ESSAYS ON MIGRATION, REMITTANCES, AND WELFARE

A Dissertation

Presented to

The Faculty of the Department

of Economics

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Doctor of Philosophy

By

Subash Khatry

May 2017

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Abstract

This dissertation is comprised of two essays. The first essay analyzes the aggregate income shocks absorbing and welfare improving roles of remittances in emerging economies. I develop a model to derive testable implications for aggregate remittance behavior. Using a panel data set of 102 developing countries from 1975 to 2013 and the generalized method of moments estimator, I find that remittances respond to fluctuations in GDP and exchange rates in a manner consistent with income smoothing implications of the model. Using a variance-decomposition framework, I find that remittances, on average, absorb about 3.5 percent of fluctuations in GDP in all 102 countries, but about 6.1 percent of such fluctuations in Africa countries. To assess the welfare gains from remittances, I use a utility-based framework that allows for level-, growth-, and volatility-effects of remittances on income. Using country-level data, I find that the average welfare gains to a representative agent are equivalent to a 1.9 percent increase in consumption. About 15 percent of these gains arise from less volatile income and the rest arises from higher income and growth. Using household data from five countries, I find that the gains for poor households are about eleven-fold larger than the gains for rich households.

In the second essay, I examine the effects of immigration on the wages of U.S. native workers at the national level. Following a general equilibrium approach and exploiting the variation in labor supply shifts across industry, education, and experience specific skill-groups of workers, I find that immigrant workers are indeed imperfect substitutes for native workers. Using my estimates of the elasticity of substitution between workers of different skill groups, I find that immigration had much smaller negative effects on the wages of unskilled native workers than what is reported in Borjas (2003) and Ottaviano and Peri (2012). Immigration (1990-2014) reduced the wages of native workers with no high school degree by about 0.3 percent while it increased the wages of average native workers by about 0.6 percent. In the

paper, I document the importance of consideration of industry (occupation) specific skill groups of workers in addition to conventionally used education and experience groups while estimating the substitutability between immigrant and native workers and, thus, evaluating the effects of immigration on wages of native workers.

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To my parents and my wife.

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Chapter 1

Income Insurance and Welfare Gains from Remittances in Emerging Economies

1.1 Introduction

High income volatility (see Table 1.1) in conjunction with low levels of financial development in developing countries lower welfare (see Loayza et al., 2007). Remittances are one way in which emigrants abroad can help offset income volatility in the home country. This is important given that other private capital flows typically do not help developing countries to insure against aggregate income shocks (see Kose et al., 2009). In recent years, remittances have become an increasingly important source of external finance in developing countries. Remittances as a share of gross domestic product (GDP) in the developing world rose from 0.7 percent in 1990 to 1.5 percent in 2010. They accounted for more than 10 percent of GDP in 2010 in 30 countries; the highest is 41 percent of GDP in Tajikistan (see Fig. 1.1). Remittances in the developing world were equivalent to 48 percent of net foreign direct investment (FDI) inflows in 2010. In addition, remittance flows were more stable than other private capital flows during periods of financial crisis (see Fig. 1.2).

The goal of this paper is to assess the extent of (partial) income insurance and welfare gains from remittances. In particular, this paper answers the following three questions: First, how do remittances respond to fluctuations in the GDP of the home and the remittances source country ("host country" hereafter), and in exchange rates? This paper addresses this question by using a large group of 102 developing countries. This is the first paper to document that remittances absorb aggregate income shocks in low-income credit constrained countries. Second, what fractions of transitory and permanent shocks to the GDP of home countries are absorbed via remittances? This is also the first paper to examine the extent and the pattern of income risk sharing via remittances across groups of countries by income and geography and to show that remittances absorb permanent shocks to GDP. Third, how large are the welfare gains from remittances in developing countries. I propose a utility-based framework that allows me to evaluate the gains from remittances for a large group of countries and also for poor and rich households separately.

In the paper, I first develop a utility maximizing model for migrants to derive testable implications for aggregate remittances behavior.[1] This model predicts that remittances respond negatively to home country income, positively to host country income, positively to the devaluation of the home country currency, and negatively to the interest rate in the host country. I test these predictions using the panel fixed effect regression and unbalanced panel data from 102 developing countries from 1975 to 2013. In order to mitigate biases due to reverse causality, I conduct Generalized Method of Moments (GMM) estimation using lagged regressors as instruments. I find that the home country income elasticity of remittances is -0.33. The negative

[1] This model is an extended version of the existing models presented in Agarwal & Horowitz (2002), Lucas & Stark (1985), and Vargas-Silva & Huang (2006).

coefficient suggests that remittances are aggregate income stabilizers. In terms of average real dollar values, this coefficient implies that if the home country real GDP per capita decreases by US$100, real remittances per migrant to the typical developing country increase by US$17.7.[2] Further, the results show that the income stabilizing roles of remittances are limited in low-income countries and in countries with shallow financial markets in Africa and Asia.[3] The host country income elasticity of remittances is positive, as predicted by the model, with an absolute value 0.15. This finding suggests that the amount of remittances sent to the home country depends on migrants' earnings in host countries. I find that remittances do not respond to the interest rate in host countries, but they are positively correlated with the depreciation of home currency implying that they further stabilize the purchasing power of consumers during recessions.

Next, I assess the extent of (partial) income risk-sharing via remittances by using a variance decomposition technique developed in Asdrubali, Sørensen, and Yosha (1996). I first derive the idiosyncratic (country-specific) fluctuations in GDP and remittances in all 102 countries and then estimate the risk-sharing regressions using Generalized Least Squares (GLS). I find that remittances, on average, absorb about 3.5 percent of temporary shocks to GDP (i.e. shocks at the one-year frequency) and 3.7 percent of permanent shocks to GDP (i.e. shocks at the five-year frequency) during the 1975-2013 period. This suggests that remittances absorb both temporary and permanent shocks in GDP. However, the extent and the pattern of risk-sharing are significantly different across different groups of countries by region and income. For example, remittances absorb about 6.1 percent of transitory shocks in GDP in Africa

[2] For a typical country in Africa, the increase in real remittances per migrant would be as high as US$35.8.

[3] I define countries below and above the median real GDP per capita ($2,026) of the sample countries in 2013 as low- and middle-income countries, respectively. Similarly, countries below and above the median value of private credit by banks and financial institutions as a share of GDP as countries with shallow and deep financial markets, respectively.

against 3.0 percent in Asia and 1.6 percent in both East Europe and Latin America; and about 4.5 percent in low-income countries against 2.2 percent in middle-income countries. Remittances also absorb the highest fraction of permanent shocks in GDP in Africa. Similarly, the degree of risk-sharing is increasing over time in Africa and Asia, but continuously decreasing in East Europe. I find that the average degree of income risk-sharing via remittances is positively related to the average ratio of remittances to GDP in all regions but Eastern Europe.

To quantify the welfare gains from (net) remittances, I use a utility-based framework for an endowment economy that allows for level-, growth-, and volatility-effects of remittances on income. I find that the welfare gains from remittances are quite sizable in developing countries. The average gains are equivalent to a 1.9 percent permanent increase in consumption for a representative agent.[4] The gains are higher in Africa (3.2 percent) and low-income countries (2.7 percent) than in Asia (1.6 percent), East Europe (2.2 percent), Latin America (1.8 percent), and middle-income countries (0.8 percent). This finding is consistent with a high negative income elasticity of remittances in Africa and low-income countries. The results further show that a given level of the remittances-to-GDP ratio can be associated with different levels of welfare gains depending on how remittances affect the income growth and volatility over time. About 15 percent of the gains arise from less volatile income and the rest arises from higher income and growth.

In addition, I use household data from Guatemala (2000), India (2012), Nepal (2011), Tajikistan (2007), and Uganda (2011), and impute income and remittances for poor and rich households in these five countries to estimate the welfare gains at the household level. I find that the gains are quite large for poor households—for

[4]The country-level measures of welfare gains implicitly assume perfect risk-sharing within a country.

example, the gains are as high as 9.3 percent for the bottom (income) quartile (of households) but only about 0.9 percent for the top quartile.[5] I finally conduct a micro household-level analysis as a complement to the macro country-level analysis using household panel data from India between 2005 and 2012. I calculate the welfare gains for all households in India as well as households in three major remittance-dependent states in India; namely, Kerala, Punjab, and Rajasthan.[6] In the case of all Indian households, the magnitude of average welfare gains turns out to be only about one-third of the welfare gains obtained for a representative agent using country aggregate data. However, the direction of the gains across income groups of panel households in India are similar to those obtained from the macro country-level analysis.[7] Overall, my results suggest that remittances provide income insurance and improve the welfare of risk-averse agents in developing countries.

This paper is closely related to existing empirical literature that examines the determinants of remittances. Bouhga-Hagbe (2006) finds that remittances increase when home country agricultural GDP falls in 5 countries in the Middle East and Central Asia. Yang and Choi (2007) find that a decrease in home income leads to an increase in remittances. A similar result is found by Singh et al. (2010) for 36 African countries. However, Vargas-Silva and Huang (2006), using data from 5 countries in Latin America, conclude that remittances respond more to fluctuations in aggregate variables in host countries than to fluctuations in aggregate variables in home countries. El-Sakka and McNabb (1999) show that officially reported remittances to Egypt decrease when the differential between the official and black-market exchange rates

[5] The bottom quartile, on average, receives only about 5 percent of total domestic income but about 30 percent of total remittances from abroad goes to these households.

[6] The share of remittances in total domestic income for all panel households in India in these two years is much lower than the remittances-to-GDP ratio reported at the national level in the same years.

[7] Micro household-level measures of welfare gains do not consider the possibility of risk-sharing between households within a country.

increases.

Several motives to remit have been proposed and tested in the literature including altruism, risk-sharing, and investment (see Agarwal and Horowitz, 2002; Amuedo-Dorantes and Pozo, 2006 & 2010; Cox et al., 2004; Funkhouser, 1995; Lucas and Stark, 1985; Rapoport and Docquier, 2006; Yang and Choi, 2007). While altruism and risk-sharing motives imply that remittances are countercyclical, investment motives imply that remittances are procyclical at the national level. However, the empirical evidence on the motives to remit and on the cyclicality of remittances has been inconclusive. Using different countries and time periods, some studies find that remittances are countercyclical (Bettin et al., 2014; Chami et al., 2005; Gupta, 2005; Frankel, 2011), but others find that they are procyclical (Lueth and Ruiz-Arranz, 2006 & 2007; Neagu and Schiff, 2009; Sayan, 2006).

Regarding the degree of international risk-sharing in developing countries, my paper is related to Kose et al. (2009) and Balli and Rana (2015). Kose et al. (2009) examine the consumption risk-sharing in 27 developing countries over 1987-2004 and find that these countries have largely been shut out of presumed international risk-sharing benefits of financial globalization. Balli and Rana (2015) investigate the determinants of international risk-sharing via remittances in 86 developing countries over 1990-2010. However, they refrain from investigating differential income risk-sharing roles of remittances across different groups of countries by region and income.

Similarly, my paper is also related to Acosta et al. (2009), Chami et al. (2006), and Mandelman and Zlate (2012), who use a calibrated dynamic model to calculate the welfare gains from remittances. Chami et al. (2006) find that remittances increase the welfare by increasing the steady-state levels of consumption and leisure but the gains are partly offset by the increase in business cycle volatility in the home country due to remittances.[8] Acosta et al. (2009) document similar channels of welfare gains. Mandelman and Zlate (2012) show that lower barriers to immigration increase the welfare in both home and host country.[9] In this paper, I use a simple utility-based framework that is flexible enough to measure the welfare gains for a large number of countries as well as for various income groups of households without relying on parameter estimates matching a particular economy.

The rest of the paper is organized as follows: Section 2 develops a model of remittances behavior. Section 3 discusses the data and estimates the aggregate remittance elasticities. Section 4 quantifies the degree of income smoothing via remittances. Section 5 documents the welfare gains from remittances, and Section 6 concludes.

1.2 Model of Remittances Behavior

In this section, I develop a model of remittances behavior based on the economics of family to derive testable predictions about how remittances respond to fluctuations in the aggregate variables in home and host countries. This model preserves some of the basic implications of many other remittances models (see Agarwal & Horowitz, 2002; Lucas & Stark, 1985; Funkhouser, 1995; Rapoport & Docquier, 2005; Vargas-Silva & Huang, 2006; and Yang & Choi, 2007 among others). However, to the best of my knowledge, this is the first model that explicitly establishes the relationship between remittances, exchange rate, interest rate, and costs of sending remittances.

[8] Chami et al. (2006) argue that remittances increase the business cycle volatility in recipient countries by changing the sign of the correlation between labor supply and domestic output from negative to positive.

[9] They find that lower immigration barriers from Mexico to the U.S. increase the welfare of unskilled workers in Mexico by increasing income and smoothing consumption, which is more than offset the welfare costs to skilled workers arising from lower wages due to a lower supply of unskilled labor in production.

Consider a representative country with a large number of identical and infinitely-lived two-person families, one an emigrant (m) living in the host country and the other is a non-migrating member in a home country who is referred to as remittances recipient (r).[10] In Becker's type economics of the family, there might be utility interdependence between the emigrant and the recipient when family members are altruistic to each other (see Becker, 1981; and Pollak, 2003). Since the objective of this paper is to explore income stabilizing and welfare improving roles of remittances in recipient countries, I assume that the emigrant values the consumption of recipient (C_r) in her utility at each time (t) according to a separable utility function of the form:[11]

$$U = U(C_m, V) = U_m(C_m) + V\{U_r(C_r), \overline{\xi}\}, \tag{1.1}$$

where U_m represents emigrant's utility from own consumption (C_m) and V(.) is the felicity that emigrant derives from recipient's utility (U_r) from consumption C_r. The amount of felicity depends on degree of attachment between the emigrant and the recipient, represented by a vector $\overline{\xi}$. I further assume that this amount of felicity can be measured by a constant altruism weight α (assume α>0) i.e. $V\{U_r(C_r), \overline{\xi}\} = \alpha U_r(C_r)$. Both utility functions satisfy concavity properties as U'_m>0, U''_m<0, U'_r>0, and U''_r<0. The expected lifetime utility of an emigrant is,

$$\sum_{t=0}^{\infty} \beta^t \Big[U_m(C_{m,t}) + \alpha U_r(C_{rt})\Big]. \tag{1.2}$$

I assume that both the emigrant and the recipient have the same rate of time preference (β). For simplicity, I assume that the recipient consumes exogenous domestic income (Y_r) plus remittances measured in home currency (R_t) i.e. $C_{rt} =$

[10]Here, I implicitly assume that migration decision has already been taken place.

[11]Incorporating mutual utility interdependence results into bi-directional flows of resources between emigrant and recipient household.

