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The Fiscal Impact of the Brain Drain: Indian Emigration to the U.S.

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ABSTRACT

Easing immigration restrictions for the highly skilled in developed countries portend a future of increased human capital outflows from developing countries. The myriad consequences of these developments for developing countries include the direct loss of the fiscal contributions of these highly skilled individuals. This paper analyzes the fiscal impact of this loss of talent for a developing country by examining human capital flows from India to the U.S. The escalation of the emigration of highly skilled professionals from India to the U.S is examined by surveying evidence on the changing nature of the Indian-born in the U.S. during the 1990s. The loss of talent to India during the 1990s was dramatic and highly concentrated amongst the prime-age work force, the highly educated and high earners. In order to estimate the fiscal losses associated with these emigrants, this paper first estimates what these emigrants would have earned in India, and then integrates the resulting counterfactual distributions with details of the Indian fiscal system to estimate fiscal impacts. Two distinct methods to estimate the counterfactual earnings distributions are implemented: a translation of actual U.S. incomes in purchasing power parity terms and an income simulation based on a jointly estimated model of Indian earnings and participation in the workforce. The PPP methods indicate that the foregone income tax revenues associated with the Indian-born residents of the U.S. comprise one-third of current Indian individual income tax receipts. Depending on the method for estimating expenditures saved by the absence of these emigrants, the net fiscal loss associated with the U.S. Indian-born resident population ranges from 0.24% to 0.58% of Indian GDP in 2001.

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1. *Introduction*

The fiscal pressures associated with demographic changes in the developed world have generated pressure for major policy shifts including changes in immigration policies. These changed immigration policies have the potential to have sweeping 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 and will potentially have large consequences on source and destination countries.[1]

This paper argues that 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 dramatic change in the flows of human capital from India to the U.S. As of March 2001, more than a million Indian-born individuals were resident in the United States—a more than doubling of this population since 1990. Of these, more than half were in the fiscally sought-after 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 38 percent of this age group had masters, professional, or doctorate degree, compared to just 9 percent with better than a bachelor's degree in the native-born population. Moreover, the human capital intensity of the flows of Indians to the U.S. has increased substantially during the 1990s. Of the Indians who came since 1990 and were still in the U.S. at the end of the decade, an estimated 78 percent had a bachelor's degree or better—21 percentage points greater than the cohort who came during the 1980s and were still in the U.S. at the end of that decade.[2]

Human capital outflows of this magnitude must affect developing countries, including India, 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" is likely to have substantial negative effects on a country as well. The loss of skilled workers will harm cooperating factors—complementary skilled workers, less-skilled workers, entrepreneurs, and capital providers. The outflow of talent will also make the country less attractive as a destination for foreign direct investment and potentially stunt the development the needed critical mass for successful high technology clusters. Critically, it may have deeply inimical consequences on a country's institutions, for instance its universities, affecting its long-term development.[3]

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[1] Desai, Kapur, and McHale (2001) outlines the various arguments for why greater mobility will characterize the next half century. See Storeletten (2000) for a specific proposal of greater skilled immigration as a solution to fiscal pressures from demographic shifts in the developed world.

[2] The most significant change in U.S immigration law was the expansion of the of the H-1B visa program for skilled workers over the last decade. An Immigration and Naturalization Service study of H-1B petitions granted between October 1999 and February 2000 suggests the likely impact on skilled Indian emigration. Of the 81,262 petitions approved, 43 percent went to Indians. Computer-related occupations alone account for 54 percent of total approved petitions, with Motorola, Oracle, and Cisco topping the employer list. The median salary for H-1Bs working in computer-related occupations was $53,000. Finally, 98 percent of the approved petitions went to individuals a bachelor's degree or better, with 42 percent having a master's, professional, or doctorate degree (INS, 2000).

[3] See Desai, Kapur and McHale (2001) and Solimano (2001) for an elaboration of these varied effects.

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 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).[4] 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 of 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 a methodology for estimating the fiscal loss to TLBs from the accumulated emigrant stock given *existing* fiscal policies. As such, the paper intends to illuminate the complex effects of a global phenomenon that will have increasing effects on LDCs in coming decades—factor mobility of human capital—and to develop a flexible methodology for considering the fiscal impact of these developments. Additionally, the paper illustrates the changing nature of the U.S.-resident Indian diaspora, the returns to human capital in the Indian labor market, and the implications for efforts to tax this stock of human capital resident abroad. 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 growing loss of highly skilled workers.[5]

[4] 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.
[5] For one set of estimates of these losses of talent, see Carrington and Detragiache (1998).

The results presented in this paper demonstrate the dramatic difference in recent emigrants from India to the U.S. and the distinctive nature of the stock of Indian emigrants relative to the native-born and other foreign born in the U.S. Indian-born residents of the U.S. are four times as likely to have a graduate degree as the native born and their median income is 16% higher than the median income of the native born. A population that is only 0.1% of the population of India has aggregate income that is 10% of Indian national income. Simulating the counterfactual earnings that these Indian-born would have earned had they stayed in India permits the analysis of the tax losses, expenditures savings and resulting net fiscal impact associated with this population. While these estimates vary, plausible calculations suggest that foregone income tax revenues associated with the Indian-born residents of the U.S. are one-third of current individual income tax receipts. Depending on the method for estimating expenditures saved by the absence of these emigrants, the net fiscal loss associated with the U.S. Indian-born resident population ranges from 0.24% to 0.58% of Indian GDP in 2001.

The remainder of the paper is structured as follows. Section 2 describes the evolution of the Indian-born population over the last decade using data from the 1990 U.S. census and annual U.S. Current Population Surveys (CPS) between 1994 and 2001. In particular, this analysis emphasizes the distinctive nature of the Indian-born population on age, education and income dimensions. Additionally, the analysis demonstrates how the 1990s cohort of Indian emigrants differed markedly from contemporaneous immigrants from other countries and from previous cohorts of Indian-born immigrants.[6]

[6] As noted in Khadria (1999), the emigrants from India in the early 1970s were of a similar educational profile as recent emigrants, although much fewer in number.

Section 3 outlines a simple model that provides the framework for estimating the fiscal impact of the stock of Indian-born residents abroad. The model shows how the net fiscal loss is a component of the overall impact of emigration on TLBs, and relates the size of the loss to pre-emigration earnings and the fiscal rules determining taxes and spending. This section concludes with a discussion of the conditions under which the size of the pecuniary fiscal loss is a sufficient measure of the welfare impact of skilled emigration on TLBs.

Section 4 presents counterfactual Indian income and earnings distributions for U.S. resident Indians; that is, estimates of the distribution of income for these individuals if they were living in India. Since this exercise requires a significant number of assumptions, two quite different estimation methods are presented that provide reasonable upper and lower bounds for the earnings loss. Unfortunately, but unsurprisingly, these estimates diverge considerably. The first method uses actual U.S. incomes and translates them into equivalent "real" Indian incomes and earnings using purchasing power parity exchange rates. Although the PPP estimates of Indian incomes are less than a fifth of what would be implied by market exchange rates, they still may be somewhat upward biased estimates of what these individuals would earn in India. The second method uses a joint model of Indian earnings and participation estimated with data from the National Sample Survey. Observed characteristics on the Indian-born residents in the U.S. are then run through this model to simulate a counterfactual earnings distribution. This regression-based simulation method is likely to be significantly downward biased as those Indians who choose (and are allowed) to work in the U.S. are likely to have unobserved characteristics that increase their earning potential in either labor market relative to observationally equivalent TLBs. While the gap between these methods is large, there are a variety of reasons to believe that the estimates based on purchasing power parity represent more reasonable estimates of income losses.

These estimates of the counterfactual earnings distribution generate the direct fiscal impact estimates presented in Section 5. The structure of income tax rates, exemptions, and deductions in the relevant years are used to estimate progressive income tax revenue losses. By assuming a year-specific linear relationship between income and indirect taxes, estimates of the indirect tax revenue loss for state and federal governments are also generated. Finally, estimates of the expenditure savings to TLBs from emigration are generated for various categories of federal and state expenditures.

Section 6 concludes with a discussion of the implications of this analysis for varied proposals to implement taxes on the populations of citizens resident abroad as a mechanism for compensating for these fiscal losses.

2. Characteristics of the Indian Population in the U.S.

Figures 1 and 2 illustrate the evolution of the Indian-born population in the U.S. over the last half-century.[7] 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 detail provided in Figure 2 of the trends in the 1990s for the 18 to 64 year old age group demonstrates that

[7] 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.

the vast majority of that growth was concentrated in the latter part of the 1990s and that this population is increasingly skewed toward non-U.S. citizens.

This trend in increased emigration toward developed countries from India appears to be mirrored in the experiences of Australia, Canada and the United Kingdom as shown in Table 1. While figures are not directly comparable across countries, the estimates provided in Table 1 similarly indicate an increasing flow of talent to these countries through the late 1990s. Consideration of just these three destination countries for Indians represents another 500,000 Indian-born individuals, at a minimum, living abroad by 2000. While the work that follows only considers the population of Indian-born residing in the U.S., it is clear that the estimates generated in the following would be magnified considerably by explicit consideration of the experience of other countries.

Tables 2, 3, and 4 consider the age, education, and income characteristics of the Indian-born population from 1990 to 2001 in comparison with the native-born and other foreign-born resident in 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-work age population. More than half of the Indian born are in the 25 to 44 year old age group compared to around 30 percent of the native born and 44 percent of the other foreign-born. It is also notable that dependents (under 18 or over 64) are 15 percent or less of the Indian-born population in each of the years covered, but roughly 40 percent for each year for the native-born population. While this compression of the age distribution might be expected for immigrants relative to the native-born, it is striking that Indian-born differ markedly from other foreign born as well.

Turning to educational achievement, Table 3 shows that the Indian-born population is even more strikingly distinct in terms of its education distribution. The average share between 1994 and 2001 of the native-born population with a bachelor's degree or better was 26.5 percent—compared with 70.8 percent for the Indian born. In contrast, the share of other foreign born was similar to the native born with an average share of 24.7 percent. The share of the Indian born with post-bachelor's degrees—master's degrees, professional degrees, and doctorates—is also high at 36.8 percent compared to 8.5 percent and 8.6 percent 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 decade in contrast to the relatively stable trends for the native-born and other foreign-born.

Table 4 demonstrates how these distinctions in age and education for the Indian-born translate into a distinctive income distribution relative to the native born and other foreign-born. While median incomes for the Indian-born and native born were approximately the same at the beginning of the 1990s, the Indian-born significantly outpaced both native and other foreign born in earning power during the 1990s. The income distribution of the Indian born appears to have shifted rightwards far more strongly than for the native born and other foreign born since 1990, reflecting both the increased inflows of highly educated Indians as well as their sectoral concentration in the booming high technology sector. The aggregate level of income associated with the India-born is depicted in Figure 3. The rapid escalation to over $40 billion in total income in 2001 dollars by 2001 is characterized by a growing component of self-employment earnings and non-earnings income demonstrating a growing level of accumulated wealth and appetite for entrepreneurial endeavors.

While Tables 2, 3 and 4 emphasize the relatively younger, more educated, higher income nature of the Indian-born relative to the native-born and other foreign-born populations, Table 5 explicitly considers how recent immigrants from India are distinctive. This analysis compares immigrants from the 1990s ("recent" in 2000) to the immigrants from the 1980s ("recent" in 1990) for both Indian-born immigrants and other foreign-born on the dimensions of age, education and income in the three panels of Table 5. Of the Indians who came during the 1990s and were still in the U.S. in 2000, 33 percent earned more than twice the native-born median for 2000. By contrast, of the Indians who came during the 1980s and were still in the U.S. in 1990, only 17 percent earned more than twice the native-born median for 1990. Interestingly, this shifting pattern of income generating power was not observed for other foreign-born individuals. The share of other recent non-Indian arrivals earning more than twice the native median was approximately the same (and considerably lower) in 1990 and 2000.

This shift in the nature of Indian-born immigrants is mirrored in their educational levels and their age profile. In contrast to both Indian-born immigrants from the 1980s and other foreign-born immigrants, the Indian-born immigrants from the 1990s were significantly more educated with a particular concentration in those individuals having earned a masters degree. Finally, Indian-born immigrants during the 1990s contributed to the compression of the age distribution of Indian-born residents as these recent immigrants were considerably more likely to be in the 18 to 44 year old age group relative to previous Indian-born migrants and other foreign-born migrants.

