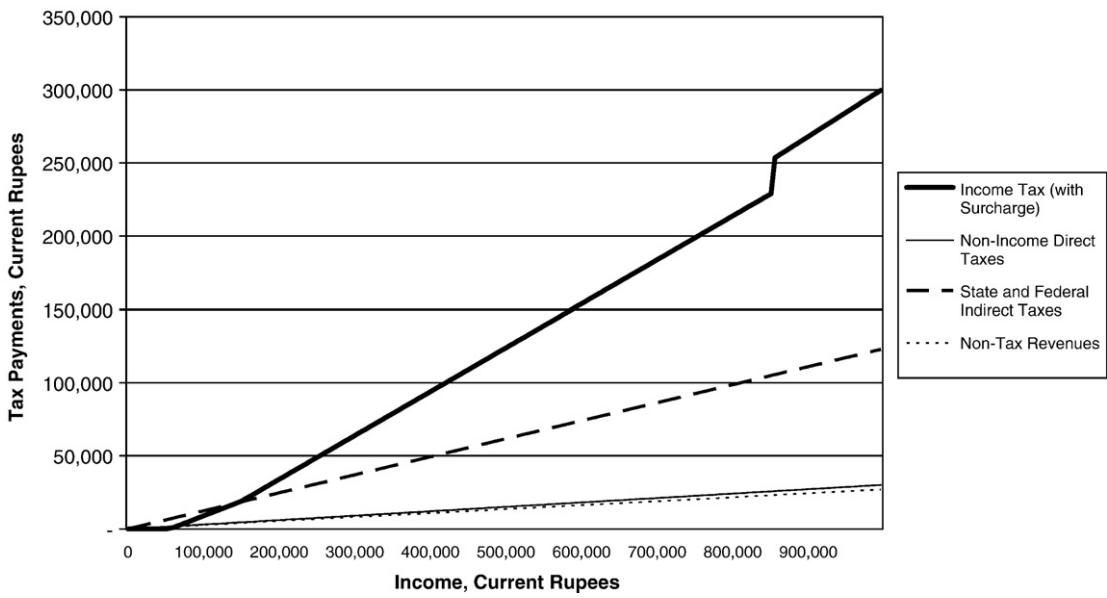


Fig. 3. The relationship between revenues and individual income, 2004/05.

Finally, the participation equation is given by,

$$Pr(p_i = 1) = Pr(u_i > -Z_i \gamma) = \Phi(Z_i \gamma). \quad (6)$$

Eqs. (4) and (6) are estimated as a system using a maximum likelihood procedure. This model is combined with the observed characteristics of the emigrants to generate the counterfactual income distributions. Applying the model in two distinct ways provide a reasonable range for the counterfactual calculations.

4.2.1. Method 1: expected earnings and participation

The first method is the most straightforward. The estimated earnings and participation equations are used to determine the expected earnings conditional on participation and the probability of participation for each U.S.-resident Indian emigrant. One complication that arises from the logged dependent variable in the earnings equation is that the log of expected earnings is not equal to expected value of log earnings. To obtain the former we use the usual approximation,

$$\ln \hat{w}_i \approx X_i \hat{\beta} + \hat{\rho} \hat{\sigma}_e \hat{\lambda}_i + \frac{\hat{\sigma}_e^2}{2}, \quad (7)$$

where $\hat{\sigma}_e^2$ is calculated using Eq. (5). This method provides the lower bound for our counterfactual income estimates.¹⁶

4.2.2. Method 2: iceberg inference

We documented earlier the success of the Indian-born population in the U.S. labor market. There is therefore good reason to worry that emigrants are positively selected from the domestic population with any given set of observable human capital characteristics. This concern is heightened given the limited human capital measures employed.¹⁷ To allow for positive selection, we make the assumption that selection on the unobservable human capital characteristics is similar to the selection on the observable characteristics. Just as with icebergs, for which the observable portion is typically about one-eighth of the total iceberg size, we infer the relative value of an individual's unobserved characteristics based on the relative value of characteristics that are observed. More precisely, Eq. (4) is used to determine what an emigrant's percentile income rank would be in the Indian income distribution based on their observed characteristics.¹⁸ This percentile rank serves to determine the draw from the appropriate error distribution, v_i , for earnings using Eq. (5). To determine participation, the estimated participation Eq. (6) is used to determine what the emigrant's percentile rank would be in the Indian participation distribution based on their observed characteristics. We then use this percentile rank to determine the draw from the standard normal distribution. This projected value for the error term is then used to evaluate the participation inequality, $u_i > -Z_i \hat{\gamma}$. For each emigrant, the left-hand side of the inequality is determined by the appropriate draw from the standard normal distribution; the right-hand side is determined using the estimated participation Eq. (6) and the emigrant's characteristics. On the assumption that emigrants are positively selected on observable