$Y_{rt} + (1-\psi)R_t$.[12] Here, ψ is the exogenous iceberg cost of remitting ($0<\psi<1$) so that recipient receives only a fraction of remittances R_t sent by emigrant. I allow the emigrant to save or borrow in the host country in addition to remitting a part of her (exogenous) income, Y_m, to the recipient in the home country. Therefore, the intertemporal budget constraint for the emigrant in period t is:

$$C_{mt} + R_t \frac{e_{jt}}{e_{it}} + b_{t+1} = (1+i)b_t + Y_{mt}, \tag{1.3}$$

where $R_t \frac{e_{jt}}{e_{it}}$ is the amount of remittances expressed in terms of home currency, e_j is the (exogenous) exchange rate between host country j's currency and the the US dollar, e_i is the (exogenous) exchange rate between home country i's currency and the US dollar, b_{t+1} are the emigrant's stock of assets tomorrow, and b_t are existing stock of assets in the host country. The value $(1+i)$ is the rate of return on assets which is now assumed to be constant. Assuming that the emigrant has no stock of assets in the host country to begin with (i.e. $b_0 = 0$), the lifetime budget constraint for this infinitely-lived emigrant with transversality condition of $\lim_{n\to\infty} \frac{b_T}{(1+i)^t} = 0$ is:

$$\sum_{t=0}^{\infty} \frac{\left(c_t + R_t \frac{e_{jt}}{e_{it}}\right)}{(1+i)^t} = \sum_{t=0}^{\infty} \frac{Y_{mt}}{(1+i)^t}. \tag{1.4}$$

The emigrant maximizes her lifetime utility given by Eq. (1.2) subject to the lifetime budget constraint given by Eq. (1.4). The first order conditions (FOCs) of the emigrant's maximization problem are then:

$$\beta_t U'_{mt}(.) - \lambda \frac{1}{(1+i)^t} = 0, \tag{1.5}$$

$$\beta_t \alpha U'_{rt}(.)(1-\psi) - \lambda \frac{1}{(1+i)^t} \frac{e_{jt}}{e_{it}} = 0, \tag{1.6}$$

[12] It means I do not take into account the labor supply decision by the recipient and so the effect of migration on the labor force in the home country is turned off.

where λ is the Lagrange multiplier that measures the marginal utility of income. The Euler equation is then:

$$-U'_{mt}(.)\frac{e_{jt}}{e_{it}} + \alpha U'_{rt}(.)(1-\psi) = 0. \tag{1.7}$$

The Euler equation (1.7) indicates that the emigrant remits so as to equate an increase in her utility from an increase in recipient's consumption resulting from remittances transfer to decrease in utility from lower own consumption due to that transfer. The Euler equation (1.7) combined with the lifetime budget constraint defines an implicit remittances function as follows:[13]

$$R_t = R(Y_{mt}, Y_{rt}, e_{it}, \psi, i_t, \alpha). \tag{1.8}$$

Using the implicit function theorem, I can derive the relationships between fluctuations in remittances and macroeconomic variables, namely home and host country GDP, exchange rate, and interest rate as follows:

$$\frac{\partial R_t}{\partial Y_{rt}} = -\frac{\left[\alpha U''_{rt}(.)(1-\psi)\right]}{D} < 0, \tag{1.9}$$

where D is the first derivative of implicit function with respect to remittances, and

$$D = U''_{mt}(.)\frac{1}{(1+i)^t}\frac{e_{jt}}{e_{it}} + \alpha U''_{rt}(.)(1-\psi)^2 < 0. \tag{1.10}$$

Eq. (1.9) indicates that the emigrant remits more when the recipient's income falls—a prediction consistent with the altruism motive to remit. At the national level, this implies a negative relationship between the growth rates of remittances and GDP of the home country. Therefore, the first testable prediction that I derive from the model in this section is:

[13]The depreciation of home currency vis-a-vis the US dollar is considered in the empirical estimation as remittances data taken from the World Bank are reported in terms of US dollar only.

Prediction 1. *Migrants remit to compensate for home income shocks:* $\frac{\Delta R_{it}}{\Delta Y_{rt}}$ < 0*, where* Y_{rt} *is home country GDP.*

Next, I can derive the relationship between remittances and host country GDP as follows:

$$\frac{\partial R_t}{\partial Y_{mt}} = -\frac{\left[- U''_{mt}(.) \frac{1}{(1+i)^t} \frac{e_{jt}}{e_{it}} \right]}{D} > 0. \tag{1.11}$$

Eq. (1.11) suggests that the emigrant tends to remit more when her income goes up. The amount of remittances sent by the emigrant, irrespective of the motives behind it, depends on her ability to remit which, in turn, depends on how much she earns. Since the data on migrants' income at the macro level are not available, GDP per capita is used as a proxy for migrants' income. So, the second testable prediction is:

Prediction 2. *Migrants remit more during good times in host countries:* $\frac{\Delta R_{it}}{\Delta Y_{mt}}$ > 0*, where* Y_{mt} *is host country GDP.*

Similarly, the model also yields relationship between remittances and exchange rate of home currency vis-a-vis the US dollar:

$$\frac{\partial R_t}{\partial e_{it}} = -\frac{\left[U'_{mt}(.) \frac{e_{jt}}{e_{it}^2} - U''_{mt}(.) \frac{1}{(1+i)^t} \left(\frac{e_{jt}}{e_{it}}\right)^2 \frac{R_t}{e_{it}} \right]}{D} > 0. \tag{1.12}$$

The emigrant is likely to remit more when the home currency depreciates. It is because a depreciation of home currency relative to the US dollar increases emigrant's purchasing power back home and thus provides incentives to remit more, which can be defined as the positive wealth effect of exchange rate movements. Because many developing countries are net importers of goods and services, the positive exchange rate elasticity of remittances also suggests that remittances help stabilize the purchasing power of consumers during recessions. The third testable prediction is then,

Prediction 3. *Remittances increase when home country currency depreciates:* $\frac{\Delta R_{it}}{\Delta e_{it}} > 0$*, where e is the exchange rate of home country currency vis-a-vis the US dollar.*

Also, variation in the rate of returns on assets in the host country may affect emigrant's decision about the amount of remittances. Income maximizing behavior of emigrant may give rise to a higher savings in host country when interest rates are high resulting into a lower amount of remittances. The model predicts such negative relationship between interest rates and remittances:

$$\frac{\partial R_t}{\partial i_t} = -\frac{\Big[U''_{mt}(.)\frac{e_{jt}}{e_{it}}\frac{t}{(1+i)^{t+1}}\big(Y_{mt} - R_t\frac{e_{jt}}{e_{it}}\big)\Big]}{D} < 0. \tag{1.13}$$

Therefore, another testable prediction that the model yields is:[14]

Prediction 4. *Remittances decrease when returns on savings in host countries increase:* $\frac{\Delta R_{it}}{\Delta i_t} < 0$*, where i is the interest rate on savings in host country.*

Finally, the model yields an ambiguous relationship between remittances and the costs of remitting to the home country as follows:

$$\frac{\partial R_t}{\partial \psi} = -\frac{\Big[-\alpha U''_{rt}(.)R_t(1-\psi) - \alpha U'_{rt}\Big]}{D} \lesseqgtr 0. \tag{1.14}$$

The costs of remitting can have two opposite effects. First, higher costs of remitting may discourage people to remit or at least discourage to use official channels of remitting money which might lead to a lower volume of remittances. Second, higher costs (ψ) means a lower amount of remittances to the recipient. If utility maximizing behavior requires emigrant to maintain the same level of consumption of recipient and hence same amount of after-costs remittances, $(1-\psi)R_t$, then higher costs require higher remittances.

[14] One can argue that the rate of return on savings in the home country may also affect remittance inflows. In that case, one can look at the response of remittances to changes in interest rate differentials between host and home country.

1.3 Aggregate Fluctuations and Remittances

1.3.1 Methodology

To test the predictions implied by the model of remittances behavior developed in Section 2, I estimate the following panel data model:[15]

$$\Delta \ln R_{it} = \alpha_i + \vartheta_t + \beta' \Delta \ln Y_{it} + \gamma' \Delta \ln Y_{it}^d + \eta' \Delta \ln RER_{it} + \kappa' \Delta r_{it}^d + \delta' \Delta Z_{it} + \epsilon_{it}, \tag{1.15}$$

where any variable $\Delta \ln X_{it}$ should be regarded as a generic expression of fluctuations in variable X at the one-year frequency. RER is the real exchange rate of home currency vis-a-vis US dollar. Y^d represents the weighted average of real GDP per capita of top 5 host countries for each home country i in period t defined as follows:

$$Y_{it}^d = Y_{\tau+k}^{i,d} = \sum_{j=1}^{5} s_\tau^{i,j} \cdot Y_{\tau+k}^{i,j},$$

for $\tau = 1970$, 1980, 1990, 2000, and 2010 and $k = 0$, 1, ..., 9 for each τ,

where $Y_{\tau+k}^{i,j}$ is the real GDP per capita of top 5 host countries j for home country i in period '$\tau + k$'. $s_\tau^{i,j}$ is the share of emigrants to host country j to total emigrants from home country i in year τ.[16] I use this weighted average real GDP per capita of top 5 host countries as a proxy for economic situations faced by migrants in host countries. Similarly, the variable r_{it}^d is the weighted average of short-term real interest

[15] Since data on costs of remitting are not available, I do not estimate the elasticity of remittances with respect of costs of remittances. In order to avoid the influence of outliers, I winsorize the data at the outer 1 percent of both tails in all empirical estimations.

[16] Using the data on the stock of out-migrants for each home country i in years 1970, 1980, 1989, 2000 and 2010, I identify the top 5 host countries for migrant workers and calculate migrants share in the total number of migrants from each home country i for those specific years. I then use that migrants share to host country j as a weight to the real GDP per capita of the same host country for the next 9 consecutive years. In the tenth year, I again identify top 5 host countries and calculate migrants shares 's' to be used as a weight to real GDP per capita of top 5 migrant host countries again for the next 9 consecutive years and so on. The migrants share in 2010 are used as a weight for the next three years only as the study covers the period only up to 2013.

rates of top 5 host countries using the same weights as for the host country real GDP per capita Y^d_{it}. The variable Z_{it} represents control variables, namely total migrant stock abroad and FDI inflows. The ϵ_{it} is error term which is assumed to be correlated within each country i but independent across countries i and j and non-identically distributed.

The estimated coefficients in Eq. (1.15) measure the elasticity of remittances with respective to right-hand side variables. A negative coefficient of β would indicate that remittances are compensatory transfers and thus absorb domestic income shocks. A positive coefficient of β would suggest procyclical remittance inflows as other profit-driven private capital flows, implying that remittances further destabilize aggregate income. Similarly, a positive coefficient of γ would indicate procyclical remittances with respect to host country's economy. The coefficient η measures the elasticity of remittances with respect to the depreciation of home currency and the coefficient κ measures the host country interest rate elasticity of remittances.

I estimate Eq. (1.15) with both country and time fixed effects to control for unobserved time-invariant country characteristics and time-variant common shocks and trends across countries. The fixed effects help to reduce the concerns of endogeneity due to relevant omitted factors. However, the bias due to reverse causality (most notably, GDP growth rate) may still be a major concern.[17] Use of valid external instruments would be the best solution to this problem. However, it is difficult to get such valid external instruments in most social science research both from the theoretical and empirical point of view. I, therefore, use lagged values of regressors as internal instruments to control this potential endogeneity and estimate Eq.(1.16) below in a dynamic system Generalized Method of Moments (GMM) framework of

[17] For example, remittances may fund productive investments in the home country that affects GDP growth rate positively. Alternatively, high remittances may lead to a decline in labor supply and an appreciation of home currency causing a decline of the tradable sector and hence a lower GDP growth.

Arellano and Bover (1995) and Blundell and Bond (1998):

$$\Delta \ln R_{it} = \alpha_i + \vartheta_t + \phi' \Delta \ln R_{it-1} + \beta' \Delta \ln Y_{it} + \gamma' \Delta \ln Y^d_{it} + \eta' \Delta \ln RER_{it} + \kappa' \Delta r^d_{it} + \delta' Z_{it} + \epsilon_{it}. \tag{1.16}$$

In particular, Eq. (1.16) and its first difference equation are estimated as part of dynamic system GMM. I use two and higher lagged values of regressors as instruments for the regressors in the first difference equation of Eq. (1.16) and two and higher lagged values of the difference of regressors as instruments for regressors in Eq. (1.16).[18] This also helps to account for the fact $\Delta \log R_{it-1}$ is by construction correlated with the unobserved country-level effects α_i.

1.3.2 Data

The econometric analysis is based on unbalanced panel data for 102 developing countries (37 African, 22 Asian, 21 Eastern European and 22 Latin American countries) over 1975-2013.[19] In addition, I use cross-sectional household data from five countries, namely Guatemala (2000), India (2012), Nepal (2011), Tajikistan (2007), and Uganda (2011), and household panel data from India between 2005 and 2012 to measure the welfare gains in section 5. A detail of these household data is provided in section 5.2.

Table 1.16 in Appendix provides the list of all 102 countries. The inclusion of a country in the study is guided by the availability of data. A country is included if it has data on all variables, and the share of remittances to GDP is bigger than 0.5 percent. It is because these countries are generally considered as the major remittances-dependent economies in the literature. Hence, any conclusion drawn

[18] In dynamic system GMM, moment conditions are applied based on the following assumptions: a) error terms are serially uncorrelated; b) explanatory variables are weakly exogenous; and c) no correlation between the changes in the right-hand side variables and the country specific effects, ξ_i

[19] I use unbalanced panel data because only a few countries have remittances data since 1975. For several developing countries, remittances data are available since the late-1990s.

on the role of remittances in these countries would be applied to all remittances-dependent economies. In addition, I exclude countries with less than 100,000 population in the year 2005.

Data on remittances, GDP, population, and CPI at 2005 base year are taken from the *World Development Indicators* (World Bank). Nominal exchange rate data is obtained from *International Financial Statistics* (IMF). I use data on the stock of migrants from *Global Bilateral Migration Database* (World Bank) for 1975-1990 period and from *UN Global Migration Database* for the 1990-2013 period. Data on short-term interest rates are taken from *World Development Indicators* and *OECD.Stat*. Similarly, the data on depth and access to financial market come from *Global Financial Development Databse*. All nominal variables are expressed in real terms using each country's CPI with the base year 2005 and then converted into US dollar terms by using the exchange rate vis-a-vis US dollar in the year 2005. Table 1.15 in Appendix provides a list of variables used in the paper and their sources.

The World Bank defines remittances as the sum of workers' remittances and compensation of employees. Chami et al. (2008) show that workers' remittances are countercyclical whereas employee compensation are procyclical, on average, and so the conclusion drawn from using only workers' remittances can be different than that using the sum of both components. However, I use the sum of both components because the availability of separate data on compensation of employees is limited. In addition, Bugamelli and Paternò (2009) argue that the statistical distinction between the two is highly problematic.

The summary statistics of data presented in Table 1.2 show that there is a considerable degree of heterogeneity in the growth rates of all dependent and independent variables across countries. For some countries, growth rates of real remittances and real GDP per capita are negative. The growth rates of remittances are on average higher than the growth rates of home country real GDP per capita. In addition, the growth rates of remittances and remittances per migrant seem to be identically distributed.

Since standard regression models are based on the stationarity assumptions of variables, I performed the Augmented Dickey-Fuller (ADF) unit root test for each variable in each country. This test suggests that all variables in logs, except interest rates and migrant stock abroad, do have unit roots in almost all countries. Therefore, using the first difference of log of each variable is appropriate in the empirical estimation. The unit root tests show that the first difference of log of each variable is stationary in almost all countries, suggesting that standard asymptotic properties hold for the estimates in the growth rates of variables in the study.

1.3.3 Results

Table 1.3 presents results from the panel data fixed effect estimation of Eq. (1.15) in the first five columns and system GMM estimation of Eq. (1.16) in the next five columns.[20] The estimated coefficients for all 102 countries reported in columns (1) and (6) are consistent with model's prediction in Section 2.[21] The results show that remittances respond negatively with fluctuations in home country GDP but positively with fluctuations in host country GDP. Similarly, remittances seem to be

[20] The Fig. 1.3 shows that the magnitude and pattern of remittances as a share of GDP are very different across Africa, Asia, Eastern Europe, and Latin America. While it increased rapidly in Eastern Europe since 1994, it dropped continuously though slowly in Latin America since the mid-2000s. The ratio is higher in Africa than in Asia although both regions experienced a more or less constant ratio over time. The ratio of remittances to total export value closely follows the pattern of the ratios of remittances on GDP. Accordingly, aggregate remittances behavior might be different across these continents. I, therefore, estimate remittances elasticities across these continents separately.