The analyses in Tables 2 through 5 outline the distinctive nature of the Indian-born population in the U.S. In addition to being younger, better educated and richer than comparable populations, these trends have accelerated considerably in the 1990s as the cohort of Indians who came during the 1990s—many associated with the expanded H-1B program and with the expanded employment-related permanent residency—have been even more concentrated in the young working age groups, are even more educated, and are even more disproportionately concentrated in the upper reaches of the income distribution.

3. From Income Losses to Fiscal Losses: A simple framework

In order to motivate the calculations that follow, this section outlines a simple framework that underlies the subsequent fiscal impact estimates. The framework centers on the Indian market for skilled workers and corresponds to Figure 4. The model assumes all factors of production are in fixed supply; all factors are paid their marginal products; and there are no externalities.[8] w is the skilled wage, and skilled workers face

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[8] 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

an income tax rate, t, and receive 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, $tw - B$.

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 Figure 4. This total loss can be divided into the net fiscal loss (NFL),

$$L_f^{TLB} = NFL = (tw_0 + B)E$$

and the non-fiscal losses to cooperating factors.[9]

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 sections of the paper 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. These net fiscal loss estimates 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 also affect the incomes of other factors and thus their net fiscal contributions. In addition, 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 fifty percent annually during the decade.

emigrant stock may engage in economic actions that have fiscal consequences for the Indian government; e.g., trade, investment, and remittances.[10]

These fiscal losses can be translated into a welfare impact under certain assumptions. These losses will force increases in the taxes paid by TLBs and/or cuts in various categories of government expenditure. In general, the welfare impact will depend on the how the adjustment is divided between tax rises and expenditure cuts. There is, however, one special case where the welfare impact depends on the total net fiscal loss and not the distribution of the adjustment between taxes and spending. Suppose the government is choosing fiscal policy to maximize the welfare of permanent Indian residents (i.e. TLBs), and that the total welfare is a function of the taxes TLBs must pay, T, and the levels of the available M categories of government expenditure, $G_1, \ldots, G_m$.

$$W = W(T, G_1, \ldots, G_m)$$

Allowing for a small amount of skilled emigration and assuming a balanced budget, the net fiscal loss must be matched by tax increases and expenditure reductions on TLBs. As a consequence, the total change in the welfare of TLBs is given by,

$$\frac{dW}{\theta^*} = dT - dG_1 - \ \ldots \ - dG_m = NFL \ ,$$

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

[10] See Nayyar (1994).

where θ^* is the common marginal social value of either a decrease in taxes or an increase in any of the categories of government spending evaluated at the social welfare optimum; that is,

$$\theta^* = \frac{\partial W^*}{\partial T} = -\frac{\partial W^*}{\partial G_1} = \ldots = -\frac{\partial W^*}{\partial G_m}.$$

The welfare effect on TLBs depends only on the size of the net fiscal loss due to emigration and not on its distribution. In other words, the net fiscal impact is a sufficient statistic for assessing the welfare impact on TLBs through the direct fiscal channel. Given that fiscal policy may not be chosen optimally and that skilled emigration has been far from small, this translation may have limited appeal given the restrictive assumptions. Thus, even though subsequent analyses emphasize the net fiscal loss, the welfare implications of the loss depends on the relative costs of the actual fiscal responses—e.g., cuts in education spending versus increases in income taxes—as well as the actual incidence of these responses.

4. Counterfactual Income/Earnings Distribution for Emigrant Indians

In order to consider the fiscal impact of the loss of the Indian-born resident in the U.S., it is necessary to consider first their counterfactual income/earnings distribution. This thought experiment involves considering the income/earnings that Indians in the U.S. would have if, counterfactually, they were resident in India, and thus the potential loss to India from the accumulated emigrant stock. These counterfactual distributions will be the primary input for the fiscal impact estimates in Section 5. In order to consider the range of possible distributions, this section employs two distinct estimation methods, one based on observed U.S. incomes and PPP exchange rates, and the other based on an earnings and participation model estimated from Indian data. These methods likely provide reasonable upper and lower bound estimates of the fiscal loss but arguments are provided for why PPP based estimates are more reasonable estimates for considering actual fiscal impacts.

A. PPP-based method for estimating counterfactual income/earnings

The PPP-based method for estimating counterfactual income/earnings begins with the simple premise that Indian-born residents of the U.S. would earn a wage in India that is approximated by PPP exchange rates. As a consequence, the method begins by using U.S. Current Population Survey (CPS) estimates of the earnings distribution of Indian-born working age individuals (18-64) to estimate of the real earning power of these individuals if they lived in India. These dollar earnings are translated using purchasing power parity (PPP) exchange rates to translate dollar earnings to Indian rupee earnings that yield equivalent living standards. The resulting distribution provides one estimate of the counterfactual earnings distribution.

B. Mincer equations for simulating counterfactual earnings

Instead of using actual earnings of the Indian-born residing in the U.S., it is possible to estimate a joint model of earnings and participation using Indian data for urban workers from the 50^{th} round of the National Sample Survey. This round was undertaken in 1993/94, before the mid- to late-1990s surge in U.S. bound emigration. It thus provides a reasonable snapshot of the pre-emigration Indian labor market.

Recognizing that earners might be a self-selected subset of the sample, an incidental truncation model estimated by maximum likelihood is employed. [11]

Having established expected earnings as a function of observable characteristics, it is possible to use these results for considering the actual population of U.S. resident Indians. By creating observational categories (indexed by education level, experience, sex, and non-labor income) for the population of U.S. resident Indians, it is possible to generate estimated probabilities of participation for each category. This provides the estimated number of participants (positive earners) and non-participants (zero earners) for each set of observed characteristics. In addition to generating participation rates from the Mincer equation results, it is also possible to use the actual U.S. data to generate participation rates. Having established the participation characteristics of the relevant

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[11] Let z^* be the difference between an individual's market wage and her reservation wage. This difference is assumed to be a linear function of characteristics, *W*, such as education, potential experience, and the presence of non-labor income. The individual participates if $z^* > 0$, and does not participate if $z^* \leq 0$. The full model is given by the participation selection mechanism,

$$
\begin{aligned}
& z^* = \gamma' W + u \qquad u \sim N[0,1] \\
& z = 1 \qquad \text{if } z^* > 0 \\
& z = 0 \qquad \text{if } z^* \leq 0 \\
& \text{Prob}[z = 1] = \Phi(\gamma' W) \\
& \text{Prob}[z = 0] = 1 - \Phi(\gamma' W)
\end{aligned}
$$

and a Mincer-type earnings equation, where earnings are a function of characteristics, *X*.

$$
\begin{aligned}
& \ln w = \beta' X + v \qquad \text{observed only if } z^* > 0 \\
& (u, v) \sim \text{bivariate normal } [0,0,1,\sigma_v,\rho]
\end{aligned}
$$

The expected value of log earnings for individual *i* is given by,

$$E\left[\ln w_i \middle| z_i = 1\right] = \beta' X_i + E\left[v_i \middle| z_i = 1\right]$$

$$= \beta' X_i + E\left[v_i \middle| u_i > -\gamma' W_i\right]$$

population, it is then possible to simulate an earnings distribution for each cell by making the appropriate number of draws from a normal distribution for log earnings with a mean given by the regression equation and a standard error given by the (constant) standard error of the log earnings regression. Finally, it is possible to aggregate the cells to get an overall earnings distribution for participants and non-participants.

C. Results and Discussion

The results of undertaking the Mincer equation estimation are provided in Tables 6a and 6b. Table 6a describes the urban population employed in the Mincer equation and illustrates the basic characteristics of the underlying population. The omitted category is the less than primary education/illiterate category. As is evident from the descriptive statistics, approximately 30 percent of the population falls into this category. A weekly wage is available for 75,906 of the 208,538 observations in the urban sample and averages Rs. 441 (about $14) in 1994.

Table 6b provides the results of estimating a Mincer equation for both genders and for males and females considered separately. Within each gender categorization, the first column provides OLS estimates while the next two columns provide the joint maximum likelihood estimates and the coefficients on the wage and selection equations. For the selection equation, the presence of interest or dividend income is used to identify the selection equation.[12] In all regressions, education dummies along with experience levels are considered. It is useful to note that the OLS estimates are not significantly

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$$= \beta' X_i + \rho \sigma_u \frac{\phi(\gamma' W_i)}{\Phi(\gamma' W_i)}.$$

different from the wage coefficients from the JML estimation suggesting that selection effects are not very significant.

The coefficients on the education dummies can be translated into returns to education as in Table 7a. These returns to education are consistent with estimates found in Duraisamy (2000) as well as other studies of returns to education in India. Unfortunately, further rounds of NSS data are not yet amenable to similar analyses preventing further analysis of returns to education in years subsequent to the sizable migration of highly skilled individuals. Subsequent drafts will undertake an analysis of the impact of the migratory flows documented in the previous section on the nature of returns to education.

Table 8 compares the participation rates of the urban population from the NSS sample, the participation rates for the Indian-born resident in the U.S. from actual CPS or census data, and the participation rates generated from the application of the results in Table 6b to the population of Indian-born residents of the U.S. The relatively low levels of participation generated by the NSS data presented in the top panel of Table 9 presumably reflect high levels of self-employment. Participation rates for the Indian-born in the U.S. are twice as high for both genders and is particularly higher for females as demonstrated in the middle panel. While simulating levels of participation for the Indian-born in the U.S. provides higher levels of participation than for the actual NSS participants, participation rates remain considerably below actual levels in the U.S. as evidenced by a comparison of the bottom two panels of Table 8.

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[12] Interest or dividend income is provided in the consumer expenditure survey at the family level and matching between the surveys allows for the use of this identifying variable.

The levels of participation from the varied methods provided in Table 8 can be coupled with the varied estimates of earnings presented in Table 9. The top panel of Table 9 provides the median annual wages and distribution of annual wages for the participants in the NSS data. The second panel demonstrates the tremendous differences between those wages and the wages generated by the application of the PPP method. Median earnings from the PPP estimates for 1994 are more than fifteen times the median salary from the NSS data and, consequently, the distribution of earnings from the PPP estimates are highly skewed toward high earners. This same pattern is evident, but to a much lesser degree, in the simulated earnings using the Mincer method based on either participation based on the results from the selection equation or from the actual participation rates. The simulated earnings from the Mincer equation are only three times the level of median earnings from the NSS data. These wage levels under the Mincer method hold regardless of the way in which participation is treated.

Combining the participation rates from Table 8 and the simulated earnings from Table 9 provides the summary results for aggregate income losses as provided in Figure 4. Figure 4 presents the lost income of Indian-born U.S. residents as a fraction of Indian GDP for three methods – the PPP method, the Mincer method using Mincer participation rates, and the Mincer method using the actual U.S. participation rates. By 2001, the PPP method yields income losses of nearly 1.5 percent of GDP for the Indian-born residents of the U.S. In contrast, the Mincer method, regardless of the participation method chosen, yields considerably smaller, yet still sizable, lost income figures of approximately 0.25 percent of GDP.

These two methods of estimating the counterfactual earnings distributions have distinct strengths and weaknesses. The primary relative advantage for the PPP method is that actual earnings from the Indian-born residents in the U.S. are employed rather than some simulated level of earnings based on populations that may not be representative of the pool of emigrants. The primary relative disadvantage of the PPP method is the implicit assumption that U.S. resident Indians would be able to enjoy identical living standards if they were in India.

In order to assess how reliable PPP estimates are, it is useful to consider how closely comparative U.S. and India salaries are to PPP figures.[13] Table 10a and 10b summarize recent research and surveys on this topic. Table 10a demonstrates that within the software sector relative wages approximate PPP rates based on a variety of studies.[14] More generally, Table 10b demonstrates that relative wages in a broad spectrum of professions depart somewhat from PPP levels but approximate PPP levels for the most mobile of those professions.