¹⁶ One limitation of this method is that it gives each emigrant their expected earnings and participation and thereby compresses the variance of the counterfactual income distribution. This underestimation of the variance will lead to an underestimation of lost income taxes given the progressive structure of the Indian income tax system. To check the effect of this compression we also simulated the counterfactual earnings and participation for each emigrant, thereby providing a better estimate of the counterfactual income distribution. To simulate earnings conditional on participation, we estimate expected earnings using Eq. (4) and then make a random draw from the relevant error distribution given the heteroscedastic variance from Eq. (5). To simulate participation, we assume that an individual will participate if $u_i > -Z_i \hat{\gamma}$. The resulting net fiscal impacts turn out to be almost identical to those obtained using Method 1.

¹⁷ For example, no distinction is made between those with undergraduate and those with post-graduate degrees.

¹⁸ The percentile ranks are bounded to fall in the range [0.01, 0.99].

characteristics, this method will tend to produce higher counterfactual incomes, thus providing the upper bound for our counterfactual income estimates.

4.3. A model of the Indian fiscal system

The final component of our methodological approach is a simple yet comprehensive model of the Indian fiscal system. It has three building blocks: income taxes, non-income taxes/non-tax revenue, and expenditures.

For the federal income tax calculations, annual Income Tax Department data on tax bands, tax rates, and the (constantly changing and elaborate) system of surcharges are employed.¹⁹ A non-linear function relating income tax payments to income given the tax rules (see Fig. 3 for the schedule for 2004) is generated.²⁰ Income tax loss calculations are based on what each absent Indian would have paid, making the assumption of full compliance, given our counterfactual income distributions. While full compliance is an aggressive assumption in the Indian setting, these high-income salaried individuals are the ones for whom this assumption is most defensible.²¹

We deal with non-income taxes and non-tax revenue in a straightforward way: we determine the amount of non-income tax/non-tax revenue paid per unit of Indian gross national income. The total non-income tax payments are from the Government of India's Indian Public Finance Statistics (various editions). Indian GNI is from the IMF's International Financial Statistics (on-line edition). Averaged over the period 1994 to 2005, non-income direct taxes were 2% of GNI, state and federal indirect taxes were 12% of GNI, and non-tax revenues were 3% of GNI. To calculate the indirect tax losses from emigration, these estimates of revenues per unit of income are simply multiplied by the counterfactual income estimates for each emigrant. This procedure assumes that these revenue sources are

¹⁹ Households can also be taxed as Hindu Unified Families, which have a separate tax schedule. For the purpose of our calculations, however, we assume that all U.S. resident Indians would be taxed as individuals in India. Constructed tax schedule are created for calendar years, where the tax schedule is a weighted average of the schedules for the overlapping fiscal years.

²⁰ We use the apply the tax rules for fiscal year 2004/05 to the calendar year 2004 since the majority of 2004 income is earned in that calendar year. We make the corresponding assumption for all other years.

²¹ Between 1990 and 2005, the number of Indian-born individuals in the United States increased by about one million of which more than half were in the 25–44 age group. Given the skills and education levels of this cohort discussed earlier in the paper, this implies that, in the absence of any emigration during this period, India would have had about one-half million additional professionals. How large is this relative to the pool of salaried tax paying professionals in India? Between 2001–01 and 2004–05 the number of assesses in India with an income of Rs 200,000 (approximately \$5000) and above increased from 1.045 million to 2.4 million. Thus this “missing” cohort represents between one-half (in 2000–01) to one-fifth (in 2004–05) of the tax-payers in India. Although at first glance the “full compliance” assumption may seem at odds with the realities of contemporary India, compliance rates are highest for the formal sector professionals that dominate the pool of U.S. emigrants. The largest share of income tax collections—about 40%—was from taxes deducted at source from salaries. (Note: Source of Indian tax data are from Comptroller and Auditor General of India. 2006. “Report No. 8 – Direct Taxes,” Chapter 2, available at: <http://cag.nic.in/html/reports/2006.htm>).