[21] All regressions include the growth in migrant stock abroad from each home country and the growth in foreign direct investment inflows to home country as control variables in order to control for possible endogeneity of home country GDP growth due to omitted variables. Poor economic conditions in the home country may encourage more people to migrate abroad looking for better job opportunities that might also lead to a higher remittances inflow.

very sensitive to the fluctuations in exchange rate but they do not respond to the changes in interest rate in host countries. Comparing the coefficients of home GDP per capita from the fixed effects and system GMM estimations, it appears that the coefficient is biased upward in fixed effect estimation.

Looking at the coefficients from system GMM estimation in column (6), all the coefficients are statistically significant at 5 percent level except the coefficient of real interest rate. The point estimate of home GDP per capita suggests that if home GDP per capita decreases by 1 percent, remittances increase by 0.33 percent. This finding implies that remittances are an aggregate income stabilizer in home countries—a finding consistent with altruism and risk-sharing motives to remit. In terms of average real dollar values, the estimated coefficient implies that if real GDP per capita decreases by US$100, real remittances per migrant to a typical country will increase by US$17.7.[22]

The point estimate of host country GDP per capita indicates that if GDP per capita in host country increases by 1 percent, remittances to home countries increase by 0.16 percent. This finding suggests that remittances help stabilize host countries' economies also. It is because higher remittances in boom times in host countries can lessen the danger of excessive monetary expansion, overheating, and inflation. Similarly, lower than average remittances during bad times would mean a needed improvement in the balance of payments in the host country.

The point estimate for the exchange rate suggests that if home currency depreciates by 1 percent, remittances measured at home currency increase by about 0.8 percent. Under the flexible exchange rate system, home currency may depreciate during recessions worsening the purchasing power of consumers for imported goods and

[22]For a typical country in Africa, the increase in real remittances per migrant would be as high as US$35.8.

services. The positive exchange rate elasticity of remittances implies that remittances stabilize the purchasing power of consumers during recessions. It further implies that migrants transfer a fraction of exogenous wealth effects of exchange rate fluctuations to their recipients in the home country. Finally, remittance inflows to developing countries do not seem to respond to variation in real interest rate in host countries. The estimated coefficient is negative as predicted by the remittances behavior model but not statistically significant. The p-values for Sargan test suggest that I failed to reject the null hypothesis that over-identifying restrictions are valid. The p-value for the test of 2nd order autocorrelation in the difference error terms indicates that I also fail to reject the null hypothesis that error terms are independent and identically distributed. This implies that the moment conditions in the model are valid.

The results in Table 1.3 also show that income elasticities of remittances differ significantly across countries in Africa, Asia, Eastern Europe, and Latin America regions as a group. For example, the coefficient of home country income elasticity is statistically significant in Africa and Asia only. In addition, the absolute magnitude of this elasticity in Africa is twice as large as in Asia. Similarly, host country income elasticity is statistically significant in Eastern European and Latin American countries only. It is then natural to ask why do remittances behave differently in different countries or groups of countries. Some recent studies document that the relationship between remittances and recipient household's income also depends on the income level of recipient households and their access to formal financial instruments for risk-sharing (See Brown and Jimenez, 2011; Cox et al., 2004; Loayza et al., 2007; and Morten, 2015).[23] I, therefore, investigate whether income stabilizing

[23]For example, Cox et al. (2004) and Brown and Jimenez (2011) document that remittances are negatively related to recipient's income among low-income households but positively related to recipient's income among rich-income households. Similarly, Loayza et al. (2007) identify the domestic financial market as one of the shock absorbers—deep financial markets help diversify macroeconomic risks whereas shallow financial markets may dry up in moments of crisis. Similarly, Morten (2015) argues that households use temporary migration of its members as a risk-mitigating

role of remittances is concentrated among low-income countries and in countries with shallow financial markets or not.[24]

The estimated coefficients are reported in Table 1.4. For income groups of countries, the results in column (1) and (2) are consistent with the non-linear income elasticity of remittances found by Cox et al. (2004) and Brown and Jimenez (2011). Remittances appear to be statistically negatively related with home country GDP per capita in low-income countries only. Similarly, results in column (3) and (4) are again broadly consistent with the findings of Morten (2015) that the income shocks absorbing roles of remittances are prevalent among countries with a shallow financial market and hence a poor access of households in formal financial credit and banking system.

Remittances may increase because each existing migrant sends more money back home (intensive margin) or because more people migrate abroad (extensive margin) and send money back home.[25] To investigate whether existing migrants remit more or not during the economic downturn in the home country, I reestimate Eq. (1.15) and Eq. (1.16) by using growth in remittances per migrant as the dependent variable. As one can see in Table 1.5, the results using remittances per migrant as the dependent variable are both qualitatively and quantitatively similar to the ones

strategy in the absence of formal insurance markets.

[24]For this, I define countries below the median real GDP per capita ($2,026) of the sample countries in 2013 as low-income economies and above this median real GDP per capita as middle-income economies. Similarly, I define countries below the median value of private credit by banks and financial institutions as a share of GDP in 2013 as countries with shallow financial markets and above the median value as countries with deep financial markets. I also use the median value of bank accounts per 1,000 adults and value of collateral needed for a loan (percent of the loan amount) to define countries with shallow and deep access to formal credit. The results are similar to that obtained by using private credit by banks and financial institutions as a share of GDP.

[25]The Figure 1.11 in Appendix shows that the percent share of intensive margins in the increase in remittances from 1975, measured in real terms using the 2005 year exchange rate, has been decreasing in contrast to that of extensive margins in all regions but Africa. For this figure, the extensive margin of remittances is defined as the annual change in migrant stocks multiplied by average remittances per migrant in the previous year. So, different from the text here, the intensive margin of remittances is the difference between change in remittances minus the extensive margin.

obtained by using remittances growth as the dependent variable.

Overall, my results suggest remittances are an aggregate income stabilizer in developing countries. If remittances are aggregate income stabilizers, to what extent do remittances provide income risk sharing in developing countries? The next section explores this question in detail.

1.4 Remittances and Income Smoothing

In this section, I quantify the fraction of GDP shocks in the home country absorbed via remittances—a phenomenon known in the literature as income smoothing. Remittances provide (partial) insurance against domestic income shocks if they covary less than one-to-one with the home country GDP.

1.4.1 Methodology

To quantify the degree of income smoothing via remittances, I use the empirical framework developed in Asdrubali, Sørensen and Yosha (1996), ASY hereafter.[26] Consider the following identity, for any country i in period t,

$$gdp_{it} = \frac{gdp_{it}}{gdprmt_{it}} \frac{gdprmt_{it}}{c_{it}} c_{it}, \tag{1.17}$$

where $gdprmt_{it}$ is the sum of domestic income (gdp_{it}) and remittance inflows (R_{it}) in country i in period t, all in per capita terms. Here, $gdprmt_{it}$ can be considered as the "total income" before other channels of risk-sharing takes place. Similarly, c is national consumption, the sum of private consumption and government consumption. Income smoothing takes place via remittance inflows if $gdp/gdprmt$ varies positively

[26] This is a metric, but not a model of risk-sharing, that has often been used in literature to measure the amount of risk-sharing.

with *gdp*. That is, an increase (decrease) in *gdp* involves a smaller increase (decrease) in *gdprmt*.

To derive a simple quantitative measure of income smoothing from identity (17), take logs and differences on both sides of (17) and multiply both sides by Δ log gdp. Then taking expectations leads to:

$$var\{\Delta \ln gdp_{it}\} = cov\{\Delta \ln gdp_{it} - \Delta \ln gdprmt_{it}, \Delta \ln gdp_{it}\}$$
$$+ cov\{\Delta \ln gdprmt_{it} - \Delta \ln c_{it}, \Delta \ln gdp_{it}\} + cov\{\Delta \ln c_{it}, \Delta \ln gdp_{it}\}.$$

Finally, dividing by var$\{\Delta \ln gdp_{it}\}$ gives:

$$1{=}\beta_r + \beta_o + \beta_u,$$

where β_r, β_o, and β_u are the OLS coefficients from the regression of $\Delta \ln gdp_{it} - \Delta \ln gdprmt_{it}$, $\Delta \ln gdprmt_{it} - \Delta \ln c_{it}$ and $\Delta \ln c_{it}$ on $\Delta \ln gdp_{it}$ respectively. The coefficient β_r measures the fractions of shocks to *gdp* absorbed via remittances. A positive (negative) coefficient of β_r implies that income smoothing (de-smoothing) is achieved via remittances. The coefficients β_o measures the fractions of *gdp* shocks absorbed through other channels and β_u measures the fractions of *gdp* shocks not smoothed at all. With the full risk-sharing, consumption in each country is a fixed proportion of world aggregate output, irrespective of idiosyncratic shocks to *gdp*. If there is full risk-sharing after income smoothing via remittances, *gdprmt* should not comove with *gdp*. In this case, both β_o and β_u would take value zero. Partial risk-sharing via remittances means there may be scope for further income smoothing via other channels, for example, other international transfers. The coefficient β_r would take value zero if remittances do not help absorbing shocks to *gdp*.

To estimate the parameter β_r, one can therefore run the following regression:[27]

$$\Delta \ln gdp_{it} - \Delta \ln gdprmt_{it} = \alpha_i + \vartheta_t + \beta_r \Delta \ln gdp_{it} + \epsilon_{it}. \tag{1.18}$$

where α_i is a country fixed effect and ϑ_t is a time fixed effect. Since the world fluctuations cannot be eliminated by the sharing of risk (Obstfeld, 1994; Sørensen et al., 2007), I subtract the aggregate component from the growth rates of each component in Eq. (1.18). Therefore, for econometric analysis, I run the following regression model:

$$\widetilde{\Delta gdp}_{it} - \widetilde{\Delta gdprmt}_{it} = \alpha_i + \vartheta_t + \beta_r \widetilde{\Delta gdp}_{it} + \epsilon_{it}, \tag{1.19}$$

where for a representative variable Z in Eq. (1.19), $\widetilde{\Delta Z}_{it} = \Delta \ln Z_{it} - \Delta \ln Z_t^{world}$, where Z=$\{gdp, gdprmt\}$. Therefore, $\widetilde{\Delta gdp}_{it}$ represents the idiosyncratic part of output fluctuation calculated as per capita real GDP growth rate of country i in period t minus the world per capita real GDP growth in period t. Similarly, $\widetilde{\Delta gdprmt}_{it}$ represents the idiosyncratic component of $\Delta gdprmt_{it}$. As mentioned by ASY, the inclusion of time fixed effects captures year-specific impacts on growth rates, most notably the impact of the growth in aggregate output of 102 countries.

If idiosyncratic part of domestic output plus remittances varies less (more) than one-to-one with idiosyncratic part of the domestic output, it would be the case of positive (negative or dis-smoothing) income smoothing via remittances. In other words, the estimated coefficient β_r measures how much of the idiosyncratic shocks to *gdp* in the home country is absorbed by remittance flows. The estimated coefficient β_r when multiplied by 100 percent quantifies the percent of income smoothing via remittances. Allowing country specific variances for the error terms, I estimate Eq. (1.19) by a two-step Generalized Least Squares (GLS) procedure. To take autocorrelation in the residuals into account, I assume that the error terms in each country

[27] Balli and Ozer-Balli (2011) and Jidoud (2015) use similar framework.

follow an AR(1) process.

About the form of smoothing via remittances, I do not make any prior assumptions. Smoothing via remittances may take place both *ex-ante* as well as *ex-post*. Since remittances may also respond to earlier period's shocks in recipient countries (See David, 2010; Mohapatra et al., 2009; Yang, 2005), it is likely that the risk-sharing dynamics are richer in a longer frequency of data than in annual frequency. Therefore, I further estimate Eq. (1.19) using k-differenced data (adjacent observations are k years apart) for k=3 and 5.

1.4.2 Results

Table 1.6 reports the estimated coefficient of Eq. (1.19) for all 102 developing countries and countries in Africa, Asia, Europe, and Latin America regions separately. The value of coefficient β_r when multiplied by 100 gives the fractions of (idiosyncratic) GDP shocks absorbed via remittances, commonly known as *degree of income smoothing* in literature. The upper panel for the whole sample period (1975-2013) shows that remittances, on average, absorb 3.5 percent of the shocks to GDP in all countries. Remittances absorb the highest fraction of GDP shocks (6.1 percent) in African countries—a finding consistent with highest negative home country income elasticity in Section 3. The fraction of GDP shocks absorbed by remittances is about 3.0 percent in Asia, 1.6 percent in Eastern Europe, and 1.6 percent in Latin America. The coefficient for Eastern Europe is statistically significant at 10 percent level only.

Remittances seem to absorb the highest fractions of GDP shocks in Asia (about 9.4 percent) than in Africa (about 2.4 percent) during the most recent period from 1994 to 2013. Also, remittances absorb a significantly higher fraction of GDP shocks in Latin America (about 6.2 percent) during the 1994-2013 period than during 1975-2013 period. There are two reasons to perform this sub-period analysis: First, the majority of Eastern European countries have data on remittances only after 1993. So, focusing on 1994-2013 sub-period provides a better comparability of the degree of incoming smoothing via remittances across different regions. Second, this portrays the international risk-sharing role of remittances in the most recent period that coincides with the period of rapid growth in remittances globally.

A year-by-year measure of income smoothing via remittances presented in Fig. 1.4 shows that the degree of income smoothing via remittances increased rapidly between 1975-1990 but also fluctuated a lot year-by-year. Since only a few countries have remittances data for the years before 1990 and also remittances data were much noisy prior to the 1990s, the coefficients of income smoothing might have been imprecisely estimated for this period. As the number of countries and observations increase significantly beginning from the 1990s, the estimated coefficients of the degree of income smoothing are now within 95 percent confidence interval of the fitted line. Beginning from the mid-1990s, the degree of income smoothing via remittances is increasing slowly and is fairly constant around 4 percent. Importantly, Fig. 1.5 shows that the extent of income smoothing via remittances is positively related to the size of the remittances-to-GDP ratio of home country in all regions but Eastern Europe. This means, the larger the remittances-to-GDP ratio the higher the degree of income smoothing via remittances. This relationship, however, doesn't hold in the case of countries in East Europe, probably because these countries either do not rely on remittances as a way to diversify macroeconomic risk or remittance inflows to these countries are driven by investment or self-interest motives.[28]

[28]Fig. 1.12 in Appendix shows that there is a wide variation in the evolution of degree of income smoothing across different geographical regions during the 1994-2013 period. For example, it is increasing in Asia but decreasing and eventually negative in Eastern Europe. It increased in Latin America until the mid-2000s and then sharply declined. In contrast to all other regions, Africa

Table 1.7 shows that the extent of income smoothing via remittances is significantly higher in low-income countries than in middle-income countries. For example, remittances absorb about 4.5 percent of GDP shocks in low-income countries against 2.2 percent of GDP shocks in middle-income countries during the 1975-2013 period. However, there is no significant difference in the extent of income risk-sharing via remittances between low- and middle-income countries over the 1994-2013 period.