Nonetheless, the assumption that the PPP method is exactly correct must be met with some skepticism. With completely free migration and no moving costs, migration will continue until the living standards are equalized between the two countries. Moving costs drive a wedge between the PPP-adjusted earnings in the two locations in equilibrium, however. Moreover, migration from India to the U.S. is not "free," as it is

[13] Comparing wage data across countries is deeply problematic since the variable and the non-wage benefits differ widely. Nonetheless, in interviews with two U.S. based firms with operations in both countries total difference in emoluments (in what they considered as equivalent talent) was between 4-5 fold (mid-2001 figures). Furthermore, comparing IT salary growth data from one source (Jayachandran, (2001)) with data from the U.S. Bureau of Labor Statistics, it appears that salary growth rates in India have been consistently higher than in the U.S., indicating that, with migration, relative salaries are moving towards PPP differences.

impeded for many individuals by U.S. immigration policies. Thus, even if moving costs were zero, migration would erode only a portion of the positive U.S. living standard differential. It is likely, then, that the PPP method gives a somewhat upward biased estimate of the earnings loss.

Although the PPP-based estimate may be slightly upward biased for the reasons discussed above, the regression-based estimate is almost certainly downward biased due to positive selection on unobservable characteristics. It is widely believed that migrants are a select group, showing, for example, more initiative than their observational equivalents who choose to stay.[15] 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 who to petition form, and immigration officials decide on which petitions to allow. Employers can observe much more about potential H-1Bs than is observable in the census or 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 an 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.

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[14] As a point of reference, PPP rates for India were approximately 5.1 in 2000 according to the World Bank.

[15] 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's 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

The evidence is strong that those who leave 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 of this evidence. The acceptance rate in these institutes is between 1 and 2 percent 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 percent of its graduates of IIT settled abroad while the estimated migration rate of engineers more generally was 7.3 percent.[16] Furthermore, the migration was significantly higher in those branches of engineering with higher ranked entrants to IIT: thus the percentage abroad in electrical engineering (which "closed" early in those years) was nearly 43 percent while in metallurgical engineering (which usually "closes" much later) was about 20 percent. Similarly, while the percent abroad was 43 percent in the top quartile of the graduating class it was 27 percent in the rest of the class.

The severe selection bias in emigration from India also exists in other disciplines. In medicine, while migration rates for doctors was about three percent during the 1980s, it was 56 percent for graduates of the All India Institute for Medical Sciences - India's most prestigious medical training establishments - between 1956-80 and 49 percent in the 1990s.[17] 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

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at best a crude pointer to positive selection, it helps us to rule out negative selection as a serious possibility for the Indian case.

[16] See Sukhatame (1987). 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.

[17] For figures between 1956-80 see Khadria (1999). According to a recent report of the Comptroller and Auditor General, 49 percent of doctors trained in the All India Institute of Medical Sciences leave for foreign jobs. 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).

Our two estimates of the counterfactual earnings and income distribution leave us with an unsatisfyingly large gap. While the PPP estimates may in fact be upward biased, survey evidence suggests that the overestimate may be relatively small. In contrast, the strong selection mechanisms that are operative in determining migration decisions suggest that Mincer equation based estimates are seriously downward biased.[18] Consequently, in the following work on fiscal impacts, both PPP and Mincer estimates are presented, but much greater weight is given to the PPP estimates of counterfactual earnings.

5. *Fiscal Impact Estimates*

What are the impacts of emigration and the associated loss of human capital on TLBs through fiscal channels? This section employs the counterfactual earnings distributions to generate estimates of the likely lost taxes (direct and indirect, federal and state) and expenditure savings that result from the Indian-born residing in the U.S.

(i) Tax loss estimates

Tax loss estimates are composed of losses in federal income tax collections and losses in federal and state indirect tax collections. For the federal income tax

[18] The very low estimated participation rates in wage and salary work are particularly troubling. It is hard to believe that participation rates would be this low for the kind of people who emigrate to the U.S. The presentation of the Mincer estimate of the earnings distribution using observed U.S. participation rates is an attempt to get around this. This estimation is essentially a mix of methods - CPS-based estimates of participation and regression based estimates of earnings. This mixed method does indeed raise the estimate of lost earnings compared with Mincer estimates.

calculations, annual Income Tax Department data on tax bands and tax rates for individuals are employed.[19] Income tax loss estimates are based on calculating what each absent Indian would have paid—making the assumption of full compliance—given our counterfactual income estimates.[20] While full compliance is an aggressive assumption in the Indian setting, these high-income salaried individuals are the individuals for whom this assumption would be the least radical.

Indirect tax effects are calculated by considering the ratio of indirect tax revenues to aggregate income and then applying those ratios to the counterfactual earnings discussed above. For both the federal and state governments we calculate indirect taxes per unit of gross national income, where gross national income (GNI) is gross national product (GNP) minus total indirect taxes. Total indirect taxes are taken from the IMF's Government Finance Statistics, and GNI is taken from the IMF's International Financial Statistics (various editions). Indirect taxes are assumed to equal the IMF category of domestic taxes on goods and services, which includes general sales taxes, turnover taxes, valued-added taxes, and excise taxes. Indirect taxes revenues of the central government are 4.7 percent of income (as measured by GNI) in 1990, falling to 3.4 percent in 1999.[21] The indirect tax revenues of the state governments were also 4.7 percent of income in

[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] At first glance the "full compliance" assumption seems quite at odds with the realities of contemporary India. The Central Board of Direct Taxes is plagued with problems and the modernization of tax administration has lagged other economic changes. Although the number of income tax assesses has climbed to about 30 million, nearly a quarter are untraceable. Barely 42,000 people in India file their annual income as more than Rs 1 million. (*Business Standard*, December 3, 2001). Moreover the cost of tax collection as a percentage of total revenue has also increased from 1.25 per cent in 1996-97 to 1.5 percent in 1999-2000.

[21] Figures for 2000 and 2001 were not available from the IMF's Government Finance Statistics; we assume that central indirect tax revenues per unit of income were constant at their 1999 levels in 2000 and 2001.

1990, but fall by less than central revenues in subsequent years. State indirect taxes are 4.5 percent of GNI in 1997 (the last year for which we have GFS data); and we assume again that they remain at this level for 1998 through 2001.[22] To estimate the indirect tax losses from emigration, these estimates of indirect tax per unit of income are multiplied by the previous estimates of the counterfactual earnings distribution to obtain estimates of total lost indirect taxes to the federal and state governments. This procedure assumes that indirect taxes are proportional to income—i.e. indirect taxation is neither progressive nor regressive.

The methodology outlined above is illustrated for 1997 in Figure 6 by mapping individual income to direct and indirect taxation receipts. At low income levels, the loss of indirect tax revenues is clearly the most important, as the emigrant would not pay much, if any, income tax. The progressivity of the Indian tax system creates an increasing relative importance of income tax revenues as counterfactual Indian incomes of the emigrant rise. It follows that that income tax losses will be relatively important given the high earning potential of the emigrant stock.

Table 11 integrates the tax structure assumptions described above with our estimates of counterfactual incomes for both the PPP and Mincer methods in order to generate the levels of central direct, central indirect, and state indirect tax revenues lost, expressed as a percentage of GDP. By 2001, the PPP method generates central direct tax losses of 0.44% of GDP that compares to an overall individual income tax base of 1.3% of GDP. Consideration of indirect taxes raises the overall loss in 2001 to 0.58% of GDP. It is interesting to note the increasing share associated with non-citizens during the course

[22] Estimates from RBI (2001) suggest that this is a reasonable assumption.

of the decade and the growing absolute magnitude of the losses during the decade. Unsurprisingly, Mincer method results are considerably smaller as the progressivity of the income tax schedule does not generate as much revenues for these lower counterfactual earnings. Figures 7 and 8 provide the absolute rupee levels of the lost tax revenue for the PPP and Mincer methods, respectively. In 2001, total tax losses are nearly 115 billion rupees under PPP and between nine and twelve billion rupees under the Mincer method depending on the participation method.

(ii) Expenditure savings

The fiscal impact of emigration may not be limited to tax revenue losses—TLBs may also save on government expenditures when individuals 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.

The calculation of actual savings appears most clear-cut for publicly funded private goods such as health and education. If 100 rupees is spent on the health care of an individual and that individual emigrates, then 100 rupees is saved. In reality, however, expenditures are sticky, and the total spending on health might be slow to change. In other words, it is likely that at least a portion of the 100 rupees will be reallocated to spending on the health care of TLBs. Thus government health expenditure does not necessarily fall by 100 rupees. As noted above, however, our interest is not in the actual changes in government expenditure, but rather in the impact on TLBs of the exit of person who had been a recipient of government spending. Suppose that the government is choosing spending optimally so that the marginal value of that spending in each category of expenditure is equal to the marginal cost of raising the revenue (see Section 3). In this case, TLBs are indifferent as a group to various allocations of the savings from emigration between more health spending for TLBs, other forms of expenditure for TLBs, and lower taxes on TLBs. With this admittedly strong optimality assumption, the following ignores the government's response and focuses only on what was being spent on the emigrant.

Pure public goods (on the rivalry definition) provide another interesting case. The nearest example to a pure public good is national defense. When an emigrant leaves there is *no cost saving* since the prior marginal cost of providing defense to that person was zero.[23] Interest costs, which have to be paid regardless of the size of the domestically resident population, are another example of an expenditure category where there are no emigration-related savings.

In order to simulate saved expenditures, the spending categories are divided between those for which zero savings from emigration are assumed (defense and interest payments)[24] and those for which positive savings are generated (everything else). Said

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[23] The government might respond to the loss of net fiscal contributors by cutting defense expenditure rather than by raising taxes on TLBs. Again, however, if defense expenditure was chosen optimally for TLBs prior to emigration, TLBs will be indifferent to tax increases and spending cuts for a small amount of emigration.

[24] Arguably, pension payments to government employees should be excluded as well but this data was not available. Given the significance of these figures in the Indian context, this will lead to an overstatement of expenditure savings and an understatement of net fiscal impacts.

another way, this methodology assumes that all government spending other than defense and interest is associated with private goods. 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 a measurement that incorporates income. Given the relatively small absolute number of Indians living in the U.S. relative to the overall population (approximately 0.1%), the per capita assumption is tantamount to ignoring expenditure savings. In this case, the net fiscal impact will be simply the tax losses presented in Table 11. 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. While making expenditure savings proportional to income is clearly an extremely conservative assumption, such an exercise provides a useful extreme upper bound on the magnitude of expenditure savings as a result of emigration.[25]

Table 12 employs expenditure savings per unit of income with previous estimates of lost income. For the PPP method, the combined expenditure saving for central and state governments reaches a high of 0.34 percent of GDP in 2001. This income based method of calculating expenditures savings clearly represents an upper bound on expenditures saved while per capita expenditures would result in close to zero saved

[25] It can be argued that while there are fiscal losses due to emigration, there may be compensating fiscal gains due to inward investment and remittances. In India's case fiscal gains from the former are negligible because FDI from NRIs is tends to be low. According to RBI figures non-resident Indian foreign direct investment flows averaged just $71 million a year between 1998-1999 and 2000-2001.[25] This is in sharp contrast to China where NRCs (non-resident Chinese) have been the principal foreign investors (in the early 1990s for instance, more than three-fourth of FDI in China was NRC investment; although the proportion has declined since then but it still remains high). Guha and Ray (2000) 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." In contrast to FDI, NRI remittances have been robust. Between 1993-94 and 2000-2001 remittances increased by about $5.5 billion (annual average).

expenditures. As such, the subsequent tables that employ income-based measures of expenditures understate net fiscal impacts to the degree that actual expenditure savings more closely track the per capita intuition.

(iii) Net fiscal impact estimates

The net fiscal impact is simply the difference between the tax losses and the expenditure savings that result from having Indian-born individuals live in the U.S rather than in India. The implied net fiscal impacts for the various years are shown in Table 13, again for both methods of generating counterfactual earning and for both Indian-born U.S. citizens and non-citizens. The results from the Mincer method, provided in the right columns of Table 13 and illustrated in Figure 8, actually show a fiscal gain from emigration in some years as a result of generous expenditures savings based on income and low levels of counterfactual earnings through the Mincer method. These results seem implausible in the context of the discussion above of the downward biases in those counterfactual earnings.