Table 3
Descriptive statistics Indian National Sample Survey, 50th round, 1993/94

Variable	Observations	Mean	Median	SD
Age	119,783	34.81	33	12.12
Sex	119,783	0.48	0	0.50
Primary	119,783	0.12	0	0.33
Middle	119,783	0.16	0	0.36
Lower-secondary	119,783	0.15	0	0.36
Higher-secondary	119,783	0.11	0	0.31
Graduate & above	119,783	0.14	0	0.34
Experience	119,783	23.05	21	14.08
Experience-squared/100	119,783	7.30	4.41	7.69
Capital income	119,783	0.09	0.00	0.30
Earnings	36,363	460.12	350	423.50
Log (earnings)	36,363	5.71	5.86	1.07

Notes

1. Sample includes only urban residents aged 18–64.
2. For sex dummy, male=0, female=1.
3. Education variables are dummies for highest level of education achieved.
4. Experience is equal to age less years of education less five.
5. Capital income is a dummy for the presence of interest or dividend income in household.
6. Earnings is the weekly wage/salary income in 1994 rupees.
7. Log earnings is the natural log of earnings.
8. Only observations with a positive wage/salary are included in wage/salary statistics.

proportional to income—i.e. indirect taxation is neither progressive nor regressive. Fig. 3 provides a visual comparison of the importance of the three sources of non-income tax revenues with income tax revenues at various income levels.

The fiscal impact of emigration may not be limited to tax revenue losses—TLBs may also save on government expenditures when their compatriots leave. Put differently, at least a portion of the tax revenues that were being paid by those who have left were being used to finance government benefits consumed by this group. The net fiscal impact is then the difference between tax losses and the expenditure savings. It is important to note that the expenditure savings of interest are the monies saved by not having to spend on those who left, not the actual changes in government spending in the various expenditure categories.

In order to determine the expenditure savings, the spending categories are divided between those for which zero savings from emigration are assumed (which we conservatively limit to interest payments) and those for which positive savings are generated (everything else). Having established the relevant categories of expenditures, the actual savings associated with the act of emigration can be considered on a per capita basis or per unit of income. Given the relatively small absolute number of Indians living in the U.S. relative to the overall Indian population (approximately 0.1%), the per capita assumption will inevitably lead to relatively small expenditure savings. Alternatively, government spending may be proportional to income because the better off are better able to “work the system” or they represent a more powerful political interest group. Based on discussions with Indian government officials, we have concluded that the per capita method best reflects the

Table 4

Empirical model of earnings and participation joint maximum likelihood estimates

	Both sexes		Men		Women	
	Earnings	Participation	Earnings	Participation	Earnings	Participation
Primary	0.3875 (0.0168)	0.0581 (0.0133)	0.1593 (0.0491)	−0.3048 (0.0253)	0.2518 (0.0175)	−0.0552 (0.0183)
Middle	0.6801 (0.0159)	0.1619 (0.0126)	0.6211 (0.0528)	−0.3477 (0.0260)	0.4903 (0.0162)	−0.0166 (0.0171)
Lower-secondary	1.0862 (0.0159)	0.2490 (0.0130)	1.4883 (0.0403)	0.0005 (0.0244)	0.8566 (0.0163)	−0.0343 (0.0173)
Higher-secondary	1.3184 (0.0190)	0.3250 (0.0156)	1.7752 (0.0474)	0.2321 (0.0296)	1.0790 (0.0194)	−0.0562 (0.0201)
Graduate & above	1.7214 (0.0185)	0.7689 (0.0138)	2.1271 (0.0510)	0.7920 (0.0252)	1.4908 (0.0165)	0.3372 (0.0182)
Experience	0.0724 (0.0020)	0.0820 (0.0011)	0.0644 (0.0044)	0.0548 (0.0020)	0.0696 (0.0024)	0.1018 (0.0015)
Experience ² /100	−0.0960 (0.0000)	−0.1386 (0.0000)	−0.0873 (0.0001)	−0.0875 (0.0000)	−0.0891 (0.0000)	−0.1814 (0.0000)
Capital income		0.2317 (0.0141)		0.1502 (0.0253)		0.1643 (0.0187)
Constant	3.9725 (0.0217)	−1.6043 (0.0167)	4.1892 (0.0232)	−1.1315 (0.0217)	3.5797 (0.0521)	−1.8473 (0.0313)
ρ	0.0689 (0.0299)		0.1631 (0.0653)		0.1171 (0.0247)	
σ_e	0.8424 (0.0036)		0.9478 (0.0116)		0.8943 (0.0038)	
$\rho\sigma_e$	0.0581 (0.0253)		0.1546 (0.0633)		0.1047 (0.0223)	
Observations	36,363	119,783	29,413	62,660	6,950	57,123