Asdrubali, Sørensen, and Yosha (1996) argue that the risk-sharing dynamics might be richer in a longer frequency of data than in annual frequency. In addition, some studies have documented that remittances to developing countries increase in the aftermath of climatic and geological disasters (for example, David, 2010; Mohapatra et al., 2009; Yang, 2005). This suggests that remittances may provide a hedge against longer lasting shocks to GDP. In order to explore this, I further estimate Eq. (1.19) using k-differenced data (adjacent observations are k years apart) for k=3 and 5. The results are presented in Table 1.8. As expected, remittances are found to smooth permanent shocks to GDP in all 102 countries as well as countries in Africa, Asia, and Latin America. About 3.5 and 3.7 percent of GDP shocks are smoothed via remittances at the three-year and the five-year differencing frequencies in a sample of all 102 countries. At the five years differencing frequency, the magnitude of income risk-sharing via remittances is still highest in Africa (5.7 percent) following by Asia (2.8 percent) as in the one-year differencing frequency. Remittances are, therefore, as important as the capital markets in providing a hedge against the permanent GDP shocks.[29] Remittances, however, do not appear to absorb GDP shocks at the five-year differencing frequency in Eastern European countries. Overall, the results in this section suggest that remittances are an important channel of income smoothing and

experienced the least variation in the amount of income smoothing via remittances.

[29] Asdrubali, Sørensen, and Yosha (1996) find that advance purchase of securities on capital markets help insure persistent shocks in GDP, which is not possible by ex-post borrowing on credit markets.

help absorb both transitory and permanent shocks to home country GDP.

1.5 Welfare Gains from Remittances

In Section 4, I show that remittances provide income risk-sharing in home countries. That means, remittances also improve the welfare of risk-averse agents in home countries. In this section, I quantify the extent of welfare gains from remittances.

1.5.1 Methodology

I calculate the welfare gains from net remittance inflows by building on the consumption certainty equivalence framework used in the literature (see Cole and Obstfeld, 1991; Kalemli-Ozcan et al., 2001; Van Wincoop, 1994 & 1999, among others) as follows. First, consumers in each country are constrained to consume their own GDP in the absence of remittances and the corresponding discounted expected utility is evaluated. This is similar to the autarky economy used as a benchmark to study welfare from financial integration in the literature. Next, I evaluate the discounted expected utility where consumers in each country consume the sum of their GDP and net remittances from abroad when countries are open to international migration.[30] Welfare gains from remittances would then be a permanent percentage increase in the level of autarkic consumption so that risk-averse consumers would be indifferent between these two economies.

[30]The existing studies on welfare gains from perfect risk-sharing assume that countries pool their output and hence agents consume an equilibrium constant fraction of world output. I deviate from this assumption in order to calculate the welfare gains from remittances only.

1.5.1.1 A Representative Agent Case

Consider a group of countries with identical risk-averse consumers, both ex-ante and ex-post, in terms of the utility function and discount rate (δ). Similar to Kalemli-Ozcan et al. (2001), I assume that these consumers derive utility from the consumption of two homogeneous non-storable goods, namely GDP per capita and net remittances (RMT) per capita received from abroad. Since consumption data may already reflect a certain degree of risk-sharing today via remittances, I use GDP data to calculate the potential (but mostly exploited) welfare gains from remittances. I further assume that both GDP and RMT are exogenous to consumers (the recipients in home countries) and generated by similar stochastic processes.[31]

Let the natural logarithm of the GDP per capita of each country (gdp_i) and the natural logarithm of the remittances per capita to each country (rmt_i) be random walks with linear trend, where countries are indexed by i.[32] I further assume that, conditional on initial values gdp_{i0} and $gdprmt_{i0}$, the joint distribution of the log-differences of gdp^i and $gdprmt^i$ is stationary and normal: $\Delta \ln gdp_{it} \sim N(\mu_i, \sigma_i^2)$ and $\Delta \ln gdprmt_{it} \sim N(\mu_i^r, \sigma_i^{r2})$ for all t for each country i. These distributional assumptions enable me to obtain closed form solutions for the gains from remittances.

For the CRRA utility function, the discounted expected utility in period $t = 0$ is:

$$V = E_0 \int_0^\infty e^{-\delta t} \frac{c_{it}^{1-\gamma}}{1-\gamma} dt, \tag{1.20}$$

where $e^{-\delta t}$ is the discount factor so that δ is the intertemporal discount rate and $\gamma \neq 1$

[31] The model of remittances behavior developed in section 3 focuses on how emigrants remit so as to maximize their own utility. So, remittances are endogenous to emigrants but exogenous to recipients in home countries.

[32] I performed Augmented Dickey-Fuller tests for a unit root in log of gross domestic product (GDP) and net remittances (RMT) for each country and fail to reject the null of unit root in almost all countries.

is the rate of relative risk aversion. Now using the property of log-normal distribution that for $x \sim N(\mu, \sigma^2)$, $Ee^{ax} = e^{a\mu + \frac{1}{2}a^2\sigma^2}$, the discounted expected utility of country i in period t=0 in an economy without remittances is:

$$\begin{aligned} V^A = U^A(gdp_{i0}) &= E_0 \int_0^\infty e^{-\delta t} \frac{gdp_{it}^{1-\gamma}}{1-\gamma} dt \\ &= \frac{1}{1-\gamma}(gdp_{i0})^{1-\gamma} \int_0^\infty e^{-\delta t}.e^{[(1-\gamma)\mu_i + \frac{1}{2}(1-\gamma)^2\sigma_i^2]t} dt \\ &= \frac{1}{1-\gamma}(gdp_{i0})^{1-\gamma} \frac{1}{\delta - (1-\gamma)\mu_i - \frac{1}{2}(1-\gamma)^2\sigma_i^2}. \end{aligned}$$

Similarly, the discounted expected utility of country i in period t=0 in an economy with remittances is:

$$\begin{aligned} V^R = U^R(gdprmt_{i0}) &= E_0 \int_0^\infty e^{-\delta t} \frac{gdprmt_{it}^{1-\gamma}}{1-\gamma} dt \\ &= \frac{1}{1-\gamma}(gdprmt_{i0})^{1-\gamma} \int_0^\infty e^{-\delta t}.e^{[(1-\gamma)\mu_i^* + \frac{1}{2}(1-\gamma)^2\sigma_i^{*2}]t} dt \\ &= \frac{1}{1-\gamma}(gdprmt_{i0})^{1-\gamma} \frac{1}{\delta - (1-\gamma)\mu_i^* - \frac{1}{2}(1-\gamma)^2\sigma_i^{*2}}. \end{aligned}$$

The welfare gains from remittances would then be the gains in utility of moving from the economy without remittances (i.e. autarky economy) to the economy with remittances, i.e. $U^R(gdprmt_{i0}) - U^A(gdp_{i0})$. I want to express this gain as a permanent percentage increase in the level of consumption in the autarky economy. More precisely, let us increase consumption permanently from gdp_{i0} to $gdp_{i0}(1+W^i)$ so that the consequent increase in utility is exactly equal to the gain in utility moving from autarky to an economy with remittances. Here W^i is the measure of welfare gains from remittances and, for CRRA utility function, it is obtained as follows: equate $U^A(gdp_{i0}(1+W^i))$ with $U^R(gdprmt_{i0})$, take logs on both sides and then use the approximation $\ln(1+W^i) \approx W^i$. Then,

$$W^i \approx \frac{1}{\gamma-1} \ln \left[\frac{\delta + (\gamma-1)\mu_i^* - \frac{1}{2}(\gamma-1)^2\sigma_i^{*2}}{\delta + (\gamma-1)\mu_i - \frac{1}{2}(\gamma-1)^2\sigma_i^2} \right] + \ln \left[\frac{gdprmt_0^i}{gdp_0^i} \right]. \tag{1.21}$$

Eq. (1.21) expresses the derived formula for welfare gains from remittances. For a given value of discount rate and the relative risk aversion parameter, the intuition is as follows: First, the higher the (average) growth rate of *gdprmt* than the growth rate of *gdp*, the higher will be the welfare gain from remittances. It is because higher growth in *gdprmt* brings additional resources to a higher permanent level of consumption. I denote this as the gains from "*growth effect*" of remittances on income. Second, the lower the variance of growth in *gdprmt* as a result of negative covariance of growth of *gdp* and *rmt*, remittances contribute to smooth consumption growth path in recipient countries and hence higher will be the gains. I denote this as the gains from "*volatility effect*" of remittances. The first term of the expression (21) captures these two effects. Third, positive net remittances in the initial period increase the level of consumption by increasing the initial level of income, which I denote as the gains from "*level effect*" of remittances. This gain is represented by the last term of the expression (21). Additionally, welfare is higher for a lower discounting rate of future utility (δ). However, the formula of welfare gains fail to establish an explicit relationship between risk aversion parameter (γ) and gains from remittances because of two opposite forces in action—the scaling factor $\frac{1}{\gamma-1}$ decreases in γ while the expression within the parenthesis of the first term increases in γ.

1.5.1.2 Heterogeneous Agents Case

The representative agent model assumes that both poor and rich households receive the same amount of remittances. Even if it is true, the welfare gains to poor households are likely to be high because of a skewed distribution of domestic income towards rich households. Moreover, recent studies show that remittances are the major sources of income to poor households and thus remittances decrease income inequality in developing countries (see Acosta et al., 2008; Khatry, 2015, among others).

To calculate potentially differential welfare gains from remittances among poor and rich households, I proceed as follows. Suppose the home economy includes a continuum of three types of infinitely lived households with shares $\varkappa^p$, $\varkappa^m$ and $\varkappa^r$ with $\varkappa^r = 1 - \varkappa^p - \varkappa^m$, where subscripts p, m and r refer to poor-, middle-, and rich-income households respectively.[33] Each of the three representative households maximizes lifetime utility as a function of consumption C_t^j, $j = p, m, r$:

$$\max_{C_t^j} \quad E_t \sum_{t=0}^{\infty} \beta_j^t U_j(C_t^j). \tag{1.22}$$

subject to

$$\sum_{t=0}^{\infty} \frac{C_t^j}{(1+i)^t} = \sum_{t=0}^{\infty} \frac{\left(\xi^j Y_{ht} + \Re^j R_{ht}\right)}{(1+i)^t}, \tag{1.23}$$

where h refers to home country, Y is GDP of home country, and R is net remittances to home country. ξ^j and $\Re^j$ indicate the household group j's share in GDP and net remittances, respectively, so that $\xi^p + \xi^m + \xi^r = 1$ and $\Re^p + \Re^m + \Re^r = 1$.

For each household (income) group j, I then impute the GDP per capita (gdp_{it}^j) and net remittances per capita (rmt_{it}^j), for $j = p, m, r$, as follows: For example, for poor households p in each country i:

$$gdp_{it}^p = \frac{\xi_i^p.GDP_{it}}{\varkappa_i^p.N_{it}} = \omega_{iy}^p.gdp_{it}, \qquad \text{and} \quad rmt_{it}^p = \frac{\Re_i^p.RMT_{it}}{\varkappa_i^p.N_{it}} = \omega_{ir}^p.rmt_{it}, \tag{1.24}$$

$$\text{such that} \quad gdprmt_{it}^p = \omega_{iy}^p.gdp_{it} + \omega_{ir}^p.rmt_{it}, \tag{1.25}$$

where GDP_{it}, RMT_{it}, and N_{it} are GDP, net remittances, and population of country i in period t, respectively, and $\omega_{iy}^p = \frac{\xi_i^p}{\varkappa_i^p}$ and $\omega_{ir}^p = \frac{\Re_i^p}{\varkappa_i^p}$. Similarly, $\varkappa_i^p = \frac{\sum_h N_{iht}^p}{N_{it}}$ is the share of population of poor households in total population. Assuming that the natural logarithms of the GDP per capita and remittances per capita are random walks with

[33] It can be extended to include n types of households, for a finitely large value of n. In empirical estimation, I also use quintile and decile groups of households.

linear trend such that $\Delta \ln gdp_{it}^{p} \sim N(\mu_i^p, \sigma_i^{p2})$ and $\Delta \ln gdprmt_{it}^{p} \sim N(\mu_i^{*p}, \sigma_i^{*p2})$, the expression of welfare gains to poor households would then become,[34]

$$W^{ip} \approx \frac{1}{\gamma - 1} \ln \left[\frac{\delta + (\gamma - 1)\mu_i^{*p} - \frac{1}{2}(\gamma - 1)^2 \sigma_i^{*p2}}{\delta + (\gamma - 1)\mu_i^{p} - \frac{1}{2}(\gamma - 1)^2 \sigma_i^{p2}} \right] + \ln \left[\frac{gdprmt_0^{ip}}{gdp_0^{ip}} \right]. \tag{1.26}$$

Using household survey data, I calculate the income share (ξ^j), remittances share ($\Re^j$), and population share ($\varkappa^j$) of each income group of households j as follow: First, I look at the distribution of (non-remittances) domestic income and remittances from abroad in five countries, namely Guatemala (2000), India (2012), Nepal (2011), Tajikistan (2007), and Uganda (2011). These household surveys are listed in Table 1.17 in Appendix. The selection of these countries is mainly guided by the availability of household survey data from the World Bank's LSMS dataset.[35] Non-remittances domestic income includes all domestic incomes except domestic remittances. Section 1.8.1 in Appendix provides the details on how this aggregate income is constructed.

Second, I use quartile (income) groups (of households) based on domestic income to define income groups of households.[36] Households in the bottom and top quartiles are defined as poor and rich households, respectively. Households in the middle two quartiles are classified as middle-income households. I then calculate the population, income, and remittances shares of each income group. For example, for poor households in country 'k' for k={Guatemala, India, Nepal, Tajikistan, and Uganda},

[34]Here, $\Delta \ln gdp_{it}^{p} = \Delta \ln gdp_{it} \sim N(\mu_i, \sigma_i^2)$, but $\Delta \ln gdprmt_{it}^{p} \neq \Delta \ln gdprmt_{it}$ so that $\mu_i^* \neq \mu_i^{*p}$ and $\sigma_i^{*2} \neq \sigma_i^{*p2}$.

[35]However, I have paid enough attention to maintain heterogeneity in the sample of countries. For example, there is at least one country from each geographic region, namely Africa, Asia, Eastern Europe, and Latin America. Similarly, the sample includes two major remittances-dependent economies (Nepal and Tajikistan), two countries that are not heavily dependent on remittances (Guatemala and Uganda), and the largest remittance recipient country in the world (India). For India, I use the data from India Human Development Survey, 2011-12 (IHDS-II), conducted by the University of Maryland and the National Council of Applied Economic Research (NCAER), New Delhi.

[36]Other household income groups based on quintiles and deciles are also used in the empirical analysis.

the population share ($\varkappa^p$) is the share of poor households' population in total population in country k. The other two ξ^p and $\Re^p$ are calculated in the same way so that,

$$\varkappa^p = \frac{\sum_{hp} N_{hp}}{\sum_h N_h}, \quad \xi^p = \frac{\sum_{hp} Y_{hp}}{\sum_h Y_h}, \quad \text{and} \quad \Re^p = \frac{\sum_{hp} RMT_{hp}}{\sum_h RMT_h},$$

where N and Y denote population and domestic income within each household, respectively. The subscript h refers to household whereas the subscript hp refers to the poor household in country k. I use income, remittances, and population shares of poor households for each country k in expression (24). In addition, I impute the shares from Uganda to countries in Africa, from India and Nepal to countries in Asia, from Tajikistan to countries in Eastern Europe, and from Guatemala to countries in Latin America to generate income and remittances shares of poor households in all 102 countries.[37]

These income and remittances shares for these households income groups are presented in column (4) and (5) of Table 1.9. This table clearly shows that poor households in all five countries have a very small share in domestic income. While rich households hold about 60 percent of the total domestic income, poor households get only about 5 percent of total domestic income. The share of rich households in total domestic income is as high as 69 percent in Uganda. In contrast, the distribution of remittances is more equal across household income groups in all five countries. For example, poor households receive about 28 percent of total remittances in Tajikistan, one of the major remittances-dependent economies in the World. The remittance shares of poor households are lowest in Uganda (16 percent) and highest in India (42 percent).