For the PPP method, the table shows that in 2001 the net fiscal impact reached 0.24 percent of GDP, having fallen between 1990 and 1997 as a result of fiscal policy changes, and then rising substantially around the end of the decade. Figure 7 shows the post-1994 evolution of the tax losses, expenditure saving, and net fiscal impact based on our PPP-based method of estimating the income loss in billions of 2001 rupees. This period coincides with the surge in human capital flows from India to the U.S., driven by the U.S. technology boom and changes in U.S. immigration policies. Even with a

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These remittances may have had important fiscal consequences through their impact on consumption and generous allowance for expenditure savings, the net fiscal impact reached close to 50 billion rupees by 2001.

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 consequences for the design of fiscal systems and the viability of alternative development strategies. The emigrants from India to the U.S. over the last decade typify the magnitude, scope and character of such flows when a developed economy seeks to attract skilled labor from a developing economy. As such, the analysis provided in this paper illuminates the fiscal impact of this emigrant flow and of future flows of skilled labor globally.

The distinct methodologies presented in the paper for estimating these consequences provide unsatisfyingly large ranges for these consequences. While even the lowest estimates of total tax losses are still significant, there are several reasons presented in the paper to believe that the higher estimates are much more credible. Future research must address the precision of these estimates by refining estimates of counterfactual earnings, by understanding the selection mechanisms associated with emigration from developing economies, and by quantifying the responsiveness of the wage structure to these large outflows of skilled labor in order to incorporate these varied effects.

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thus on indirect tax receipts.

The results presented in the paper for Indian emigrants to the U.S. indicate a quickly escalating fiscal loss and one that is concentrated amongst Indian citizens living abroad. Additionally, the Indian case shows that although the emigrant population can represent a small fraction of the total population, the fiscal effects are considerable and place an even greater burden on governments trying to develop a fiscal base and shift from indirect to direct taxes. Tax losses are largely income taxes – this greater impact on income taxes impacts the central government disproportionately relative to the states. Moreover, since most remittance-based expenditures are on items like housing and consumer goods, the resulting indirect tax gains accrue largely to the states. These imbalances are likely to have implications for the future of center-state fiscal relations in India.

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 (2001) 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 future consideration and design of such policies.

Data Appendix

Current Population Survey, March Supplement (March CPS)

Also referred to as the Annual Demographic Survey, the March CPS supplement is the primary source of detailed annual information on the income, labor and unemployment in the United States. It is used to generate the annual Population Profile of the United States, reports on geographical mobility and educational attainment, and detailed analysis of income and poverty status. For our purposes, since 1994 it has also contained detailed data on immigrants: basic demographic information, the country of origin, their citizenship status, when they immigrated to the United States, and various measures of earnings and income. The sample sizes were 113,085 – 136,761 native-born, 13,876-15,338 non-Indian immigrants, and 287-398 Indian-born.

Each observation is then assigned a weight that is adjusted to agree with independent estimates of the civilian non-institutional population of the U.S. by age, sex, race, state of residence, etc. Among the independent sources for weight adjustment used is the 1990 Decennial Census of Population and Housing and statistics on births, deaths, immigration, and emigration.

In analyzing the characteristics of the Indian-born population living in the U.S., the data in the March CPS was altered as following: all individuals were used in analyzing age; only individuals ages 25-64 were used in analyzing educational attainment; only individuals ages 18-64 were used in analyzing income and wage/salary earnings.

In generating counterfactual incomes for the Indian-born in the U.S. if they had remained in India using the PPP Method, reported incomes in U.S. dollars for individuals ages 18-64 were multiplied by the PPP conversion factor for that year (PPP conversion factor source: World Development Indicators), generating an income in rupees that would afford them the same standard of living if they had remained in India. (The PPP conversion factors for 2000 and 2001 were forecast based on its relationship with the nominal exchange rate over the past 25 years, and the nominal exchange rates for 2000 and 2001 to date.)

Calculating the estimated lost tax revenues from these counterfactual incomes was a matter of applying the appropriate tax schedules to incomes, all subjected to the standard deduction (source of tax schedules and standard deductions: Income Tax Department, Delhi, India). We assume that the standard deduction for assessment year 99-00 is used for all previous assessment years. Each year's lost tax estimate is then adjusted to 2001 rupees.

Integrated Public Use Microdata Series (IPUMS)

The Integrated Public Use Microdata Series, or IPUMS, at the University of Minnesota represents the one of the richest sources of information, allowing access to twenty-five samples that span over a 140-year period. For Indian-born, we extracted a 5 percent sample of the Decennial Census of Population and Housing for 1990. For data on native-born and other non-Indian-born immigrants, we extracted 1 percent of the Decennial Census of Population and Housing for 1990.

This resulted in a sample size of about 2.3 million native-born and 197,084 non-Indian immigrants for the 1990 census. The 5 percent extract resulted in a sample size of 27,926 Indian-born for the 1990 census. All of the variables we use are the also found in the March CPS after 1994 and also include the important factors pertaining to international migrants like citizenship status, country of birth, year of immigration, educational attainment, and basic demographics. See References for full citation.

In analyzing the characteristics of the Indian-born population living in the U.S., the data in the IPUMS microdata was altered as following: all individuals were used in analyzing age; only individuals ages 25-64 were used in analyzing educational attainment; only individuals ages 18-64 were used in analyzing income and wage/salary earnings.

In generating counterfactual incomes for the Indian-born in the U.S. if they had remained in India using the PPP Method, reported incomes in U.S. dollars for individuals ages 18-64 were multiplied by the PPP conversion factor for that 1990 (PPP conversion factor source: World Development Indicators), generating an income in rupees that would afford them the same standard of living if they had remained in India.

Calculating the estimated lost tax revenues from the counterfactual income was a matter of applying the appropriate tax schedule to the income, all subjected to the standard deduction (source of tax schedules and standard deductions: Income Tax Department, Delhi, India). We assume that the standard deduction for assessment year 99-00 is used for all previous assessment years. The lost tax estimate for 1990 is then adjusted to 2001 rupees.

National Sample Survey Organization

The 50th (1993-1994) and 55th (1998-1999) rounds of the National Sample Survey in India contain surveys on both employment and consumption. Only the urban sample ages 18-64 of the 50th round were used to generate a Mincer equation, with the log of weekly wage as a function of educational attainment dummies, experience, and the presence of interest or dividend (this variable is unviable for the 55th round). The 55th round is used to compare returns to education. The results of the equation used to generate counterfactual income for the Indian-born living in the U.S. using information from the March CPS (1990) and IPUMS. For non-1994-years, the wages in rupees are adjusted to account for wage growth (assumed equal to growth in GDP) and inflation. These incomes are then subjected to the same tax deductions and income tax schedules discussed above to generate lost income tax estimates.

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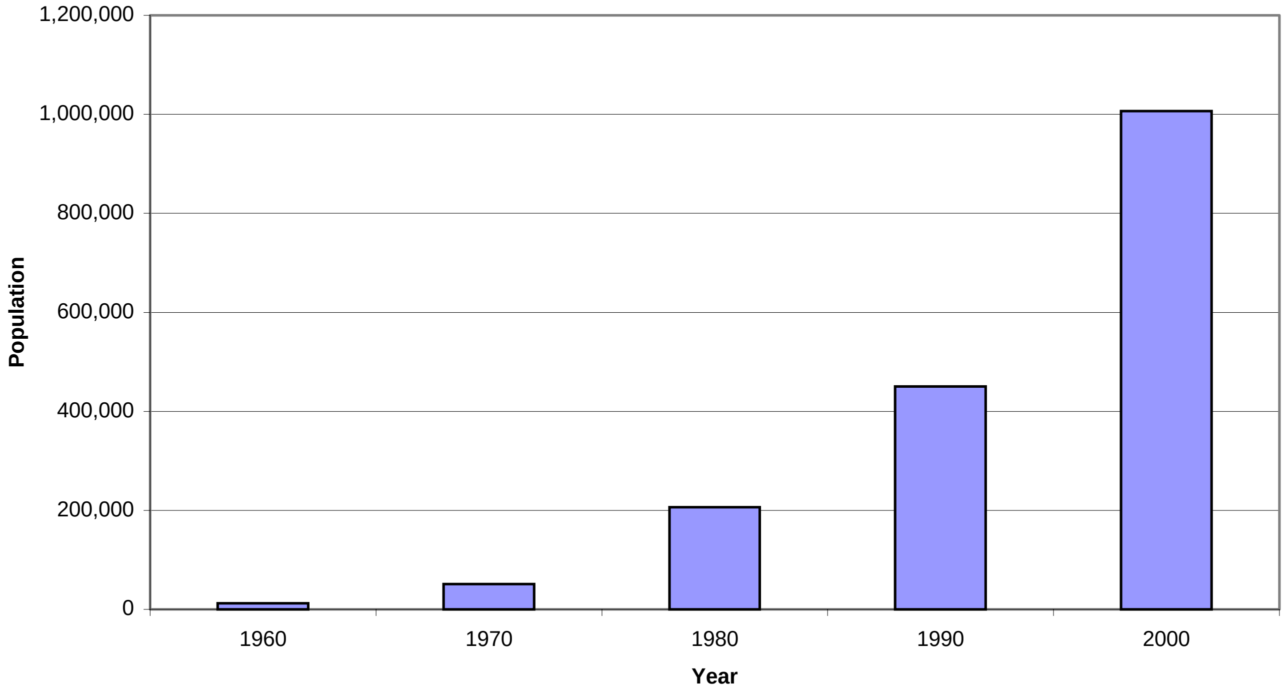
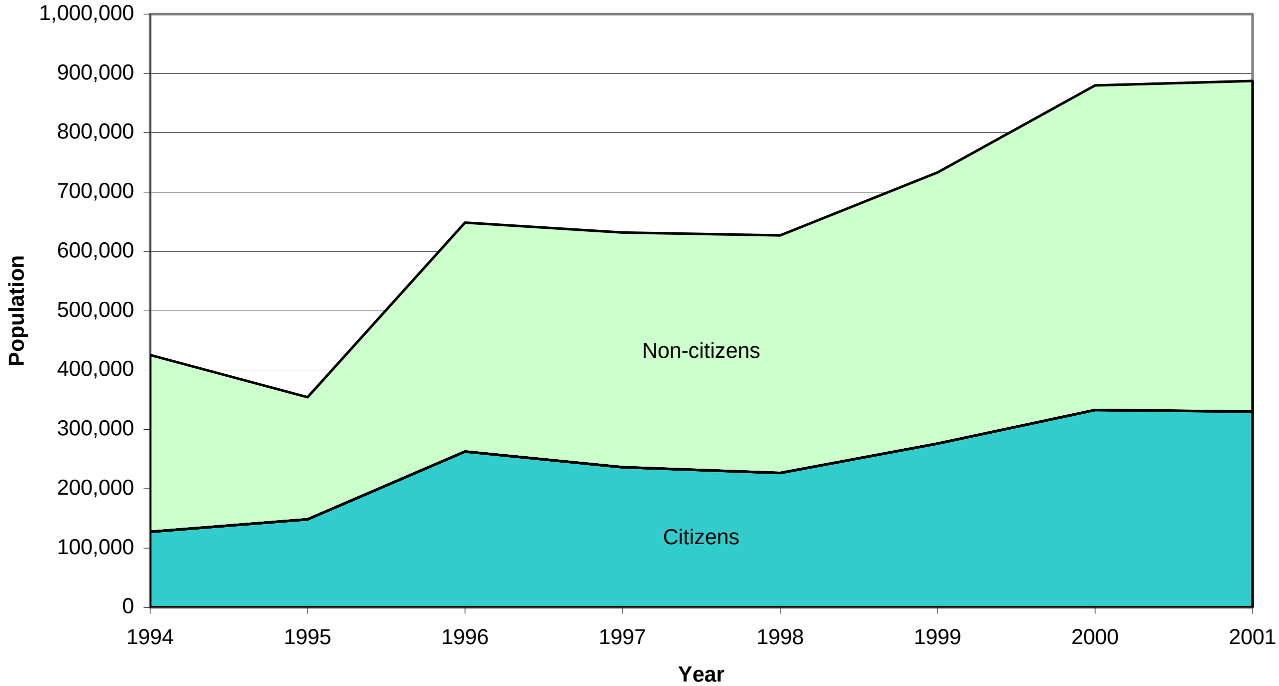
Figure 1: Indian-born Population in the U.S.