Notes

1. Data source: National Sample Survey, 50th round.
2. Standard errors are in parentheses.
3. Omitted education categories are illiterate, literate with no formal schooling, and below primary education.

likely expenditure savings, and we focus on it in the calculations that follow.²²

5. Results and discussion

5.1. Estimated earnings and participation model

The first step in implementing the methodology outlined in Section 5 is the estimate the joint model of earnings and participation. The model is estimated using the 50th round of the NSS. The 50th round is employed as it was undertaken in 1993/94, which is before the surge in skilled emigration to the U.S.

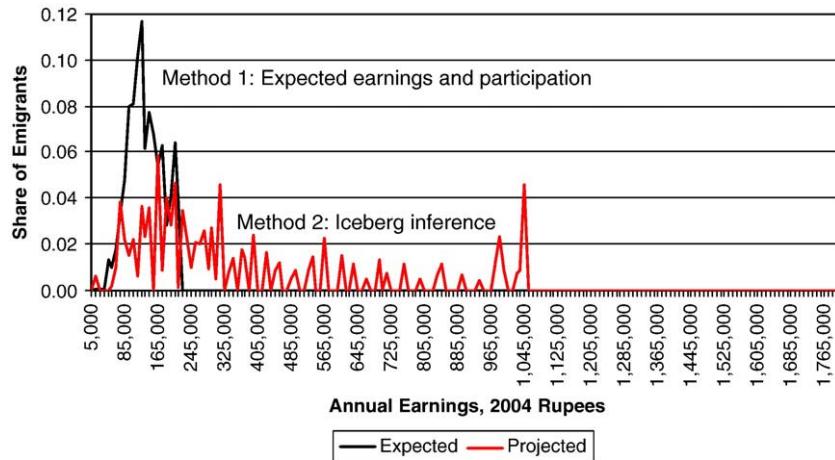
As such, the estimated returns to human capital should not be significantly impacted by emigration-related reduction in skill supplies. The sample is restricted to working-age urban residents. Table 3 records the descriptive statistics on the variables used. The total sample contains 119,783 observations, of which 36,363 (or 30%) received wage or salary income in the reference week. Table 4 records the results of estimating the joint model using maximum likelihood. We estimate the model for men and women together, and also for each gender separately. The gender-specific models are used to generate the counterfactual distributions.²³

5.2. Counterfactual distributions based on the estimated model

Fig. 4 records the counterfactual earnings distributions based on the two methods outlined in Section 5. In comparison with Method 1, the mean of the distribution for Method 2 is shifted significantly

²² In choosing between these alternatives, a reading of the Indian public finance literature suggests that any expenditure savings resulting from migration would have been small. During this period, India has had one of the highest fiscal deficits in the world (nearly 8% of GDP, with primary deficits averaging 4% of GDP), the result of what the head of India's central bank has termed, "the runaway growth of public expenditure." (Jalan, 1997, p. 48). Despite the high fiscal deficits, government consumption expenditures (wages for politically powerful government employees, defense and interest payments) increased during this period and expenditure reductions have proven to be politically impossible (IMF, 2002). The private sector salaried class—the so-called middle-class from which our migrating cohort is drawn—is not politically strong, and indeed is an important reason why it leaves India in such large numbers in the first case. Consequently we believe that that given India's political economy, any expenditure savings arising from migration would have been negligible.

²³ The estimated coefficients on the human capital dummies in the earnings regression can be used to determine the returns to additional years of schooling. These returns to education are consistent with estimates found in Duraisamy (2002) as well as other studies of returns to education in India. The implied average returns per additional year of schooling are: primary (7.75%); middle (9.75%); lower-secondary (20.31%); higher-secondary (11.61%); and graduate & above (13.43%).