Column (6) in Table 1.9 shows the fraction of households within each income

[37] I also use the population-weighted average of income and remittances shares to calculate the gains to poor households in 102 countries.

group that receive remittances and column (7) shows the average amount of remittances in local currency unit received by these households, conditional on households receive remittances. It can be seen that the largest fraction of households that receive remittances are among the poor households and the average amount of remittances received by poor households is similar to the one received by rich households except in Nepal and Uganda. Looking at the distribution of remittances' share in total income (the sum of domestic income and remittances from abroad) within households, Fig. 1.6 shows that remittances constitute a higher fraction of total income more among the poor households than among the middle-income and/or rich households.[38] This indicates that remittances bring significant additional resources for consumption to poor households than to rich households.

Overall, the distribution of remittances is skewed towards poor and middle-income households in all countries. As a result, the share of poor and middle households in total income improves (see Fig. 1.13 and 1.14 in Appendix).[39]

1.5.2 Results

In the estimation of welfare gains, I translate both GDP and remittances to the amount of consumption that it can buy by deflating them by the Consumer Price Index (CPI) instead of a GDP-deflator.[40] Data are first transformed into per capita terms and then converted into constant dollars using 2005 (end of the year) exchange rates. This means the growth rates in the corresponding variable measure the changes

[38] I find a similar pattern in all other four countries.

[39] In the estimation, I assume that income shares of household income groups remain constant over time. This might cause my estimates of gains for different income groups of households to be biased. However, Fig. 1.7 shows that the domestic income and remittances shares of income quintile of households in India between 2005 and 2012 did not change much.

[40] Sørensen and Yosha (2007) show that deflating nominal GDP by CPI deflator is appropriate while measuring the risk-sharing. Kalemli-Ozcan et al. (2001) also argued that one should deflate GDP by the CPI so that GDP reflects consumption because the measure of welfare gains are utility base.

in purchasing power in terms of local currency. Following standard papers in the literature, I assume the discount rate, δ=0.02 and the risk aversion parameter, γ=3.

Table 1.10 reports the calculated gains from remittances. The calculated average welfare gains from net remittances are equivalent to 1.9 percent for all 102 countries. Remittances seem to generate highest welfare gains (3.2 percent) in African countries. This is not surprising given that remittances are found to absorb the highest fraction of GDP shocks in Africa in Section 4. The calculated gains in other regions, namely Asia, Eastern Europe, and Latin America, are 1.6, 2.2, and 1.8 percent, respectively.[41] It can also be seen that remittances improve welfare more in low-income countries and in countries with shallow financial markets than elsewhere. The gains to low-income countries (2.7 percent) are about four-fold larger than the gains to middle-income countries (0.7 percent). Similarly, the gains to the countries with shallow financial markets (3.4 percent) are about three-fold larger than the gains to countries with deep financial markets. This paper, therefore, reveals a regularity in the data that remittances are compensatory transfers, help smooth domestic income, and increase the welfare of risk-averse consumers mainly in low-income credit-constrained countries than in elsewhere. The welfare gains over the most recent period 1994-2013 seem to be slightly larger than that over the full sample period 1975-2013.[42] The gains are within the range of [–15, 24] for 102 developing countries. Remittances are found to decrease the welfare in 14 countries but increase the welfare in 88 countries. The lowest gain is measured in Madagascar (–14.59 percent) while the highest is measured in Comoros (23.9 percent).[43]

[41]The population-weighted measure of welfare gains might have been affected by the presence of a heavily populated country like China. I, therefore, re-estimate the gains excluding China and find that the average gains significantly increase from 1.9 to 2.5 percent for all 102 countries and from 1.6 percent to 2.4 percent for countries in Asia.

[42]Since Chad has data on remittances before 1994 only, there are only 101 countries after 1994. Also, most of the countries in Eastern Europe have data after 1994 only.

[43]In Madagascar, net remittances are negative in the initial year 1975 and several years of negative net remittances in this country also reduces the growth of total income. In Comoros, the domestic

Fig. 1.8 plots the welfare gains from remittances against the average ratio of remittances-to-GDP (in percent). This figure highlights two important facts about the gains from remittances. First, the average remittances-to-GDP ratio is not a good measure of gains from remittances. It is because about 60 percent countries have higher welfare gains than the average remittances-to-GDP ratios and the rest 40 percent countries have lower welfare gains than the average remittances-to-GDP ratios. Second, the certainty-equivalence framework developed in the paper is able to show that a particular (steady state) level of the remittances-to-GDP ratio can lead to heterogeneous welfare gains depending on how remittances affect the level, growth, and volatility of total income in home countries.

The decomposition of total welfare into the gains from income level-, growth-, and volatility-effects of remittances is presented in Table 1.11. The average welfare gains from remittances by lowering the income volatility are about 0.3 percent only, which is about 15 percent of the total gains. The rest of the gains arises from the level and growth effects of remittances. The highest gains resulting from a lower income volatility is measured in Africa (1.1 percent, which is about 35 percent of the total gains in the region). There are positive gains from volatility effects of remittances in all regions but Eastern Europe. Remittances, on average, increase the volatility of income in Eastern European countries resulting in negative welfare gains.

Next, the calculated gains for heterogeneous income groups of households in Guatemala, India, Nepal, Tajikistan, and Uganda are reported in Table 1.12. It can be seen that remittances provide a significantly large welfare gains to poor and middle-income households than to rich households in all these countries. The gains to the poor households in Guatemala, for example, are about 47.6 percent in column

income growth is negative for several years and remittances contributed to a positive growth of total income. Variances of income played little role in both these countries.

(2) against 13.3 percent gains to the middle-income households in column (3) and 4.3 percent gains to the rich households in column (4). The last row in Table 1.12 shows that the population-weighted average gains to poor households in all five counties (9.3 percent) are about four-fold of those to middle-income households (2.2 percent) and about 11-fold of those to the rich households (0.9 percent).[44] Column (5) shows that the population-weighted averages of the gains to the poor, middle-income, and rich households in column (2) through (4) are significantly higher than the gains to the representative agent reported in column (1).

Finally, I use the income shares from these five countries to impute the GDP and remittances by various income groups of households in other countries and calculate the gains to poor and rich households in all 102 countries. For this, I use income shares from Guatemala to other countries in Latin America, from India and Nepal to other countries in Asia, from Tajikistan to other countries in Eastern Europe, and from Uganda to other countries in Africa.[45] Table 1.13 presents the population-weighted average of welfare gains of various income groups in all 102 countries. As we can see in column (2) of panel B, the welfare gains to poor households (7.6 percent) are significantly larger than to middle-income households (2.3 percent) and rich

[44] I also calculate the gains for quintile and decile income groups. The results verify that the gains from remittances to poor households are always much larger than to rich households. In fact, welfare gains to poorer of the poor households increases while that to richer of the rich households decreases.

[45] I also use the population-weighted average shares of all these five countries to all other 97 countries. On the one hand, having only one survey from each geographic region may lead to measurement error so that pooling all five countries (namely Guatemala, India, Nepal, Tajikistan, and Uganda) together and using a population-weighted average of income shares might produce better measures of welfare gains. On the other hand, taking the average may also lead to measurement error if countries in different geographical regions are significantly different in terms of remittances and domestic income distribution. In such case, estimations without pooling countries from different regions may yield better measures of welfare gains. However, I find that the magnitude of the gains are similar irrespective of the income shares I use.

households (0.9 percent).[46] The magnitudes of these gains are similar to the magnitudes of average gains of households in Guatemala, India, Nepal, Tajikistan, and Uganda presented in Table 1.12. The existing literature document that the gains from perfect risk-sharing in OECD countries and in the United States are within the range of 0.6 percent to 1.6 percent.[47] Given this, the average welfare gains from remittances in the amount of 1.9 percent in developing countries are quite sizable.

The framework that I use to calculate welfare gains from remittances does not incorporate the general equilibrium effects of remittances on labor-leisure decisions by recipient households. On the one hand, the utility-maximizing behavior of recipient household may result in a higher steady-state level of leisure as they receive additional resources from remittances, as argued by Chami et al. (2006). In this case, my estimates of welfare gains may be underestimated. On the other hand, a higher level of leisure implies a lower steady-state level of labor supply and hence a lower domestic output. Emigration of skilled workers may also reduce domestic output by reducing research and development (R&D) activities and the rate of technological innovation in home countries. As a result, my estimates may be overestimated. However, a recent study by Dinkelman and Mariotti (2016) finds that (temporary) labor migration raises human capital formation of the next generation in origin communities of home countries. Similarly, Djajic (2014) document that physical capital stock in home countries increases as some of the returned emigrants repatriate large amounts of

[46] A close look at the slopes of welfare gains within decile groups of households shows that (See Fig. 1.16 in Appendix) gains from remittances for the majority countries decline slowly from bottom decile household to higher decile households as in the case of Mexico and Moldova in the figure. There are also countries with gains concentrated mainly in lower decile households like in Sudan. The gains are almost the same across different income groups of households in China. Moreover, negative gains, if any, are also concentrated among lower income households like in Ecuador due to higher share of remittances in their total income.

[47] For example, Van Wincoop (1999) finds that the potential gains from perfect risk-sharing in OECD countries over the 1970-1989 period are equivalent to 1.13 percent permanent increase in tradable consumption. Similarly, Kalemli-Ozcan et al. (2001) find that such gains would be 0.62 percent for OECD countries and 1.55 percent in the US over 1963-1993 and 1963-1994 periods respectively.

accumulated savings. Because the majority of remittances-dependent countries are low-income economies with a high rate of unemployment, migrants workers would probably remain unemployed had they not migrated at the first place. Moreover, many of these countries are heavily dependent on agriculture, which is subject to the diminishing returns in labor. In view of all these possibilities, I expect my estimates of the gains are not significantly biased.

1.5.3 Micro Panel Data Evidence

I now conduct a micro household-level panel analysis to complement the macro country-level analysis of welfare gains. The advantage of the household-level analysis is it allows to observe the same households over time so that the gains from remittances can be measured without any information on income shares. In other words, it enables one to observe income and remittances shocks at each household.

For micro panel evidence, I use a panel household data from India between 2005 and 2012. Although the selection of country India is guided by the availability of household panel data, it is an important sample for the analysis of gains from remittances because India is the largest recipient of international remittances in the world. The data used in this section come from India Human Development Survey (IHDS), which is a nationally representative multi-topic panel survey of more than 40,000 households covering all states in India.[48] Two rounds of surveys have been conducted so far. The first round survey, IHDS-I, conducted in 2005, interviewed 41,554 households of which about 83 percent were re-interviewed by IHDS-II in 2012.[49] There are 680 households who received international remittances either in 2005, 2012

[48] IHDS is conducted by the University of Maryland and the National Council of Applied Economic Research (NCAER).

[49] IHDS-II interviewed 42,152 households including the split households that were covered in IHDS-I and additional replacement sample of 2,134 households.

or in both years. Out of these 680 remittance-recipient households, about 65 percent households (i.e. 438 households) are from three states, namely, Kerala, Punjab, and Rajasthan. These three states consist of 5,676 households, which is about 15 percent of total panel households, including the split ones.

The average ratio of remittances to total domestic income for all 38,514 panel households (including split ones) in India between 2005 and 2012 is about 0.8 percent whereas this ratio for all households in Kerala, Punjab, and Rajasthan states for the same years is about 3.7 percent. Similarly, the average ratio of remittances to GDP in India for the same years is about 3 percent. This means the magnitude of remittances in Kerala, Punjab, and Rajasthan states are similar to the magnitude of annual remittance at the national level.[50] Also, the ratio of remittances to GDP is as high as 20 percent in many remittances-dependent economies. I, therefore, calculate the gains from remittances for all households in India as well as for households only in Kerala, Punjab, and Rajasthan states. I argue that the gains from remittances in these three states are the better proxies of welfare gains to other remittances-dependent economies.

Since this is a panel of households over two periods only, I use the cross-sectional variance of change in income between 2005 and 2012 as a proxy for the average idiosyncratic variances of household income over the same period as follows:

$$\frac{1}{N}\sum_{h=1}^{N}(\Delta \ln Y_h - \Delta \ln \bar{Y})^2 \approx \frac{1}{N}\sum_{h=1}^{N}\sigma_{ht}^2, \tag{1.27}$$

where Y_h is the income of household h, $\bar{Y}$ is the cross-sectional average income, and σ_{ht}^2 is the idiosyncratic variance of $\Delta \ln Y_h$ of household h over time t. This paper is not the first to use this approximation of idiosyncratic variances from the cross-sectional variance in the empirical literature. Goyal and Santa-Clara (2003) show

[50]This might be because of under-representation of remittance-recipient households from other states in IHDS.

that the cross-sectional variance of stock returns is closely related to the idiosyncratic variance of the stock in the market. Similarly, Garcia et al. (2012), by using Central Limit arguments, show that the cross-sectional variance of stock returns is an excellent proxy for the idiosyncratic variance. While income data are different from stock price data, I use this approximation because no alternatives are available. Using this approximation, I find that the variance of the log of total income (i.e. the sum of domestic income and remittances) is lower than the variance of domestic income in the sample of all households in India and households from the three states of India.[51] This suggests that remittances help reduce the variance of income at the household level.

To calculate the welfare gains from remittances at the household level, I use the same expressions (21) and (26) of welfare gains developed in Section 5.1, but use the expression (27) to proxy for the average of idiosyncratic variances at the household level. The calculated gains are reported in Table 1.14. Column (1) presents the gains for all panel households between 2005 and 2012 and column (3) presents the gains between 1975 and 2013 reported in Section 5.2. As can be seen in Panel A of Table 1.14, the average gains to all households between 2005 and 2012 are about 0.5 percent, which is about one-third of the gains (1.4 percent) over 1975-2013 calculated using the country aggregate data.

The small gains from remittances while using household survey data might be arising for two reasons. First, household survey data show that a significantly large fraction of households does not receive remittances. In addition, remittances actually lower welfare of about 15 percent of households by significantly increasing the volatility of household income. The country-level analysis doesn't capture this

[51] The variance of total income is 1.26 against the variance of 1.28 of domestic income between 2005 and 2012 for all households in India. For households in Kerala, Punjab, and Rajasthan states, the variance of total income is 1.29 against the variance of 1.35 of domestic income between 2005 and 2012.

heterogeneous welfare effect of remittances. Second, the reported size of remittances relative to GDP at the national level is found larger than the size of remittances relative to total domestic income using household survey data. For example, comparing the last two rows in Table 1.14, one can see that the ratio of remittances to GDP at the country level is about three to five times higher than the ratio of remittances to domestic income at the household level. Despite this difference in the magnitude of gains, household panel data analysis also shows that the gains from remittances are significantly large for poor households than for rich households. For example, Panel B clearly shows that the gains to poor households (1.0 percent) are twice as large as the gains to middle-income households (0.5 percent) and thrice as large as the gains to rich households (0.3 percent). The results in Panel C shows that the gains to the bottom quintile (1.1 percent) are about five times larger than the gains to the top quintile of households.

The welfare gains to panel households in Kerala, Punjab, and Rajasthan, the major remittances-dependent states of India, are reported in column (2) of Table 1.14. Not quite surprisingly, both the magnitudes and the patterns of gains to poor and rich households are now similar to the ones obtained using country aggregate data from India, reported in column (3), and to the average welfare gains for all 102 developing countries reported in Table 1.13. The average gains to all households in Kerala, Punjab, and Rajasthan states are about 2.9 percent. The gains to poor households (6.7 percent) are about three-times larger than the gains to middle-income households (2.1 percent) and seven-times larger than the gains to rich households (0.9 percent). In Panel C, the gains to the bottom quintile households (7.5 percent) are about nine-times larger than the gains to the top quintile households.