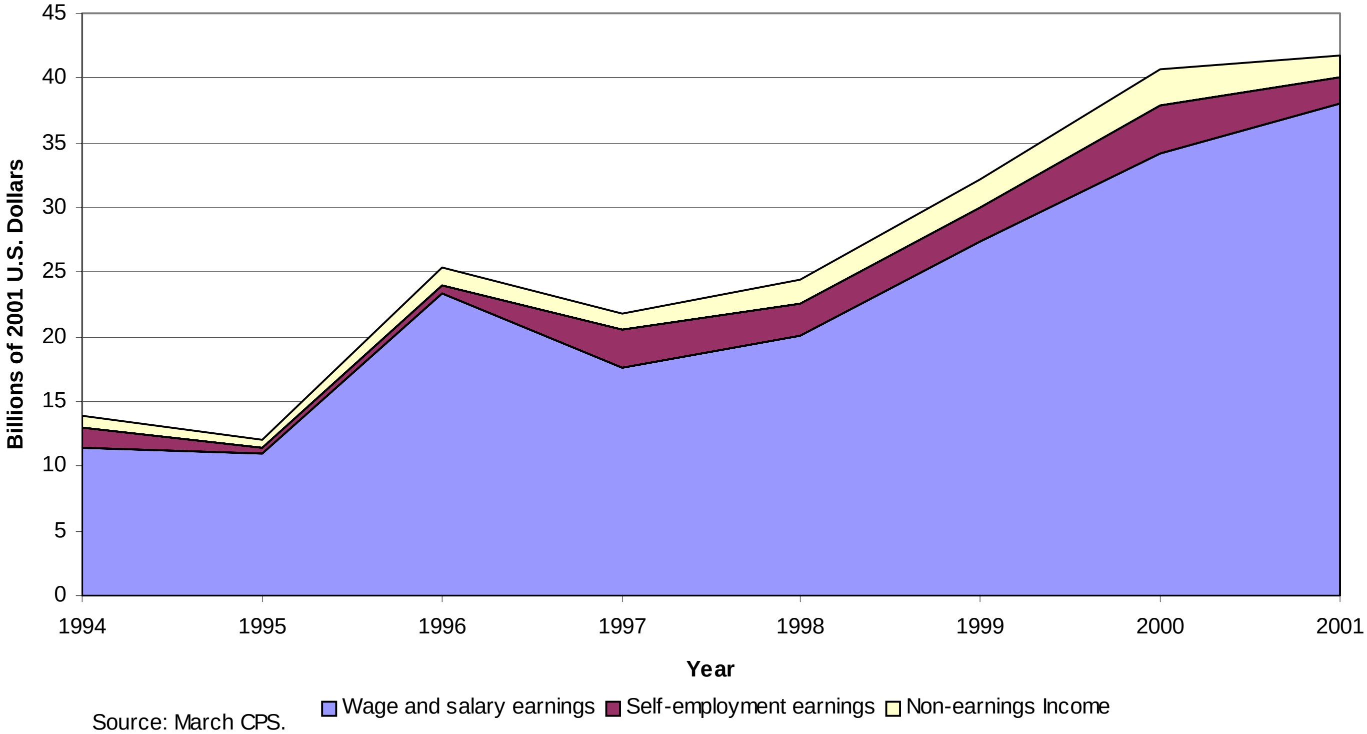
Source: 1960-1990, U.S. Census Bureau; 2000, March CPS

Figure 2: Indian-born Population ages 18-64 in the U.S., by citizenship status, 1994-2001



Source: March CPS.

Figure 3: Total Income of Indian-born, Ages 18-64 in the U.S.



Source: March CPS.

Figure 4: The Fiscal Impact of Emigration on "TLBs"

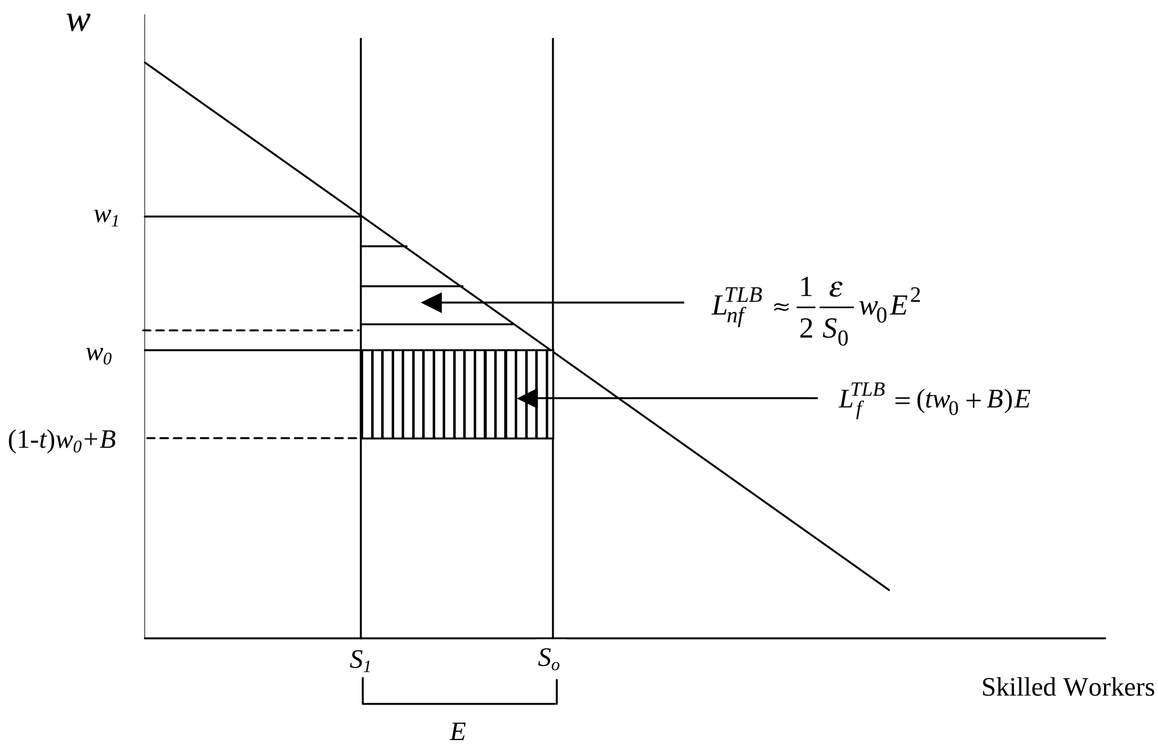
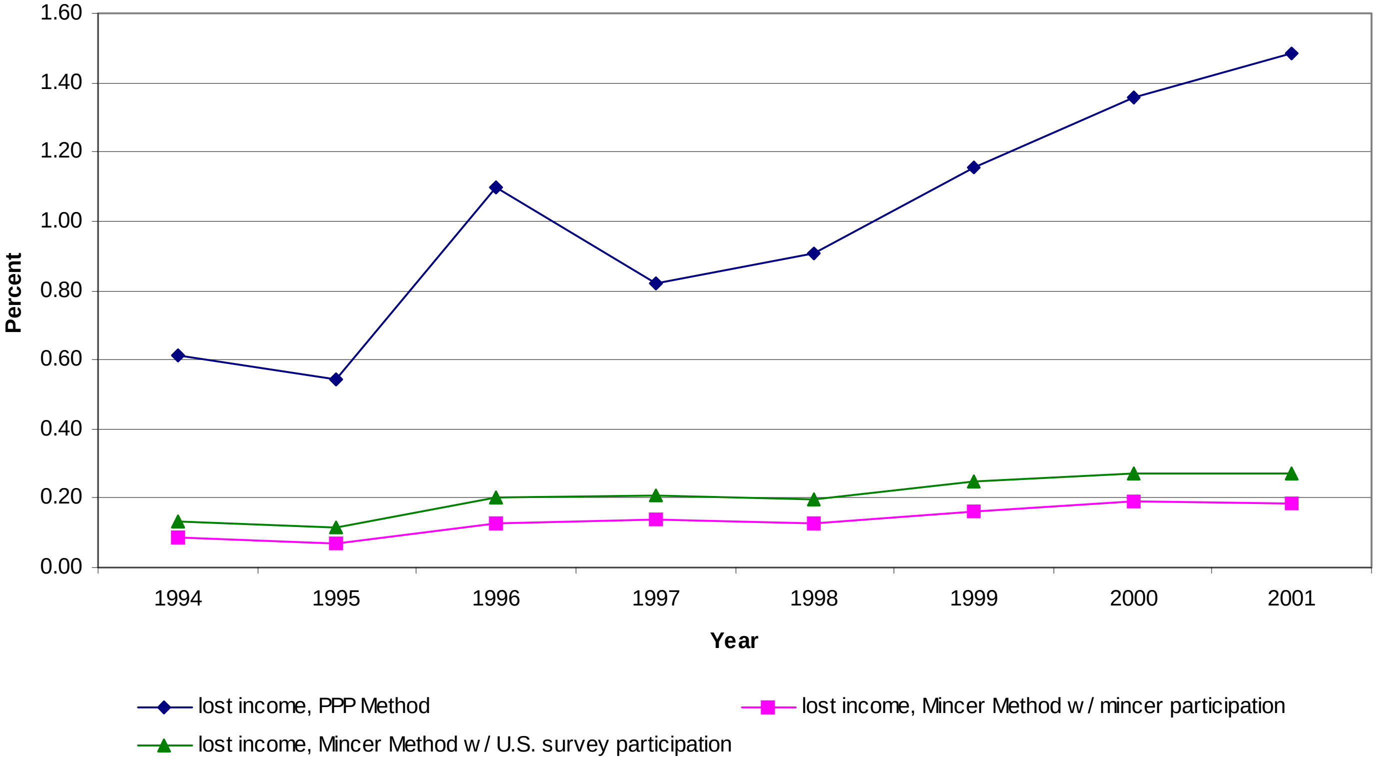


Figure 5: Estimates of lost income from Indian-born as percentage of Indian GDP



Note: Diamonds depict the lost income estimate using the PPP Method, squares depict the lost income estimate using the Mincer Method and mincer participation, and triangles depict the lost income estimate using the Mincer Method and U.S. survey participation.