Note: Bin size = 10,000 rupees. The mid-point of each bin is shown along the horizontal axis.

Fig. 4. Counterfactual earnings distributions for 2004. Conditional on participation.

to the right. (Recall that Method 2 uses “iceberg inference” to infer the value of the error term based on the relative value of emigrant’s observed human capital in the Indian labor market.)

In terms of participation, Method 1 predicts an average overall employment participation rate of 42% for the period 1994 to 2005. This is above the 30% participation rate observed in the resident Indian sample, but is still striking low. It is noteworthy that the observed average participation of the emigrants in the U.S. is 73% for the same period based on observations from the CPS. This is quite close to the overall average predicted participation rate of 75% found using Method 2. To the extent that the observed U.S. participation is a good indicator of what participation would be if the individuals were in India, this finding provides an additional reason to favor Model 2.

5.3. Net fiscal impact estimates

Fig. 5 and Table 5 show the results of running the counterfactual distributions generated by each of the two methods through our model of the Indian fiscal system. As expected, Fig. 5 shows that Method 2 produces substantially higher net fiscal impacts than Method 1. For the Method 2, the net fiscal impact rises from 0.20% of GNI in 1994 to 0.44% of GNI in 2005. The corresponding impacts for Method 1 are fairly described as negligible.

Table 5 demonstrates why the results of the two methods differ so much. The total estimated income loss under Method 1 is just 0.225% of GNI in 2005, while this loss is roughly five times higher at 1.15% of GNI under Method 2. The corresponding tax losses are thus much larger under the iceberg method. In contrast,

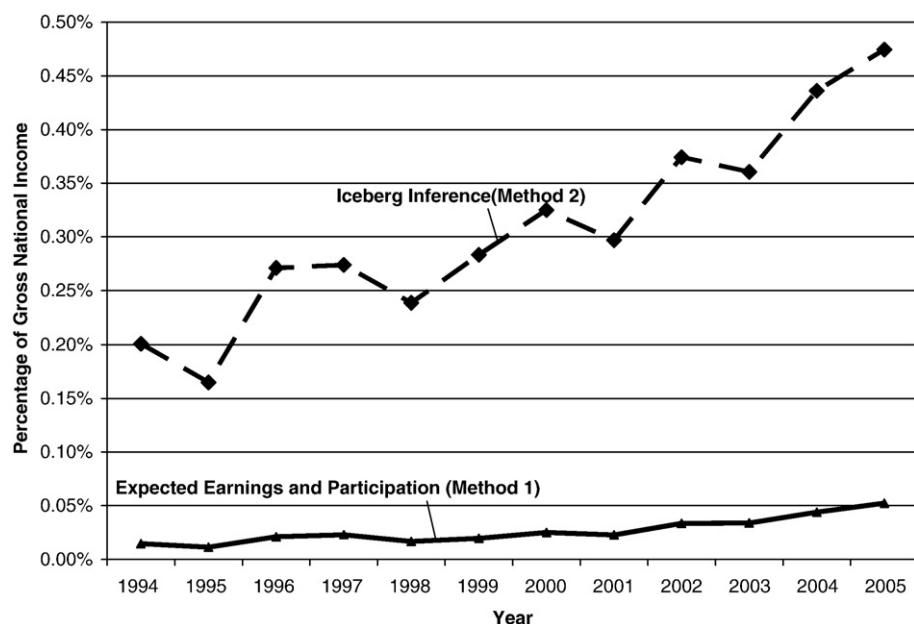


Fig. 5. Estimated net fiscal impact of Indian emigration to the U.S.

Table 5

Net fiscal impact calculations percentage of gross national income, selected years

Counterfactual income (%)	Income tax loss (%)	Non-income direct tax loss (%)	Indirect tax loss (%)	Non-tax revenue loss (%)	Expenditure saving (%)	Net fiscal impact (%)
Method 1 (expected earnings and participation)						
1995	0.08	0.01	0.00	0.01	0.01	0.01
2000	0.17	0.02	0.00	0.02	0.02	0.02
2005	0.23	0.03	0.01	0.03	0.02	0.05
Method 2 (iceberg inference)						
1995	0.40	0.11	0.01	0.05	0.01	0.16
2000	0.87	0.21	0.02	0.10	0.02	0.33
2005	1.15	0.29	0.04	0.13	0.02	0.47

See notes to Fig. 5 for a brief description of each method.

the expenditure saving is the same under both methods. This follows from our measurement of expenditure savings based on per capita non-interest public expenditure, which makes the savings independent of the counterfactual incomes.