About one-third of the remittance-recipient households are dropped by the program codes mainly because of noisy data, for example, no data on domestic income.[52] A closer look at the data shows that the average remittances-to-domestic-income ratio for 37,291 households in India is 0.45 percent against the 0.54 percent welfare gains from remittances. Similarly, for 5,383 households in Kerala, Punjab, and Rajasthan states, the average remittances-to-domestic-income ratio is 2.18 percent against the 2.93 percent welfare gains from remittances. Finally, Fig. 1.9 plots the histogram of the gains to all remittance-recipient households in India (upper panel figure) and to those in Kerala, Punjab, and Rajasthan states (lower panel figure). It can be noticed from these figures that the majority of households have welfare gains within the range of 1 to 100 percent and the measure of average welfare gains is not much influenced by the outliers. The figure also shows the gains are negative for about 15 percent of the total households.

Overall, although both macro country-level analysis in Section 5.2 and micro household-level analysis in this section are not free of drawbacks, both analyses illustrate three important facts about welfare gains from remittances. First, the welfare gains from remittances are, on average, large in developing countries. Second, the gains to poor households are significantly larger than the gains to rich households. Third, a given level of the remittances-to-GDP ratio can be associated with various levels of welfare gains depending on how remittance inflows affect the income growth and volatility over time.

[52] Also, there are several households with negative domestic income in 2005, which are also automatically dropped by the program codes.

1.6 Conclusion

In this paper, I assess the income stabilizing and welfare improving roles of remittances in migrants' country of origin. I develop a utility maximizing model based on the economics of family to derive implications on aggregate remittances behavior. Using a panel of 102 developing countries from 1975-2013, I show that remittances respond to fluctuations in GDP and exchange rates in a manner consistent with the model. Remittances, on average, absorb about 3.5 percent of transitory and permanent shocks to GDP. To measure the welfare gains from remittances, I propose a framework for an endowment economy that allows for level-, growth-, and volatility-effects on income. Using country-level data, I find that the average gains from remittances are equivalent to a 1.9 percent increase in consumption. Using household-level data from five countries, I find that the gains are about 9.3 percent for poor households and 0.9 percent for rich households. My results suggest that a policy that aims at removing barriers to remittances, and thus reducing reliance on more volatile private capital flows, may help developing countries mitigate income volatility and increase the welfare.

The paper complements the existing research on macroeconomic effects and insurance roles of remittances in home countries. There are two possible directions for future extension of this research. One is to investigate in further details why remittances behave differently in different geographic regions and income groups of countries. How important are the factors like geographic proximity, migration networks, and trade links between home and host countries in explaining such aggregate remittance behavior and hence determining the aggregate shocks absorbing roles of remittances? Another possible direction for future research is to use the panel of households over more than two periods to capture the idiosyncratic variance of income for each household. Developing a better framework to measure welfare gains for heterogeneous income groups of households could also be a further extension. This paper indicates that the gains from remittances are much larger to poor households than to rich households. However, households may not remain in the same income group over time. Additionally, households' shares in domestic income may not be a good proxy of their shares in GDP because capital gains which may comprise a large fraction of income to rich households is not a part of GDP. Future research should be directed toward addressing these issues.

1.7 References

1. Acosta, Pablo, Calderon, Cesar, Fajnzylber, Pablo, and Lopez, Humberto, 2008. What is the Impact of International remittances on Poverty and Inequality in Latin America? *World Development, 36(1), 36-114.*

2. Acosta, Pablo, Lartey, Emmanuel K.K., and Mandelman, Federico, 2009. Remittances and the Dutch Disease. *Journal of International Economics, 79, 102-116.*

3. Agarwal, Reena, Demirguc-Kunt, Asli, and Peria, M.S. Martinez, 2011. Do Remittances Promote Financial Development? *Journal of Development Economics, 96, 255-264.*

4. Agarwal, Reena and Horowitz, Andrew W., 2002. Are International Remittances Altruism or Insurance? Evidence from Guyana Using Multiple-Migrant Households. *World Development, 30, 2033-44.*

5. Amuedo-Dorantes, Catalina and Pozo, Susan, 2006. Remittances as Insurance: Evidence from Mexican Immigrants. *Journal of Population Economics, 19, 227-254.*

6. Amuedo-Dorantes, Catalina and Pozo, Susan, 2010. International Remittances and Migrant's Portfolio Interests.

7. Arellano, M. and Bover, O., 1995. Another Look at the Instrumental Variable Estimation of Error-Components Models. *Journal of Econometrics, 68, 29-51.*

8. Asdrubali, Pierfederico, Sørensen, Bent E., and Oved, Yosha, 1996. Channels of Interstate Risk-Sharing: United States 1963-90. *Quarterly Journal of Economics, 111(4), 1081-1110.*

9. Balli, Faruk and Ozer-Balli, Hatice, 2011. Income and Consumption Smoothing and Welfare Gains across Pacific Island Countries: The Role of Remittances and Foreign Aid. *Economic Modelling, 28, 1642-1649.*

10. Balli, Faruk and Rana, Faisal, 2015. Determinants of Risk-Sharing through Remittances. *Journal of Banking and Finance, 55, 107-116.*

11. Banergee, Biswajit, 1984. The Probability, Size, and Uses of Remittances from Urban to Rural Areas in India. *Journal of Development Economics, 16, 293-311.*

12. Becker, Gary S., 1981. Altruism in the Family and Selfishness in the Market Place. *Economica, 48(189), 1-15.*

13. Bettin, Giulia, Presbitero, Andrea F., and Spatafora, Nikola, 2014. Remittances and Vulnerability in Developing Countries. *IMF Working Paper*, WP/14/13.

14. Blundell, R. and Bond, S., 1998. Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics, 87, 115-143.*

15. Bouhga-Hagbe, Jacques., 2006. Altruism and Workers' Remittances: Evidence from Selected Countries in the Middle East and Central Asia. *IMF Working Paper*, WP/06/130.

16. Briere, Benedicte de la, Sadoulet, Elisabeth, de Janvry, and Lambert, Stkvue, 2002. The Roles of Destination, Gender, and Household Composition in Explaining Remittances: An Analysis for the Dominican Sierra. *Journal of Development Economics, 68, 309-328.*

17. Brown, Richard P.C. and Jimenez, Eliana V., 2011. Subjectively-assessed Welfare and International Remittances: Evidence from Tonga. *Journal of Development Studies, 47(6), 829-845.*

18. Bugamelli, Matteo and Paterno, Francesco, 2011. Output Growth Volatility and Remittances. *Economica, 78, 480-500.*

19. Chami, Ralph, Cosimano, Thomas F., and Gapen, Michael T., 2009. Beware of Emigrants Bearing Gifts: Optimal Fiscal and Monetary Policy in the Presence of Remittances. *IMF Working Paper*, WP/06/61.

20. Chami, Ralph, Fullenkamp, Connel, and Jahjah, Samir, 2005. Are Immigrant Remittances Flows a Source of Capital for Development? *IMF Staff Papers, 52 (1).*

21. Chami, Ralph, Hakura, Dalia, and Montiel, Peter, 2009. Remittances: An Automatic Output Stabilizer? *IMF Working Paper*, WP/09/91.

22. Cole, Harold L. and Obstfeld, Maurice, 1991. Commodity Trade and International Risk-sharing: How much do Financial Markets Matter? *Journal of Monetary Economics, 28, 3-24.*

23. Cox, Donald, Hansen, Bruce E., and Jimenez, Emmanuel, 2004. How Responsive are Private Transfer to Income? Evidence from a Laissez-faire Economy. *Journal of Public Economics, 88, 2193-2219.*

24. Cox, Donald, and Rank, Mark R., 1992. Inter-Vivos Transfers and Intergenerational Exchange. *The Review of Economics and Statistics, 74(2), 305-314.*

25. David, Antonio C., 2010. How do International Financial Flows to Developing Countries Respond to Natural Disasters? *IMF Working Paper*, WP/10/166.

26. De, Supriyo, Islamaj, Ergys, and Kose, M. Ayhan, 2016. Remittances over the Business Cycle: Theory and Evidence. *CAMA Working Paper 13/2016.*

27. Dinkelman, Taryn and Mariotti, Martine, 2016. The Long-Run Effects of Labor Migration on Human Capital Formation in Communities of Origin *American Economic Journal: Applied Economics, 8(4), 1-35.*

28. Djajic, Slobodan, 2014. Temporary Emigration and Welfare: The Case of Low-Skilled Labor. *International Economic Review, 55(2).*

29. Ebeke, Christian H., 2011. Remittances, Countercyclicality, Openness, and Government Size. *Louvian Economic Review, 77(4), 89-114.*

30. El-Sakka, M.I.T. and McNabb, Robert, 1999. The Macroeconomic Determinants of Emigrant Remittances. *World Development, 27(8), 1493-1502.*

31. Frankel, Jeffrey, 2011. Are Bilateral Remittances Countercyclical? *Open Economies Review, 22, 1-16.*

32. Funkhouser, Edward, 1995. Remittances form International Migration: a Comparison of El Salvador and Nicaragua. *The Review of Economics and Statistics, 77, 137-46.*

33. Garcia, R., Mantilla-Garca, D., and Martellini, L. (2012). Aggregate Idiosyncratic Volatility and the Cross-Sectional Variance of Stock Returns. *In Working paper.*

34. Goyal, Amit and Santa-Clara, Pedro, 2003. Idiosyncratic Risk Matters! *The Journal of Finance, LVIII(3).*

35. Gupta, Poonam, 2005. Macroeconomic Determinants of Remittances: Evidence from India. *IMF Working Paper*, WP/05/224.

36. Huidan Lin, Hannah, 2011. Determinants of Remittances: Evidence from Tonga. *IMF Working Paper*, WP/11/18.

37. Im, K.S., Pesaran, M.H., and Shin, Y., 2003. Testing for Unit Roots in Heterogeneous Panels. *Journal of Econometrics, 115, 5374.*

38. Jidoud, Ahmat, 2015. Remittances and Macroeconomic Volatility in African Countries. *IMF Working Paper*, WP/15/49.

39. Johnson, G.E. and Whitelaw, W.E., 1974. Urban-Rural Income Transfers in Kenya: An Estimated-remittances Function. *Economic Development and Cultural Change, 22, 473-79.*

40. Kalemli-Ozcan, Sørensen, Bent E., and Yosha, Oved, 2001. Economic Integration, Industrial Specialization, and the Asymmetry of Macroeconomic Fluctuations. *Journal of International Economics, 55, 107-137.*

41. Kose, M. Ayhan, Prasad, Eswar S., and Terrones, Marco E., 2009. Does Financial Globalization Promote Risk-sharing? *Journal of Development Economics, 89, 258-270.*

42. Koechlin, Valerie and Leon, Gianmarco, 2007. International Remittances and Income Inequality: An Empirical Investigation. *Journal of Economic Policy Reform, 10(2), 123-141.*

43. Lim, Sokchea and Morshed, A.K.M. Mahbub, 2015. International Migration, Migrant Stock and Remittances: Reexamining the Motivations to Remit. *The Quarterly Review of Economics and Finance, 57, 101-115.*

44. Loayza, Norman V., Ranciera, Romain, Serven, Luis, and Ventura, Jaume, 2007. Macroeconomic Volatility and Welfare in Developing Countries: An Introduction. *The World Bank Economic Review, 21(3), 343-357.*

45. Lucas, Robert E.B and Stark, Oded, 1985. Motivations to Remit: Evidence from Botswana. *Journal of Political Economy, 95, 901-918.*

46. Luith, Erik and Ruiz-Arranz, Marta, 2006. A Gravity Model of Workers' Remittances. *IMF Working Paper*, WP/06/290.

47. Mandelman, Federico S. and Zlate, Andrei, 2012. Immigration, Remittances and Business Cycles. *Journal of Monetary Economics, 59, 196-213.*

48. Mohapatra, Sanket, Joseph, George, and Ratha, Dilip, 2009. Remittances and Natural Disasters: Ex-post Response and Contribution to Ex-ante Preparedness. *World Bank Policy Research Paper 4972.*

49. Morten, Melanie, 2015. Temporary Migration and Endogenous Risk-sharing in Village India. *NBER Working Paper No. 22159.*

50. Neagu, Ileana C. and Schiff, Mauricep, 2009. Remittances Stability, Cyclicality and Stabilizing Impact in Developing Countries. *World Bank Policy Research Paper 5077.*

51. Obstfeld, Maurice, 1994. Are Industrial-Country Consumption Risks Globally Diversified? In: Leiderman and Razin, A. (Eds.), Capital Mobility: The Impact of Consumption, Investment and Growth. Cambridge University Press, New York, pp. 13-47.

52. Pollak, Robest A., 2003. Gary Becker's Contribution to Family and Household Economics. *Review of Economics of the Household, 1, 111-141.*

53. Raddatz, C., 2007. Are External Shocks Responsible for the Instability of Output in Low-Income Countries? *Journal of Development Economics, 84(1), 155-187.*

54. Ramirez, M.D. and Sharma, H., 2008. Remittances and Growth in Latin America: A Panel Unit Root and Panel Co-integration Analysis. *Yale Economics Department Working Papar, 51.*

55. Rapoport, Hillel and Docquier, Frederic, 2006. The Economics of Migrants' Remittances. *Handbook of the economics of giving, altruism and reciprocity, 2, 1135-1198.*

56. Ratha, Dillip, 2003. Worker's Remittances: An Important and Stable Source of External Development Finance. *Global Development Finance, 157-172.*

57. Ratha, Dillip and Shaw, William, 2007. South-South Migration and Remittances. *World Bank Working Paper, 102.*

58. Sayan, Serdar, 2006. Business cycles and Workers' Remittances: How do Migrant Workers Respond to Cyclical Movements of GDP at Home. *IMF Working Paper*, WP/06/52.

59. Singh, Raju Jan, Haacker, Markus, Lee, Kyung-woo, and Goff, Maelan Le, 2010. Determinants and Macroeconomic Impact of Remittances in Sub-Saharan Africa. *Journal of African Economies, 20(2), 312-340.*

60. Sørensen, Bent E., and Yosha, Oved, 2007. Producer Prices versus Consumer Prices in the Measurement of Risk-sharing. *Applied Economics Quarterly, 53(1).*

61. Sørensen, Bent E., and Yosha, Oved, 1998. International Risk-sharing and European Monetary Unification. *Journal of International Economics, 45, 211-238.*

62. Sørensen, Bent E., Wu, Yi-Tsung, Oved, Yosha, and Zhu, Yu, 2007. Home Bias and Internatinal Risk-sharing: Twin Puzzles Separated at Birth. *Journal of International Money and Finance, 26, 587-605.*

63. Spatafora, N.L., 2005. Workers' Remittances and Economic Development.

Chapter II in World Economic Outlook: Globalization and External Imbalances. International Monetary Fund, 69-84.