Figure 6: The Relationship Between Tax Revenues and Income, 1997

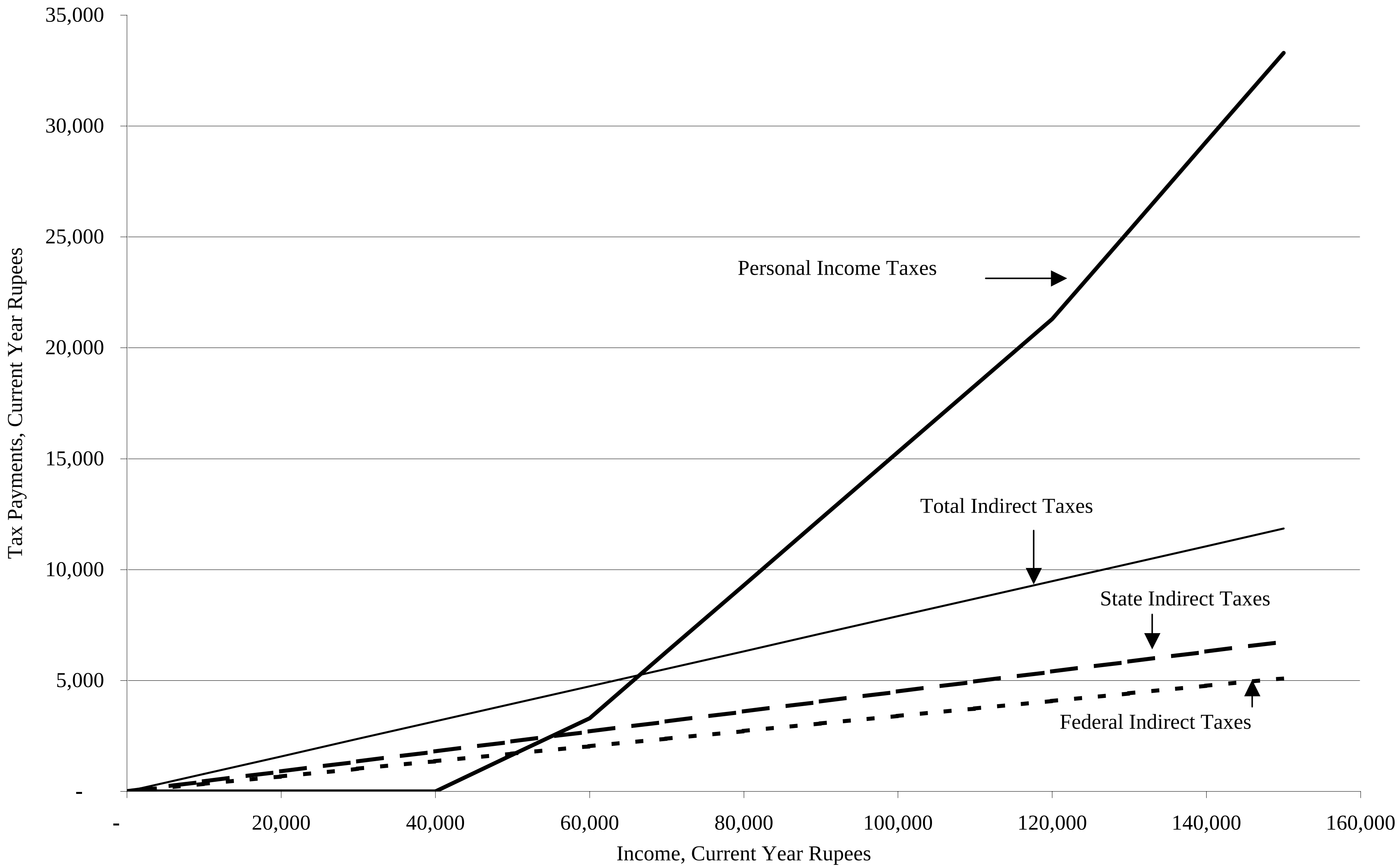
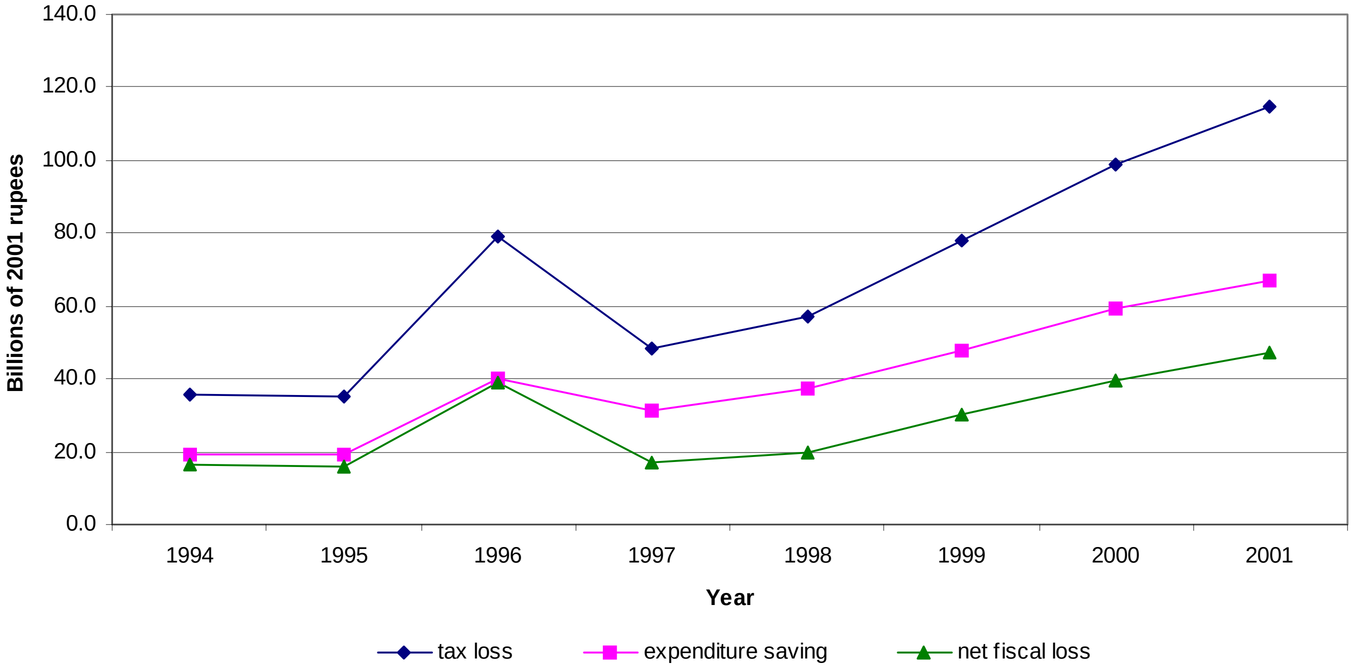
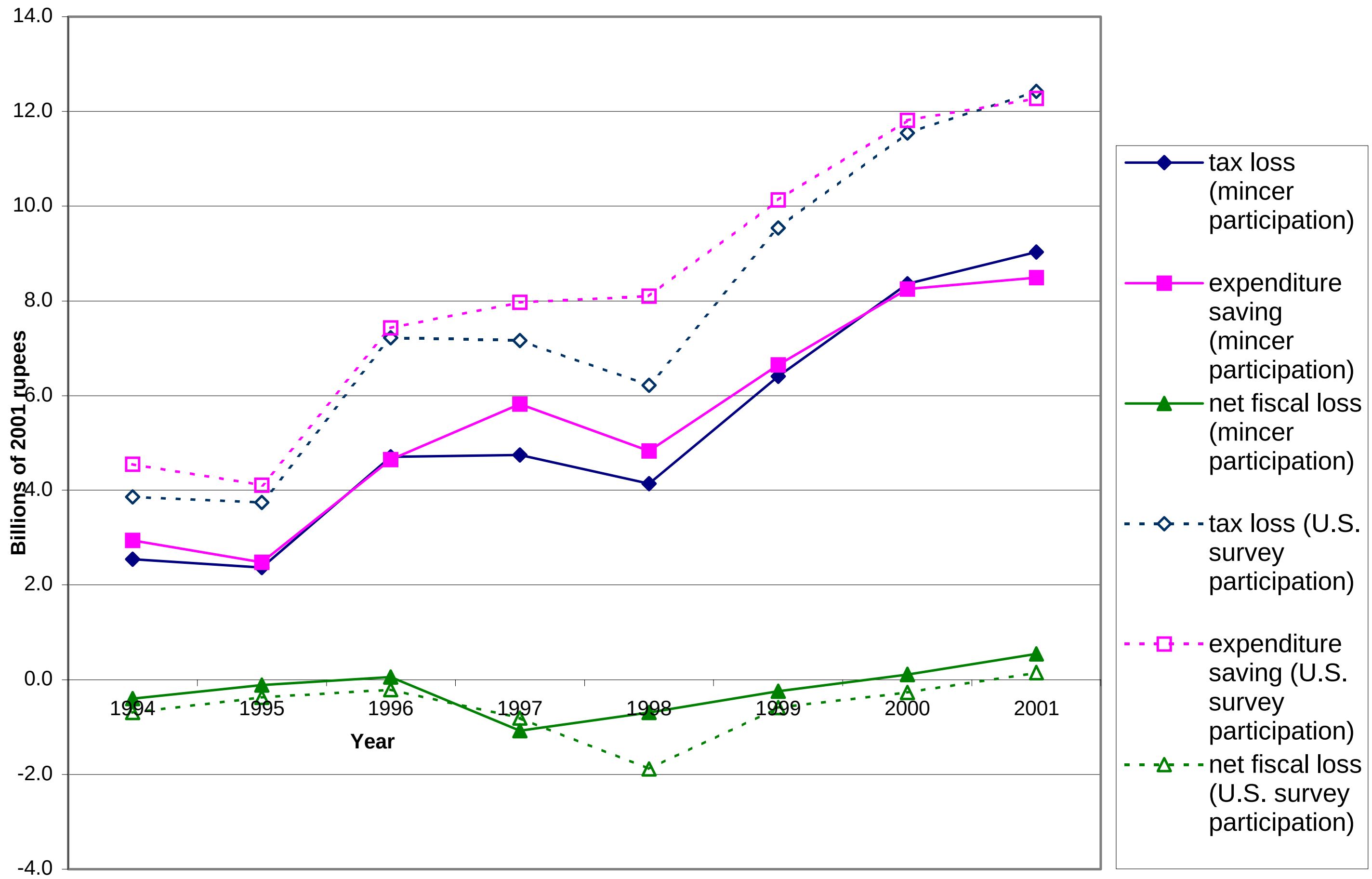


Figure 7: Indian Fiscal Impact Estimates based on PPP Method



Note: Diamonds depict the estimated total tax revenue losses using the PPP Method, squares depict the estimated expenditure savings using the PPP Method, and triangles depict the estimated net fiscal loss using the PPP Method.

Figure 8: Indian Fiscal Impact Estimates based on Mincer Method



Note: Filled diamonds depict the estimated total tax revenue losses using the Mincer Method with mincer participation, filled squares depict the estimated expenditure savings using the Mincer Method with mincer participation, and filled triangles depict the estimated net fiscal loss using the Mincer Method with mincer participation. Hollow diamonds depict the estimated total tax revenue losses using the Mincer Method with U.S. survey participation, hollow squares depict the estimated expenditure savings using the Mincer Method with U.S. survey participation, and hollow triangles depict the estimated net fiscal loss using the Mincer Method with U.S. survey participation.

Table 1
Stock of Indian Immigrant Population in Australia, Canada, and UK for Selected Years

	1985	1990	1995	1999	2000
Australia	.	61,500	80,000	100,700	.
Canada*	130,100	173,700	235,900	.	.
United Kingdom	138,000	156,000	114,000	149,000	153,000

Sources: Australian Bureau of Statistics; Quinquennial censuses, Statistics Canada; and Labour Force Survey, Home Office (U.K.). As found in, OECD: Trends in International Migration, SOPEMI 2000 & 2001 Editions.
Note: Figures for United Kingdom are defined as "foreign population."
* Years for Canada: 1986, 1991, 1996

Table 2
Age Distribution for Native-, Indian-, and Other Foreign-born, 1990, 1994-2001

Native-born:

		Population Shares				
Year	**Median**	**<18**	**18-24**	**25-44**	**45-64**	**65+**
1990	32	27	10	31	19	13
1994	32	28	10	31	19	12
1995	33	28	9	31	19	12
1996	33	29	9	31	20	12
1997	33	28	9	30	20	12
1998	34	28	9	30	21	12
1999	34	28	9	29	21	12
2000	34	28	10	29	22	12
2001	34	28	10	28	22	12

Indian-born:

		Population Shares				
Year	**Median**	**<18**	**18-24**	**25-44**	**45-64**	**65+**
1990	35	10	12	53	21	4
1994	35	9	8	53	25	5
1995	37	8	11	52	24	6
1996	35	10	9	54	23	4
1997	36	8	7	54	24	7
1998	36	6	10	48	29	7
1999	36	6	7	52	28	7
2000	35	6	10	51	26	6
2001	33	8	9	55	23	5

Other foreign-born:

		Population Shares				
Year	**Median**	**<18**	**18-24**	**25-44**	**45-64**	**65+**
1990	37	11	12	41	22	14
1994	36	11	12	43	22	12
1995	37	11	12	43	23	12
1996	37	11	11	43	23	11
1997	37	10	12	43	24	11
1998	37	10	11	44	24	11
1999	38	9	11	44	24	12
2000	37	10	11	43	24	11
2001	38	10	11	44	25	11

Source: IPUMS for 1990. March CPS for 1994-2001.
Note: The second column shows the median age in years for all native-born, Indian-born, or other foregin-born for years 1990, 1994-2001. The five under "population shares" display the percentage of native-born, Indian-born, or other foreign-born of all ages columns living in the U.S. that fall within the appropriate age groups for 1990, 1994-2001.