Which of the methods provides the most reasonable measure of the net fiscal impact? Based on our earlier findings of the high level of achievement of Indian emigrants in the U.S., we think it is essential to make allowance for positive selection. One reason to expect positive selection is that emigrants from distant places have typically shown themselves to be a more select group, showing, for example, more initiative than their observational equivalents in making costly migration decisions.²⁴

The most likely source of positive selection is not the voluntary migration decisions of Indians, but the decisions of U.S. universities, employers and immigration officials through the employment-based temporary and permanent visa system. For the important H-1B category, employers decide whom to petition for, and immigration officials decide on which petitions to allow. Employers can observe much more about potential H-1Bs than is observable in the CPS data, aided in part by Indians who are already in the U.S. For example, an employer can observe the quality of the school a H-1B applicant has graduated from. Given the costs of the process, these observable markers of quality will provide a distinct advantage to graduates of the most prestigious schools.

The importance of H-1Bs as driver of high-skilled emigration from India is highlighted by the following facts. First, while the

²⁴ Borjas (1987) points out, however, that it is quite possible that immigrants to the U.S. are negatively selected. Intuitively, the argument is that if income distribution is less compressed in the source country than in the U.S.—which is the case for many countries in Latin America, for example—it is high earner types that will find migration relatively unattractive. (This is true both within and across observational categories.) While Borjas' argument alerts us against any automatic assumption of positive selection, it actually tends to support the assertion that positive selection is an issue for U.S.-bound Indian migration. In the late 1990s, measured inequality in India was lower than in the U.S. (UNDP, 2001, Table 12). The Gini coefficient in 1997, for example, was 37.8 for India and 40.8 for the U.S. For the same year, the ratio of the incomes of the richest decile to the poorest decile was 16.6 in the U.S. and 9.5 in India. While this is at best a crude pointer to positive selection, it helps us to rule out negative selection as a serious possibility for the Indian case. For a more recent empirical effort on migration selection issues, see Chiquiar and Hanson (2005) on how Mexican migratory flows to the U.S. do not conform to the negative selection hypothesized in Borjas.

share of H-1Bs going to Indians was stable at around 20% in the first half of the 1990s, the share rose steadily to reach 49% in fiscal year 2001 (Desai et al., 2004; Kapur and McHale, 2005). Second, in fiscal year 2001 almost 162,000 H-1B petitions were approved for Indians (Kapur and McHale, 2005). Third, more than 98% of approved petitions went to workers with a bachelor's degree or better, with more than 40% having a graduate degree. Finally, almost 60% of approved petitions were in technically-demanding, computer-related occupations.

There is also evidence from the sending side that Indian emigrants to the U.S. are not drawn randomly from the population of graduates, let alone the population at large. Studies of the graduates of the Indian Institutes of Technology provide a good illustration. The acceptance rate in these institutes is between 1 and 2% from a pool that is already highly selective. An analysis of the "brain-drain" of the graduates of IIT Mumbai in the 1970s revealed that 31% of its graduates of IIT settled abroad while the estimated migration rate of engineers more generally was 7.3%.²⁵ Furthermore, the migration was significantly higher in those branches of engineering with higher ranked entrants to IIT: thus the percentage abroad in electrical engineering was nearly 43%, while in metallurgical engineering it was about 20%. Similarly, while the percent abroad was 43% in the top quartile of the graduating class it was 27% in the rest of the class.

The selection bias in emigration from India also exists in other disciplines. In medicine, while migration rates for doctors was about 3% during the 1980s, it was 56% for graduates of the All India Institute for Medical Sciences—India's most prestigious medical training establishments—between 1956–80, and 49% in the 1990s.²⁶ And in management training, a recent analysis of graduates of India's premier management school in February 2000 found that the typical recruit in the international

²⁵ See Sulhatne (1994). The survey population was students who graduated from IIT Mumbai between 1973–1977 and was conducted in 1986. Students taking the entrance exam for the IITs are ranked based on their performance in a written exam. Based on their rankings the students rank both their choice of institute and branch of engineering, and once these are filled, the lower ranked students choose from the remaining disciplines.