64. Stark, Oved, Taylor, J. Edward, and Yitzhaki, Shlomo, 1986. Remittances and Inequality. *The Economic Journal, 96(383), 722-740.*

65. van Wincoop, Eric, 2006. How Big are Potential Welfare Gains from International Risk-sharing? *Journal of International Economics, 47, 109-135.*

66. Vargas-Silva, Carlos and Huang, Peng, 2006. Macroeconomic Determinants of Workers' Remittances: Host versus Home Country's Economic Conditions. *Journal of International Trade and Economic Development, 15(1), 81-99.*

67. Yang, Dean, 2005. Coping with Disaster: The Impact of Hurricanes on International Financial Flows, 1970-2001. *JFord School of Public Policy Working Paper No. 2005-003.* Available at SSRN: http://ssrn.com/abstract=697521 or http://dx.doi.org/10.2139/ssrn.697521

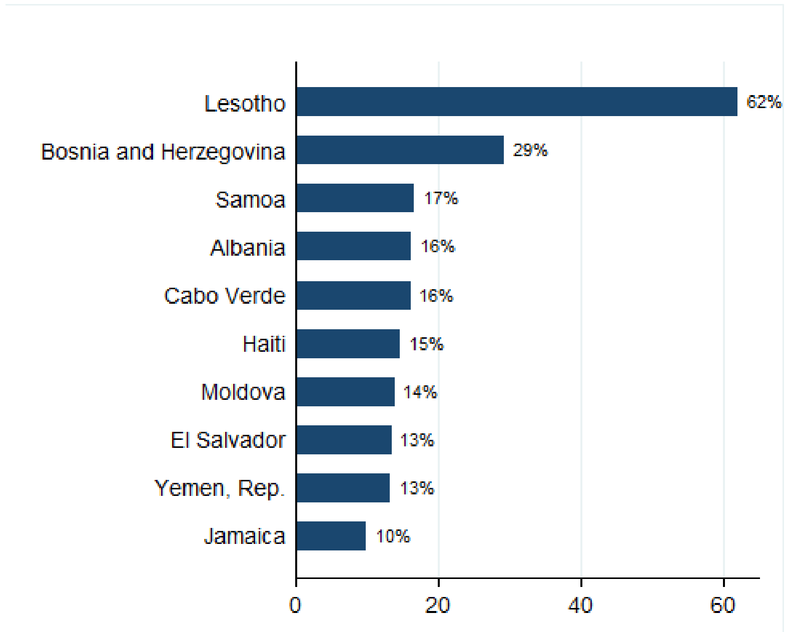
68. Yang, Dean, and Choi, Hwajung, 2007. Are Remittances Insurance? Evidence from Rainfall Shocks in the the Philippines. *The World Bank Economic Review, 21(2), 219-248.*

Table 1.1: Volatility of Real GDP Growth, 1975-2013

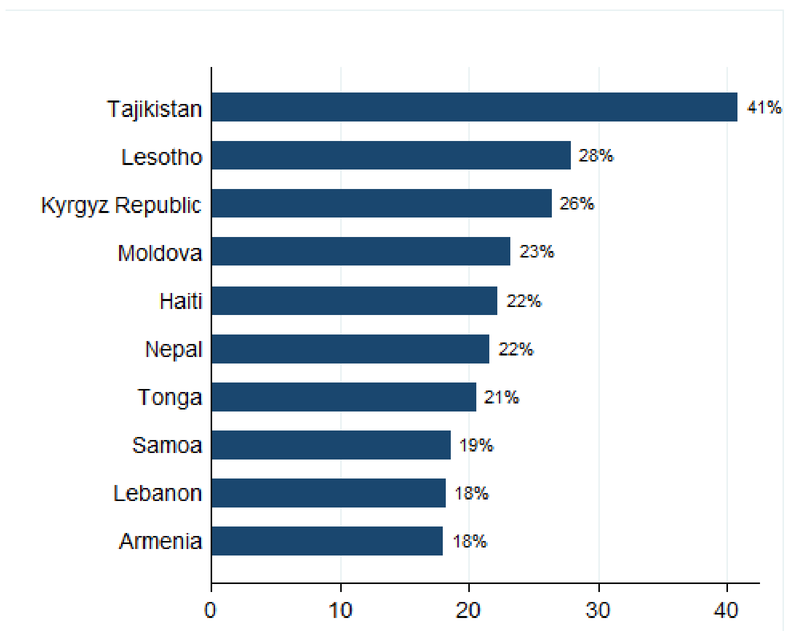
	Standard deviation		
	Full Sample	Sub Sample	
Group of countries	1975-2013	1990-1999	2000-2013
A. Advanced countries			
All countries	0.029	0.023	0.030
G-7 countries	0.022	0.016	0.021
Countries in Euro-zone	0.032	0.021	0.035
B. Developing countries			
All countries	0.058	0.056	0.041
Emerging economies	0.040	0.042	0.028
Other developing countries	0.061	0.058	0.042

Note: Volatility is measured by standard deviation. Using IMF(2015) classification, there are 36 advanced countries, 22 emerging developing countries and 139 other developing countries. There are 19 countries in Euro-zone as of August, 2016. Values reported are the averages of each group of countries.

Figure 1.1: Top 10 Remittances Recipient Countries in 2000 and 2010



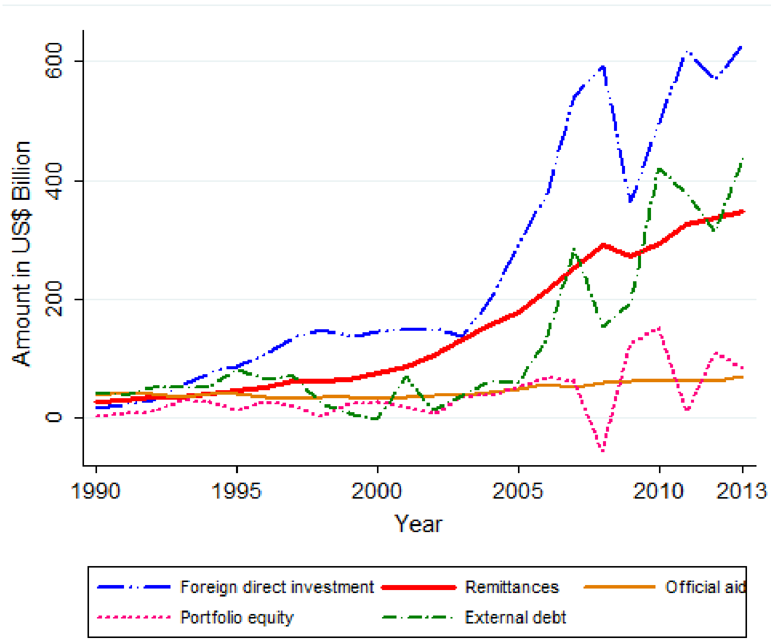
(a) 2000



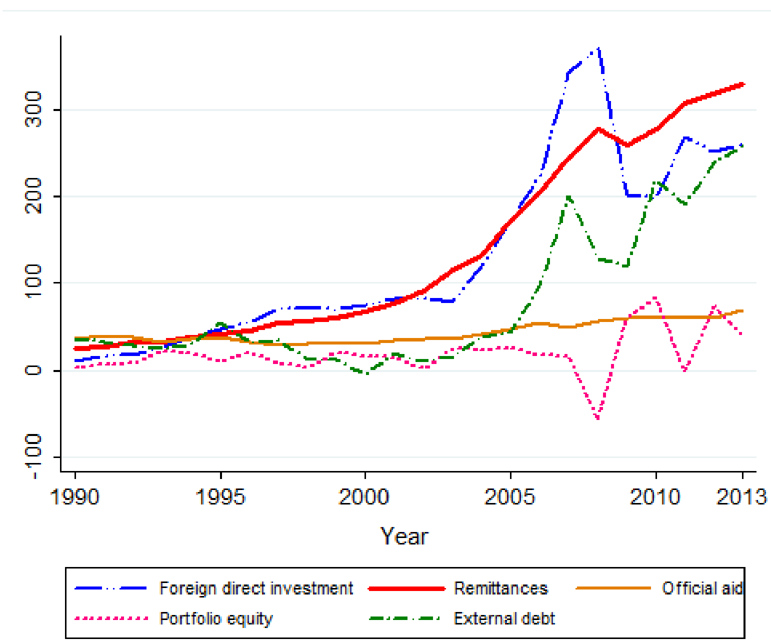
(b) 2010

Note: Figures plot remittances as a share of GDP (in percent).
Source: World Development Indicators, World Bank.

Figure 1.2: Remittances and Other Financial Flows to Developing Countries (1990-2013)



(a) All 102 countries



(b) All 100 countries except China and Brazil

Source: World Development Indicators, World Bank.

Table 1.2: Summary Statistics of Variables

Variable	Observations (1)	Mean (2)	Std. Dev. (3)	Min (4)	Max (5)
Δlog(Remittances)	2305	0.091	0.381	-0.882	2.149
Δlog(Remittances per migrant)	2305	0.087	0.390	-0.928	2.132
Δlog(Home GDP per capita)	2305	0.027	0.079	-0.353	0.429
Δlog(Host GDP per capita)	2305	0.022	0.129	-0.741	1.108
Δlog(Exchange rate)	2305	-0.003	0.115	-0.393	0.566
Δ Interest rate	2305	-0.061	4.606	-18.808	17.206

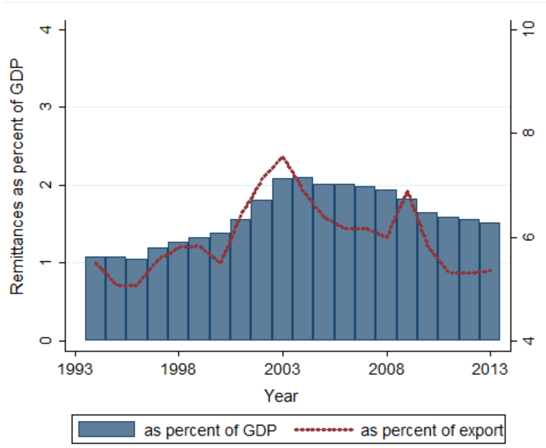
Note: All variables are measured in real terms.

Table 1.3: Panel Fixed Effect and System GMM Estimation: By Geographic Regions

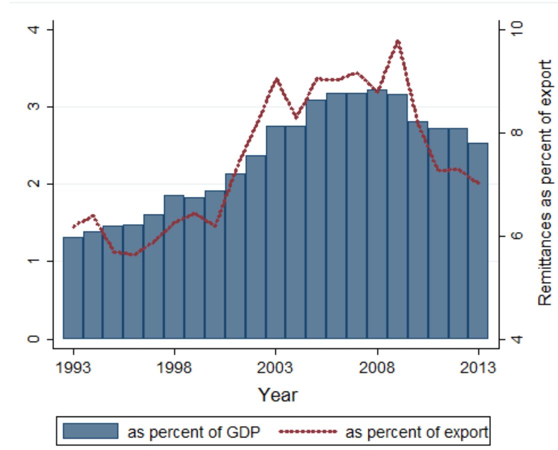
Variable	Fixed effect					System GMM				
	All	Africa	Asia	Europe	America	All	Africa	Asia	Europe	America
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Home GDP per capita	-0.171	-0.284*	-0.219*	0.380	-0.382*	-0.331**	-0.518**	-0.267**	0.367	-0.161
	(0.123)	(0.161)	(0.117)	(0.371)	(0.197)	(0.154)	(0.228)	(0.133)	(0.362)	(0.209)
Host GDP per capita	0.079	0.005	-0.168	0.230	0.254	0.159***	0.062	-0.189	0.294**	0.264*
	(0.063)	(0.101)	(0.107)	(0.158)	(0.174)	(0.063)	(0.100)	(0.143)	(0.130)	(0.143)
Real exchange rate	0.775***	0.760***	1.286***	0.423*	0.769***	0.831***	0.768***	1.440***	0.319	0.776***
	(0.077)	(0.107)	(0.169)	(0.240)	(0.120)	(0.096)	(0.114)	(0.167)	(0.280)	(0.125)
Real interest rate	-0.001	0.001	-0.007**	0.000	-0.002	-0.001	0.001	-0.006**	-0.003	-0.002
	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effets	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2305	909	476	331	589	2305	909	476	331	589
No. of countries						102	37	22	21	22
Adjusted R^2	0.083	0.064	0.134	0.127	0.089					
p-value for Sargan test						0.079	0.323	0.877	0.948	0.985
p-value for 2nd order autocorrelation						0.994	0.915	0.184	0.596	0.884

Note: Dependent variable is Δlog(remittances). Variables in the estimations are first-difference of logs of real values, except real interest rate. Variable real interest rate represents the first difference of real deposit rate in percent. To compute the AB dynamic system estimator, variables in difference in difference are instrumented with lags of variables in difference (two and higher), while variables in difference are instrumented with lags of their own differences (two and higher). Included control variables are growth in migrant stock abroad and foreign direct investment inflows to home country. Standard errors clustered at country level are in parentheses. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively. All regressions include lag of dependent variable as a regressor.

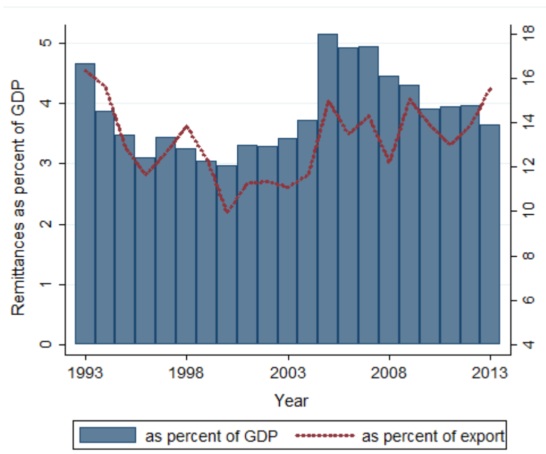
Figure 1.3: Remittances as Percent of Gross Domestic Product and Export, 1993-2013



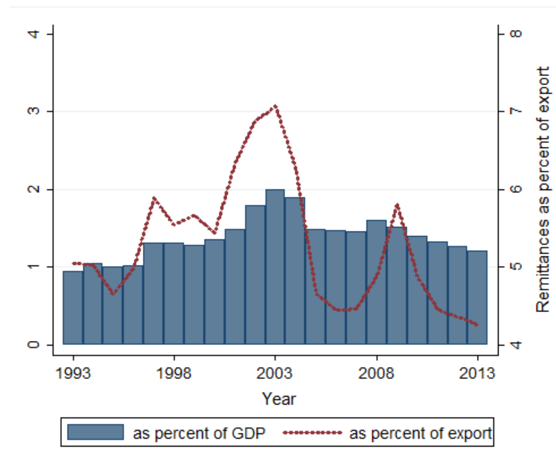
(a) All 102 countries



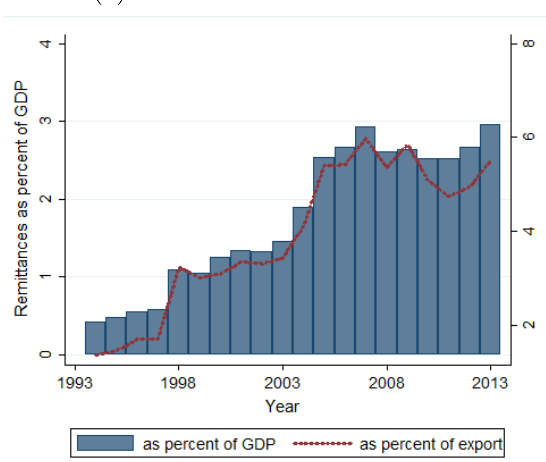
(b) All countries wihtout China and Brazil



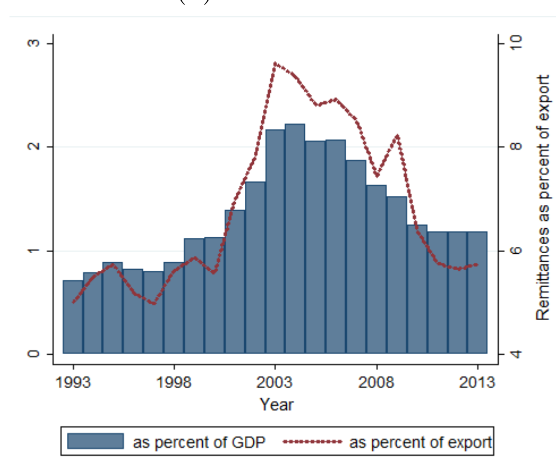
(c) 37 African countries



(d) 22 Asian countries



(e) 21 European countries



(f) 22 American countries

Note: All variables are measured in current US dollar terms.
Source: World Development Indicators, World Bank.