Table 3
Educational Attainment for Native-, Indian-, and Other Foreign-born, Ages 25-64; 1990, 1994-2001

Native-born:

	Population Shares					Graduate Breakdown		
Year	< High School	High School Graduate	Some College	Bachelor's Degree	Graduate Level	Masters	Profes-sional	PhD
1990	17	32	28	15	8	5	2	1
1994	13	36	27	16	8	6	1	1
1995	12	35	28	17	8	6	2	1
1996	12	35	28	18	8	6	1	1
1997	11	35	28	18	8	6	1	1
1998	11	35	28	18	8	6	1	1
1999	10	34	28	19	9	6	1	1
2000	10	34	29	19	9	7	1	1
2001	9	33	29	19	9	7	1	1

Indian-born:

	Population Shares					Graduate Breakdown		
Year	< High School	High School Graduate	Some College	Bachelor's Degree	Graduate Level	Masters	Profes-sional	PhD
1990	12	11	14	27	36	21	9	6
1994	8	9	15	35	32	17	11	4
1995	8	10	12	26	44	24	13	7
1996	8	13	12	30	38	27	7	4
1997	7	16	10	34	33	23	6	4
1998	6	14	15	35	31	22	5	3
1999	6	10	10	36	38	25	7	6
2000	6	8	9	35	41	27	6	8
2001	3	9	10	40	38	28	6	4

Other foreign-born:

	Population Shares					Graduate Breakdown		
Year	< High School	High School Graduate	Some College	Bachelor's Degree	Graduate Level	Masters	Profes-sional	PhD
1990	38	20	20	13	9	5	2	1
1994	34	25	17	16	8	5	2	2
1995	35	25	17	15	8	5	2	2
1996	35	23	18	15	8	5	2	2
1997	34	24	18	16	9	5	2	2
1998	33	25	16	17	9	6	2	2
1999	33	25	17	16	9	6	2	2
2000	32	26	17	16	9	5	2	2
2001	32	25	17	17	9	5	2	2

Source: IPUMS for 1990. March CPS for 1994-2001.

Note: The five columns under "population shares" display the percentage of native-born, Indian-born, or other foreign-born ages 25-64 living in the U.S. that have attained various levels of education for years 1990, 1994-2001 . For those that have attained "Graduate Level," a further breakdown by degree type provided in the three columns under "Graduate Breakdown."

Table 4
Income Distribution for Native-born, Indian-born, and Other Foreign-born
Ages 18-64; 1990, 1994-2001

Native-born:

		Population Shares (as % of Median)				
Year	**Median**	**0-50%**	**50-100%**	**100-200%**	**200-400%**	**>400%**
1990	$20,293	33	17	27	18	4
1994	$19,836	31	19	28	18	4
1995	$20,100	30	20	28	18	5
1996	$20,626	30	20	29	17	4
1997	$21,418	30	20	29	17	4
1998	$21,580	30	20	29	16	4
1999	$22,826	30	20	30	16	4
2000	$23,126	30	20	29	16	5
2001	$23,925	29	21	30	16	4

Indian-born:

		Population Shares (as % of Median)				
Year	**Median**	**0-50%**	**50-100%**	**100-200%**	**200-400%**	**>400%**
1990	$20,670	35	14	21	20	10
1994	$21,943	32	14	24	21	9
1995	$24,980	28	14	26	22	11
1996	$25,145	31	16	25	19	10
1997	$24,301	29	18	24	21	8
1998	$27,915	29	15	23	24	9
1999	$31,715	30	11	24	26	9
2000	$29,986	35	9	18	24	14
2001	$28,121	34	11	18	25	12

Other foreign-born:

		Population Shares (as % of Median)				
Year	**Median**	**0-50%**	**50-100%**	**100-200%**	**200-400%**	**>400%**
1990	$14,483	39	21	23	13	4
1994	$13,053	42	23	21	11	3
1995	$13,803	41	24	21	11	4
1996	$13,562	42	24	22	10	3
1997	$13,729	41	24	22	10	3
1998	$14,443	40	25	21	10	4
1999	$14,816	41	26	21	9	3
2000	$15,510	40	26	21	11	3
2001	$16,084	37	26	23	10	3

Source: IPUMS for 1990. March CPS for 1994-2001.

Note: The second column shows the median incomes for native-born, Indian-born, or other foreign-born ages 18-64 living in the U.S. for years 1990, 1994-2001 in 2001 U.S. dollars. The five columns under "population shares" display the percentage of native-born, Indian-born, or other foreign-born ages 18-63 living in the U.S. for years 1990, 1994-2001 that lie between various fractions and multiples of the median Native-born income for that year.

Table 5
Income, Educational Attainment, and Age Distributions for Indian-born and Other Foreign-born Recent Immigrants to the U.S.

Incomes:

		Population Shares (as % of Median)				
	Median	**0-50%**	**50-100%**	**100-200%**	**200-400%**	**>400%**
Indian-born						
2000 CPS	$19,673	44	9	14	24	9
1990 Census	$13,780	43	18	23	14	3
Difference	$5,893	1	-9	-9	11	6
Other non-natives						
2000 CPS	$11,374	51	27	15	6	2
1990 Census	$10,749	49	24	19	7	2
Difference	$625	2	3	-4	-1	0
Difference-in-Difference	$5,267	-1	-12	-5	11	6

Educational attainment:

	Population Shares					Graduate Breakdown		
	< High School	**High School Graduate**	**Some College**	**Bachelor's Degree**	**Graduate Level**	**Masters**	**Profes-sional**	**PhD**
Indian-born								
2000 CPS	7	6	8	39	39	29	5	5
1990 Census	15	13	14	28	30	20	6	5
Difference	-8	-7	-6	12	9	9	-1	1
Other non-natives								
2000 CPS	33	25	15	18	8	5	2	2
1990 Census	41	18	18	14	9	6	2	1
Difference	-7	7	-4	5	-1	-1	0	0
Difference-in-Difference	-1	-14	-2	7	10	10	-1	0

Age:

		Population Shares				
	Median	**<18**	**18-24**	**25-44**	**45-64**	**65+**
Indian-born						
2000 CPS	29	10	16	58	11	4
1990 Census	30	15	14	56	12	4
Difference	-1	-5	2	2	-1	1
Other non-natives						
2000 CPS	28	21	19	45	12	3
1990 Census	27	21	19	46	10	3
Difference	1	-1	0	0	1	0
Difference-in-Difference	-2	-4	3	3	-2	1

Note: The top panel provides the median income of either Indian-born or other foreign-born ages 18-64 in 2001 U.S. dollars and the percentages of either Indian-born or foreign-born ages 18-64 that fall within certain fractions and multiples of the median income for Native-born in that year, for those that immigrated to the U.S. within the past 10 years from when the survey (Census or CPS) was taken. The second panel provides the percentages of either Indian-born or other foreign-born ages 25-64 that have attained various levels of education, for those that immigrated to the U.S. within the past 10 years from when the survey was taken. The third panel provides the median age of either Indian-born or other foreign-born and percentages of either Indian-born or other foreign-born that lie within various age groups, for those that immigrated to the U.S. within the past 10 years from when the survey (Census or CPS) was taken.

Table 6a
Descriptive Statistics of NSSO Data, 1994

Variable	Obs	Mean	Median	Std. Dev.
age	208,538	35.04	34.00	11.77
sex	208,538	0.37	0.00	0.48
primary	208,538	0.13	0.00	0.33
middle	208,538	0.16	0.00	0.37
lower-secondary	208,538	0.10	0.00	0.30
higher-secondary	208,538	0.15	0.00	0.36
graduate & above	208,538	0.15	0.00	0.36
experience	208,538	23.16	22.00	13.57
(experience^2)/100	208,538	7.20	4.84	7.41
weekly wage/salary	75,906	441.46	175.00	416.36
log(weekly wage/salary)	75,906	5.65	5.78	1.09
int. or div. income	199,552	0.09	0.00	0.28

Note: Includes only urban sample, individuals 18-64. For sex dummy, male=0, and female=1. Primary, middle, lower-secondary, higher-secondary, and graduate & above are dummy variables for highest education level attained. Each of these levels corresponds with having completed 5, 8, 10, 12, and 15 years of schooling respectively. Experience is equal to age less years of education less 5. "Int. or div. Income" is a dummy variable for the presence of interest or dividend income in the individual's household. Weekly wage/salary information is in 1994 rupees. Only observations with a positive weekly wage/salary are included in the "weekly wage/salary" statistics.

Table 6b
Mincer Equation Results, by Gender, India, 1994
Dependant Variable: log(weekly wage/salary) in 1994 Rupees

	Both Sexes			Men			Women		
	OLS	JML		OLS	JML		OLS	JML	
Variables	Wage	Wage	Selection	Wage	Wage	Selection	Wage	Wage	Selection
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
primary	0.3564	0.3509	0.0170	0.2311	0.2216	-0.0628	0.1707	0.1525	-0.3059
	(0.0123)	(0.0123)	(0.0100)	(0.0130)	(0.0125)	(0.0127)	(0.0334)	(0.0364)	(0.0197)
middle	0.6268	0.6295	0.1276	0.4522	0.4481	0.0055	0.6561	0.6259	-0.3297
	(0.0115)	(0.0116)	(0.0095)	(0.0121)	(0.0121)	(0.0119)	(0.0352)	(0.0414)	(0.0203)
lower-secondary	0.9912	1.0020	0.2378	0.7889	0.7895	0.0428	1.3977	1.3939	0.0706
	(0.0113)	(0.0112)	(0.0097)	(0.0121)	(0.0119)	(0.0121)	(0.0284)	(0.0294)	(0.0193)
higher-secondary	1.2293	1.2459	0.3179	1.0220	1.0249	0.0538	1.6799	1.6966	0.3376
	(0.0134)	(0.0130)	(0.0116)	(0.0144)	(0.0141)	(0.0141)	(0.0327)	(0.0324)	(0.0236)
graduate & above	1.5828	1.6155	0.7067	1.3989	1.4104	0.3975	1.9545	1.9965	0.8660
	(0.0108)	(0.0111)	(0.0103)	(0.0118)	(0.0122)	(0.0127)	(0.0249)	(0.0266)	(0.0199)
experience	0.0657	0.0689	0.0741	0.0648	0.0672	0.0813	0.0600	0.0613	0.0583
	(0.0011)	(0.0012)	(0.0008)	(0.0012)	(0.0013)	(0.0010)	(0.0024)	(0.0027)	(0.0016)
experience^2	-0.0856	-0.0912	-0.1250	-0.0816	-0.0861	-0.1427	-0.0808	-0.0835	-0.0923
	(0.0021)	(0.0022)	(0.0016)	(0.0023)	(0.0023)	(0.0020)	(0.0042)	(0.0046)	(0.0027)
int. or div. Inc.	.	.	-0.1177	.	.	-0.0825	.	.	-0.0595
	.	.	(0.0108)	.	.	(0.0134)	.	.	(0.0209)
constant	3.9567	3.8497	-1.3660	4.1733	4.1174	-1.0114	3.5371	3.4170	-0.6748
	(0.0159)	(0.0175)	(0.0126)	(0.0172)	(0.0191)	(0.0154)	(0.0371)	(0.0553)	(0.0249)
rho	.	0.0676		.	0.0405		.	0.0780	
	.	(0.0057)		.	(0.0071)		.	(0.0221)	
sigma	.	0.9373		.	0.8980		.	0.9633	
	.	(0.0055)		.	(0.0064)		.	(0.0121)	
no of obs	75,906	72,610		61,520	58,822		14,378	13,780	

Data source: NSSO.

Note: For the JML estimates, a Heckman selection procedure is used with the presence of interest or dividend income in the household dummy as an identifier in the selection equation.