²⁶ For figures between 1956 and 1980 see Khadria (1999). Data on the 1990s are based on submissions by the Comptroller and Auditor General to the Indian Parliament. Synopses of Debates, Rajya Sabha, Proceedings other than Questions and Answers, August 22, 2001. <http://parliamentofindia.nic.in/rs/rsdebate/synopsis/193/22082001.html>.

sector has a CGPA (cumulative grade point average) that is significantly higher than his counterpart in the domestic sector (See Bhattacharjee, Krishna and Karve, 2001).

It can be argued that while there are fiscal losses due to positively selected emigration, there may be compensating fiscal gains due to inward investment and remittances from the migrants. In India's case, fiscal gains from the former are negligible because FDI from Non-Resident Indians (NRIs) has been extremely modest to date.²⁷ In contrast to FDI, NRI remittances have been robust. These remittances undoubtedly have some fiscal consequences through their impact on consumption and thus on indirect tax receipts. We have estimated the indirect tax yields as a result of remittances to have reached about 0.07% of GNI in 2005.²⁸ This leads to a partial offset of our net fiscal loss estimate under our preferred : Method 2, but a sizable net loss remains.

6. Conclusion

The demographic pressures transforming the developed world are likely to raise the mobility of skilled labor globally. For developing countries, this development has important and wide-ranging consequences. In this paper we highlight a specific and hitherto unexamined effect of international human capital flows: the fiscal consequences on the country of origin. The nature of recent emigration from India to the U.S.— where a relatively small share of the tertiary-educated Indians have emigrated but these individuals are disproportionately rich in human capital— reflects the broader phenomenon of highly skilled migration from poor to rich countries. Indeed, some regions such as the Caribbean, much of Africa and Central America are losing extremely high shares of the tertiary-educated to emigration. The methodologies developed in the paper allow for evaluation of different patterns of emigration.²⁹

²⁷ According to RBI figures non-resident Indian foreign direct investment flows averaged just \$71 million a year between 1998–1999 and 2000–2001 (Reserve Bank of India, 2001). This is in sharp contrast to China where NRIs (non-resident Chinese) have been the principal foreign investors (in the early 1990s for instance, more than three-fourth of FDI in China was NRI investment; although the proportion has declined since then but it still remains high). Guha and Ray (2002) argue that this difference is less due to substantially different policy regimes, but rather the lack of skills amongst the NRIs “in the management of export production with low wage labor.”

²⁸ The remittance estimates are based on Reserve Bank of India estimates for inward private transfers in “invisibles” section of the balance of payments (Reserve Bank of India, 2006). This remittance flow is estimated to have reached 3.11% of GNI in fiscal year 2005, of which 1.05% (one-third) is estimated to come from the U.S. The Reserve Bank of India further estimates that 54% of this flow went to support “family maintenance” (with the remaining 20% going into bank accounts, 10% into real estate, and 16% into “other”). We assume that portion that supports family maintenance is spent and generates corresponding indirect tax revenues. Applying the total indirect tax rate for 2005 of 11.5% yields the estimated tax yield of 0.07% of GNI. This gain is significant enough under the first method to lead to a net fiscal gain.

²⁹ The emigration rate for the tertiary educated is estimated to have been 42% for the Caribbean region as a whole in 2000. Western and Eastern Africa had emigration rates of 27% and 18% respectively. Even in Central America, where emigration is not usually considered a highly skilled phenomenon, the tertiary emigration rate is estimated to have been 16% in 2000 (see Kapur and McHale, 2005; Docquier and Marfouk, 2006).

More broadly, the analysis in the paper suggests further implications of international skilled migration for the viability of alternative development strategies. As human capital becomes more mobile, policy makers are more likely to respond to pressures to reduce the progressivity of their tax systems to limit the exit of the highly skilled. As developing countries survey the policy responses available to them in the wake of these developments, fiscal responses associated with tax regimes for capturing some of this lost income may grow in importance. Desai, Kapur and McHale (2004) discuss broadly the issues in designing tax regimes to capture such lost income including the adoption of worldwide tax regimes by developing countries and the cooperative, bilateral sharing of tax revenues. The methodology and analysis of this paper will hopefully lay the empirical basis for the consideration of such policies.

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