Table 7a

Returns to an Additional Year of Education from OLS and JML Results for 1994

Educational Level	Both Sexes		Men		Women	
	OLS	JML	OLS	JML	OLS	JML
primary	7.13	7.02	4.62	4.43	3.41	3.05
middle	9.02	9.29	7.37	7.55	16.18	15.78
lower-secondary	18.22	18.62	16.84	17.07	37.08	38.40
higher-secondary	11.91	12.20	11.65	11.77	14.11	15.14
graduate & above	11.78	12.32	12.56	12.85	9.15	9.99

Table 7b

Returns to an Additional Year of Education from OLS and JML Results for 1998

Educational Level	Both Sexes		Men		Women	
	OLS	JML	OLS	JML	OLS	JML
primary	na	na	na	na	na	na
middle	na	na	na	na	na	na
lower-secondary	na	na	na	na	na	na
higher-secondary	na	na	na	na	na	na
graduate & above	na	na	na	na	na	na

Note: Computed using results from Table 9b and the following equation:

$$R = (Bi - Bj)/Y$$

where R represents returns, Bi represents the coefficient from the given level of education, Bj represents the coefficient from the next-highest level of education, and Y represents years of schooling at that level.

Table 8
Actual Percentage of Domestically Resident Indians Receiving a Wage/Salary, 1994; And Counterfactual Percentages of U.S. Resident Indians Receiving a Wage/Salary, 1990, 1994, 2001

Actual percentages earning w/s

Year	Men	Women	Both Sexes
1994	46.9	18.6	36.4

Percentages in U.S. earning w/s in the U.S.

Year	Men	Women	Both Sexes
1990	85.5	60.0	74.6
1994	86.2	55.6	73.7
2001	84.9	51.4	69.2

Counterfactual percentages earning w/s, from selection equation

Year	Men	Women	Both Sexes
1990	52.6	32.8	44.7
1994	52.5	35.8	45.8
2001	52.7	35.6	44.7

Source: For actual percentages, NSSO. For counterfactual percetages, PPP Method and Mincer Method with U.S. survey participation, IPUMS for 1990, March CPS for 1994-2001.
Note: Ages 18-64. Actual percentages are for only Indians from urban sample.

Table 9
Actual Wage/Salary Earnings Distributions for Domestically Resident Indians Receiving a Wage/Salary, 1994, and Counterfactual Wage/Salary Earnings Distributions for U.S. Resident Indians Receiving Wage Salary, 1990, 1994, 2001

Actual earnings

		Population Shares (as % of Median)				
Year	**Median**	**0-50%**	**50-100%**	**100-200%**	**200-400%**	**>400%**
1994	Rs. 15,607	22	28	21	18	11

Counterfactual earnings, PPP Method with participation based on actual U.S. experience

		Population Shares (as % of Median)				
Year	**Median**	**0-50%**	**50-100%**	**100-200%**	**200-400%**	**>400%**
1990	Rs. 278,309	2	2	3	5	89
1994	239,994	4	2	4	4	86
2001	408,600	2	1	5	5	88

Counterfactual earnings, Mincer Method w/ participation based on selection equation

		Population Shares (as % of Median)				
Year	**Median**	**0-50%**	**50-100%**	**100-200%**	**200-400%**	**>400%**
1990	Rs. 34,360	4	10	21	27	38
1994	45,432	3	9	20	27	41
2001	68,378	3	9	20	27	40

Counterfactual earnings, Mincer Method w/ participation based on actual U.S. experience

		Population Shares (as % of Median)				
Year	**Median**	**0-50%**	**50-100%**	**100-200%**	**200-400%**	**>400%**
1990	Rs. 31,058	5	12	22	27	34
1994	42,695	4	10	21	27	39
2001	63,977	4	10	21	28	37

Source: For actual median wage and salary earnings and distributions, NSSO. For counterfactual median wage and salary earnings and distributions, PPP Method and Mincer Method with U.S.survey participation, IPUMS for 1990, March CPS for 1994-2001.

Table 10a
Comparative Studies of Relative Wages

Year	Metric	U.S./Indian Ratio of wages (worker category)	Source
1994	Software Industry Cost Comparisons	11.2 (systems analyst) 11.6 (programmer)	Economist (1994)
1995	Salaries paid to Software professionals	2.3 (Project Leader) 5.9 (Test engineer)	Heeks (1996)
1997	Salaries of software Professionals	3.43 (Data base administrator) 14.7 (Programmers)	OECD (2000)
2000	Starting Salaries for International and domestic jobs in India's premier business school	5.4 (Consulting) 5.6 (Finance) 7.4 (Systems) 5.9 (Total)	Bhattacharjee et.al. (2001)

Table 10b
Median Monthly Salaries in 2000, U.S. Dollars, Various Occupations

Position	U.S.	India	Ratio
CEO	31,200	1,764	17.7
Controller	11,867	1,066	11.1
Human Resources Director	9,853	965	10.2
Systems Director	10,433	984	10.6
Manufacturing Director	11,592	937	12.4
Sales Director	11,933	831	14.4
Factory/Plant Manager	8,025	724	11.1
Sales Manager	6,708	651	10.3
Accountant	4,463	417	10.7
Systems Engineer	5,460	490	11.1
Software Developer	5,250	490	10.7
Field Services Engineer	3,417	429	8.0
Production Supervisor	3,917	384	10.2
Executive Secretary	2,933	336	8.7
Secretary	2,208	176	12.5
Chauffeur	2,442	147	16.6
Mean	8,231	674	11.6

Source: Asiaweek Salaries Survey 2000. Available online at: http://www.asiaweek.com/asiaweek/features/salaries/2000
Note: Data is from Watson Wyatt annual salary surveys. Salaries exclude bonuses. Indian salaries are converted to U.S. d
the exchange rate of Rs. 43.61per U.S. dollar.

Table 11
Tax Revenue Loss Estimates by U.S. Citizenship Status, as % of Indian GDP

Central Direct	PPP Method			Mincer Method		
Year	Total	Citizens	Non-Cit.	Total	Citizens	Non-Cit.
1990	0.357	0.205	0.152	0.008	0.004	0.004
1994	0.196	0.089	0.108	0.010	0.004	0.005
1995	0.180	0.083	0.097	0.009	0.005	0.004
1996	0.395	0.230	0.165	0.018	0.009	0.009
1997	0.210	0.093	0.117	0.016	0.009	0.008
1998	0.242	0.122	0.119	0.012	0.006	0.006
1999	0.310	0.134	0.176	0.020	0.011	0.009
2000	0.379	0.169	0.211	0.026	0.014	0.012
2001	0.439	0.205	0.235	0.027	0.015	0.013

Central Indirect	PPP Method			Mincer Method		
Year	Total	Citizens	Non-Cit.	Total	Citizens	Non-Cit.
1990	0.079	0.041	0.038	0.005	0.002	0.003
1994	0.031	0.013	0.019	0.004	0.002	0.002
1995	0.028	0.013	0.015	0.003	0.002	0.002
1996	0.050	0.027	0.023	0.005	0.003	0.003
1997	0.037	0.015	0.021	0.005	0.003	0.003
1998	0.036	0.017	0.019	0.005	0.002	0.003
1999	0.048	0.020	0.028	0.006	0.003	0.003
2000	0.054	0.024	0.031	0.007	0.004	0.004
2001	0.059	0.027	0.032	0.008	0.004	0.004

State Indirect	PPP Method			Mincer Method		
Year	Total	Citizens	Non-Cit.	Total	Citizens	Non-Cit.
1990	0.080	0.042	0.038	0.005	0.002	0.003
1994	0.040	0.016	0.023	0.005	0.002	0.003
1995	0.035	0.016	0.019	0.004	0.002	0.002
1996	0.067	0.036	0.031	0.007	0.003	0.004
1997	0.048	0.020	0.028	0.007	0.003	0.004
1998	0.051	0.024	0.027	0.007	0.003	0.004
1999	0.063	0.027	0.037	0.008	0.004	0.004
2000	0.072	0.031	0.041	0.010	0.005	0.005
2001	0.079	0.036	0.043	0.010	0.005	0.005

Total	PPP Method			Mincer Method		
Year	Total	Citizens	Non-Cit.	Total	Citizens	Non-Cit.
1990	0.516	0.288	0.228	0.018	0.008	0.009
1994	0.267	0.118	0.149	0.019	0.008	0.011
1995	0.243	0.111	0.132	0.016	0.009	0.008
1996	0.512	0.293	0.219	0.030	0.015	0.015
1997	0.295	0.129	0.167	0.029	0.015	0.014
1998	0.329	0.164	0.165	0.024	0.011	0.013
1999	0.421	0.181	0.240	0.035	0.018	0.017
2000	0.505	0.223	0.282	0.043	0.022	0.021
2001	0.577	0.268	0.310	0.046	0.024	0.022

Notes: The four panels provide estimates of central direct, central indirect, state indirect, and total tax revenue losses associated with Indian-born residents in the U.S. The two columns provide estimates generated by the PPP and Mincer methods and results are broken out for U.S. citizen and non-citizens.

Table 12
Expenditure Savings Estimates, as percentage of Indian GDP

Central Government

	PPP Method			Mincer Method		
Year	**Total**	**Citizens**	**Non-Cit.**	**Total**	**Citizens**	**Non-Cit.**
1990	0.115	0.060	0.055	0.011	0.005	0.006
1994	0.056	0.028	0.028	0.010	0.004	0.006
1995	0.059	0.026	0.032	0.008	0.004	0.004
1996	0.114	0.062	0.052	0.013	0.006	0.007
1997	0.085	0.036	0.050	0.016	0.009	0.007
1998	0.095	0.045	0.050	0.012	0.006	0.006
1999	0.113	0.047	0.066	0.016	0.008	0.008
2000	0.133	0.057	0.075	0.019	0.009	0.010
2001	0.148	0.068	0.081	0.019	0.009	0.010

State Government

	PPP Method			Mincer Method		
Year	**Total**	**Citizens**	**Non-Cit.**	**Total**	**Citizens**	**Non-Cit.**
1990	0.133	0.069	0.063	0.013	0.006	0.007
1994	0.087	0.036	0.051	0.012	0.005	0.007
1995	0.075	0.033	0.041	0.010	0.005	0.005
1996	0.146	0.079	0.067	0.017	0.008	0.009
1997	0.105	0.044	0.061	0.020	0.011	0.009
1998	0.120	0.057	0.063	0.016	0.007	0.008
1999	0.145	0.061	0.084	0.020	0.010	0.010
2000	0.170	0.073	0.097	0.024	0.011	0.012
2001	0.190	0.087	0.104	0.024	0.011	0.013

Total

	PPP Method			Mincer Method		
Year	**Total**	**Citizens**	**Non-Cit.**	**Total**	**Citizens**	**Non-Cit.**
1990	0.248	0.130	0.119	0.023	0.011	0.013
1994	0.143	0.064	0.079	0.022	0.009	0.013
1995	0.133	0.059	0.074	0.017	0.009	0.009
1996	0.260	0.141	0.119	0.030	0.014	0.016
1997	0.191	0.080	0.111	0.036	0.019	0.017
1998	0.215	0.102	0.113	0.028	0.013	0.014
1999	0.258	0.108	0.150	0.036	0.017	0.019
2000	0.303	0.131	0.172	0.042	0.020	0.022
2001	0.339	0.154	0.185	0.043	0.020	0.022

Notes: The three panels provide estimates of central, state and total expenditure savings associated with Indian-born residents in the U.S. The two columns provide estimates generated by the PPP and Mincer methods and results are broken out for U.S. citizen and non-citizens.

Table 13

Net Fiscal Impact Estimates, as percentage of Indian GDP

	PPP Method			Mincer Method (regression participation)		
Year	**Total**	**Citizens**	**Non-Citizens**	**Total**	**Citizens**	**Non-Citizens**
1990	0.268	0.158	0.110	-0.006	-0.002	-0.003
1994	0.124	0.054	0.070	-0.003	-0.001	-0.002
1995	0.110	0.052	0.058	-0.001	0.000	-0.001
1996	0.252	0.153	0.100	0.000	0.001	0.000
1997	0.105	0.049	0.056	-0.007	-0.004	-0.002
1998	0.114	0.062	0.052	-0.004	-0.002	-0.002
1999	0.163	0.073	0.090	-0.001	0.001	-0.002
2000	0.203	0.093	0.110	0.001	0.002	-0.001
2001	0.239	0.113	0.125	0.003	0.003	-0.001

Notes: The table provides estimates of the net fiscal impact (total tax revenues less expenditure savings) associated with Indian-born residents in the U.S. The two columns provide estimates generated by the PPP and Mincer methods and results are broken out for U.S. citizen and non-citizens.