Table 1.4: System GMM Estimation: By Income Groups

Variable	By income group		By depth of financial market	
	Low-income (1)	Middle-income (2)	Shallow market (3)	Deep market (4)
Home GDP per capita	-0.385**	-0.026	-0.438**	-0.078
	(0.183)	(0.185)	(0.214)	(0.174)
Host GDP per capita	0.147**	0.093	0.077	0.175**
	(0.068)	(0.138)	(0.103)	(0.082)
Real exchange rate	0.802***	0.730***	0.817***	0.618***
	(0.108)	(0.142)	(0.107)	(0.129)
Real interest rate	0.000	-0.001	-0.002	0.000
	(0.002)	(0.004)	(0.004)	(0.002)
Control variables	Yes	Yes	Yes	Yes
Time fixed effets	Yes	Yes	Yes	Yes
Country fixed effets	Yes	Yes	Yes	Yes
Observations	1134	1171	1136	1169
No. of countries	51	51	51	51
p-value for Sargan test	0.451	0.529	0.435	0.948
p-value for 2nd order autocorrelation	0.607	0.388	0.867	0.832

Note: Dependent Variable is Δlog(remittances). Variables in the estimations are first-difference of logs of real values, except real interest rate. Variable real interest rate represents the first difference of real deposit rate in percent. To compute the AB dynamic system estimator, variables in difference in difference are instrumented with lags of variables in difference (two and higher), while variables in difference are instrumented with lags of their own differences (two and higher). Included control variables are growth in migrant stock abroad and foreign direct investment inflows to home country. Countries below and above the median real GDP per capita in 2013 are defined as low- and middle-income countries respectively. Similarly, countries below and above the median value of private credit by banks and financial institutions as a share of GDP in 2013 are defined as countries with shallow and deep financial market respectively. Standard errors clustered at country level are in parentheses. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively. All regressions include lag of dependent variable as a regressor.

Table 1.5: System GMM Estimation. Dependent Variable is Remittances per Migrant

Variable	All (1)	Africa (2)	Asia (3)	Europe (4)	America (5)
Home GDP per capita	-0.315**	-0.528**	-0.241**	0.345	-0.169
	(0.163)	(0.237)	(0.120)	(0.358)	(0.226)
Host GDP per capita	0.149**	0.057	-0.219	0.285**	0.264*
	(0.064)	(0.099)	(0.161)	(0.133)	(0.153)
Real exchange rate	0.823***	0.774***	1.445***	0.299	0.770***
	(0.095)	(0.116)	(0.167)	(0.282)	(0.122)
Real interest rate	-0.001	0.001	-0.006*	-0.003	-0.002
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes
Time fixed effets	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2305	909	476	331	589
No. of countries	102	37	22	21	22
p-value for Sargan test	0.081	0.356	0.882	0.946	0.969
p-value for 2nd order autocorrelation	0.959	0.907	0.181	0.647	0.871

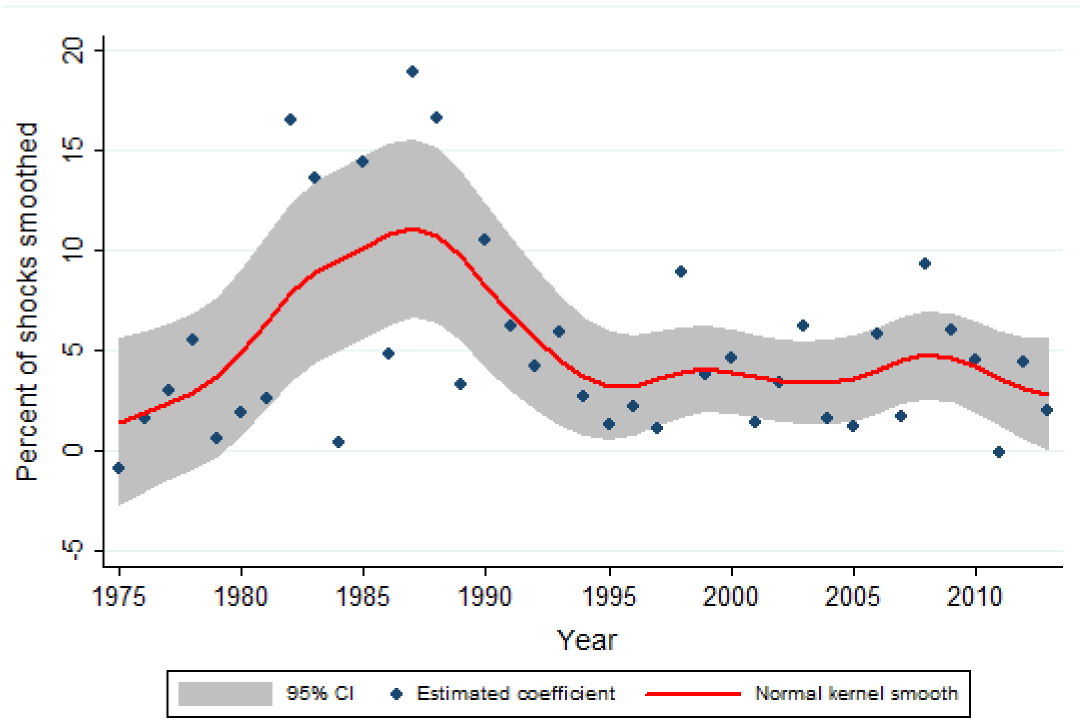
Note: Variables in the estimations are first-difference of logs of real values, except real interest rate. Variable real interest rate represents the first difference of real deposit rate in percent. To compute the AB dynamic system estimator, variables in difference in difference are instrumented with lags of variables in difference (two and higher), while variables in difference are instrumented with lags of their own differences (two and higher). Included control variables are growth in migrant stock abroad and foreign direct investment inflows to home country. Standard errors clustered at country level are in parentheses. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively. All regressions include lag of dependent variable as a regressor.

Table 1.6: GLS Estimation of Income Risk-sharing via Remittances

	All	Africa	Asia	Europe†	America
	(1)	(2)	(3)	(4)	(5)
A. 1975-2013 period					
Coefficient (β_r)	0.035***	0.061***	0.030***	0.016*	0.016***
	(0.004)	(0.008)	(0.007)	(0.010)	(0.005)
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	2634	1046	573	360	655
No. of countries	102	37	22	21	22
B. 1994-2013 period					
Coefficient (β_r)	0.039***	0.024***	0.094***	0.016*	0.062***
	(0.003)	(0.006)	(0.012)	(0.010)	(0.006)
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	1775	621	367	360	427
No. of countries	102	37	22	21	22

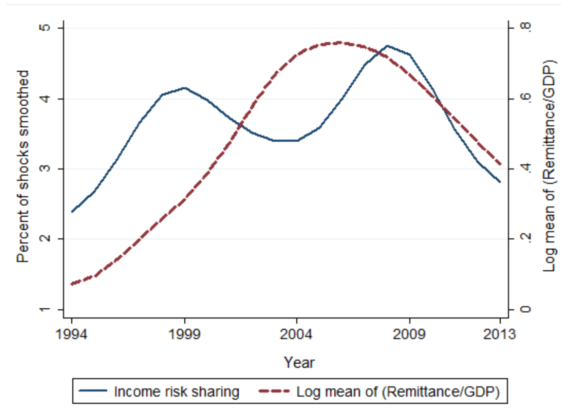
Note: Results reported above are obtained by estimating the equation $\widetilde{GDP}_{it} - \widetilde{GDPREM}_{it} = \vartheta_{r,t} + \beta_r \widetilde{GDP}_{it} + \epsilon_{it}$ by two-step GLS method. Here, $\widetilde{Z}_{it} = \Delta logZ_{it} - \Delta logZ_t^{world}$ for any representative variable Z, where Z=$\{GDP, GDPREM\}$. $GDPREM_{it}$ is the sum of domestic income (GDP_{it}) and remittances flows (R_{it}) in country i in year t,. $\widetilde{GDP}_{it}$ represents the idiosyncratic part of output calculated as per capita real GDP growth rate of country i in period t minus the world per capita real GDP growth in period t. Similarly, $\widetilde{GDPREM}_{it}$ represents the idiosyncratic part of output calculated as per capita real GDPREM growth rate of country i in period t minus the world per capita real GDPREM growth in period t. The estimated coefficient β_r when multiplied by 100 percent quantifies the percent of income smoothing via remittances. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively.
† Eastern European countries have remittances data only from 1994.

Figure 1.4: Year by Year Measures of Income Smoothing via Remittances

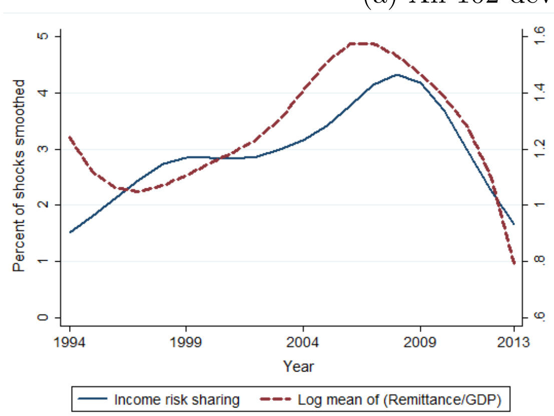


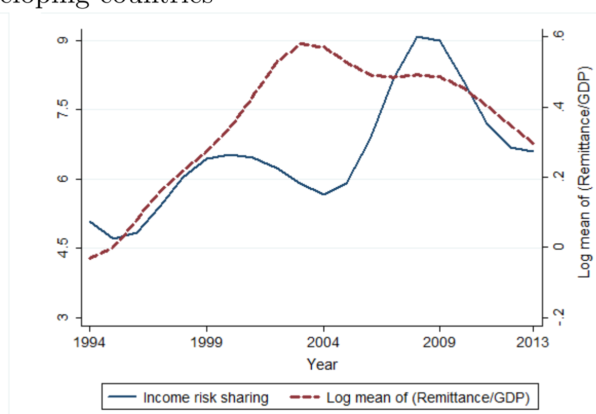
Note: Income smoothing is estimated cross-sectionally in each year and is smoothed by using a Normal kernel with bandwidth equal to 2.

Figure 1.5: Income Risk-sharing (in Percent) and Remittances as Percent of GDP, 1994-2013



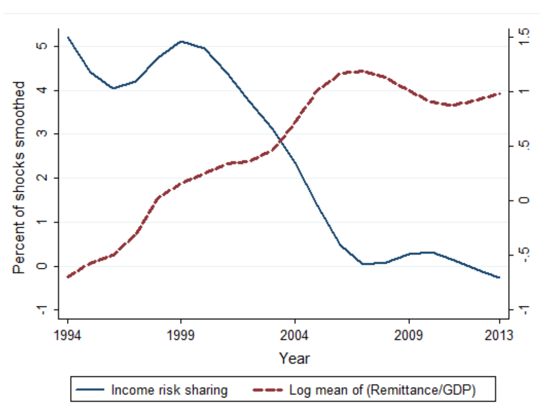
(a) All 102 developing countries

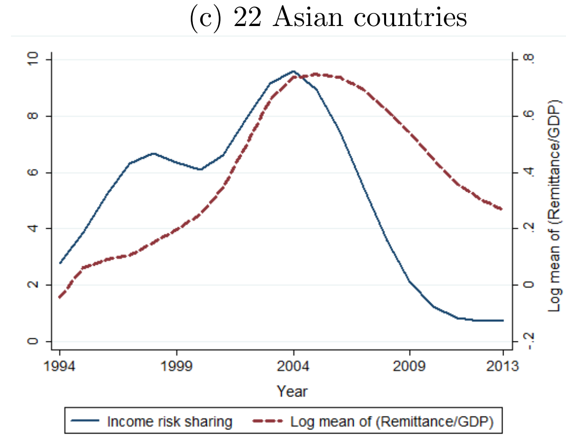




(b) 37 African countries

(c) 22 Asian countries





(d) 21 European countries

(e) 22 American countries

Note: Income smoothing is estimated cross-sectionally in each year and is smoothed by using a Normal kernel with bandwidth equal to 2.

Table 1.7: GLS Estimation of Income Risk-sharing: By Income Groups

	Low-income countries (1)	Middle-income countries (2)
A. 1975-2013 period		
Coefficient (β_r)	0.045***	0.022***
	(0.007)	(0.003)
Observations	1329	1306
No. of countries	51	51
B. 1994-2013 period		
Coefficient (β_r)	0.044***	0.039***
	(0.005)	(0.005)
Observations	847	928
No. of countries	51	51

Note: Results reported above are obtained by estimating the equation $\widetilde{GDP}_{it} - \widetilde{GDPREM}_{it} = \vartheta_{r,t} + \beta_r \widetilde{GDP}_{it} + \epsilon_{it}$ by two-step GLS method. Here, $\widetilde{Z}_{it} = \Delta log Z_{it} - \Delta log Z_t^{world}$ for any representative variable Z, where Z=$\{GDP, GDPREM\}$. $GDPREM_{it}$ is the sum of domestic income (GDP_{it}) and remittances flows (R_{it}) in country i in year t,. $\widetilde{GDP}_{it}$ represents the idiosyncratic part of output calculated as per capita real GDP growth rate of country i in period t minus the world per capita real GDP growth in period t. Similarly, $\widetilde{GDPREM}_{it}$ represents the idiosyncratic part of output calculated as per capita real GDPREM growth rate of country i in period t minus the world per capita real GDPREM growth in period t. The estimated coefficient β_r when multiplied by 100 percent quantifies the percent of income smoothing via remittances. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively.

Table 1.8: GLS Estimation of Income Risk-sharing at Various Differencing Frequencies

	All	Africa	Asia	Europe[†]	America
	(1)	(2)	(3)	(4)	(5)
A. Three years					
Coefficient (β_r)	0.035***	0.046***	0.026***	0.028***	0.019***
	(0.004)	(0.008)	(0.007)	(0.010)	(0.005)
Observations	2433	974	525	319	615
Time fixed effect	Yes	Yes	Yes	Yes	Yes
No. of countries	102	37	22	21	22
B. Five years					
Coefficient (β_r)	0.037***	0.057***	0.028***	0.014	0.021***
	(0.004)	(0.009)	(0.007)	(0.012)	(0.006)
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	2231	902	477	277	575
No. of countries	100	36	21	21	22

Note: Results reported above are obtained by estimating the equation $\widetilde{GDP}_{it} - \widetilde{GDPREM}_{it} = \vartheta_{r,t} + \beta_r \widetilde{GDP}_{it} + \epsilon_{it}$ by two-step GLS method. Here, $\widetilde{Z}_{it} = \Delta log Z_{it} - \Delta log Z_t^{world}$ for any representative variable Z, where Z=$\{GDP, GDPREM\}$. $GDPREM_{it}$ is the sum of domestic income (GDP_{it}) and remittances flows (R_{it}) in country i in year t,. $\widetilde{GDP}_{it}$ represents the idiosyncratic part of output calculated as per capita real GDP growth rate of country i in period t minus the world per capita real GDP growth in period t. Similarly, $\widetilde{GDPREM}_{it}$ represents the idiosyncratic part of output calculated as per capita real GDPREM growth rate of country i in period t minus the world per capita real GDPREM growth in period t. The estimated coefficient β_r when multiplied by 100 percent quantifies the percent of income smoothing via remittances. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively.

† Eastern European countries have remittances data only from 1994.

Table 1.9: Non-remittances and Remittances Income Shares by Income Groups of Households (HHs)

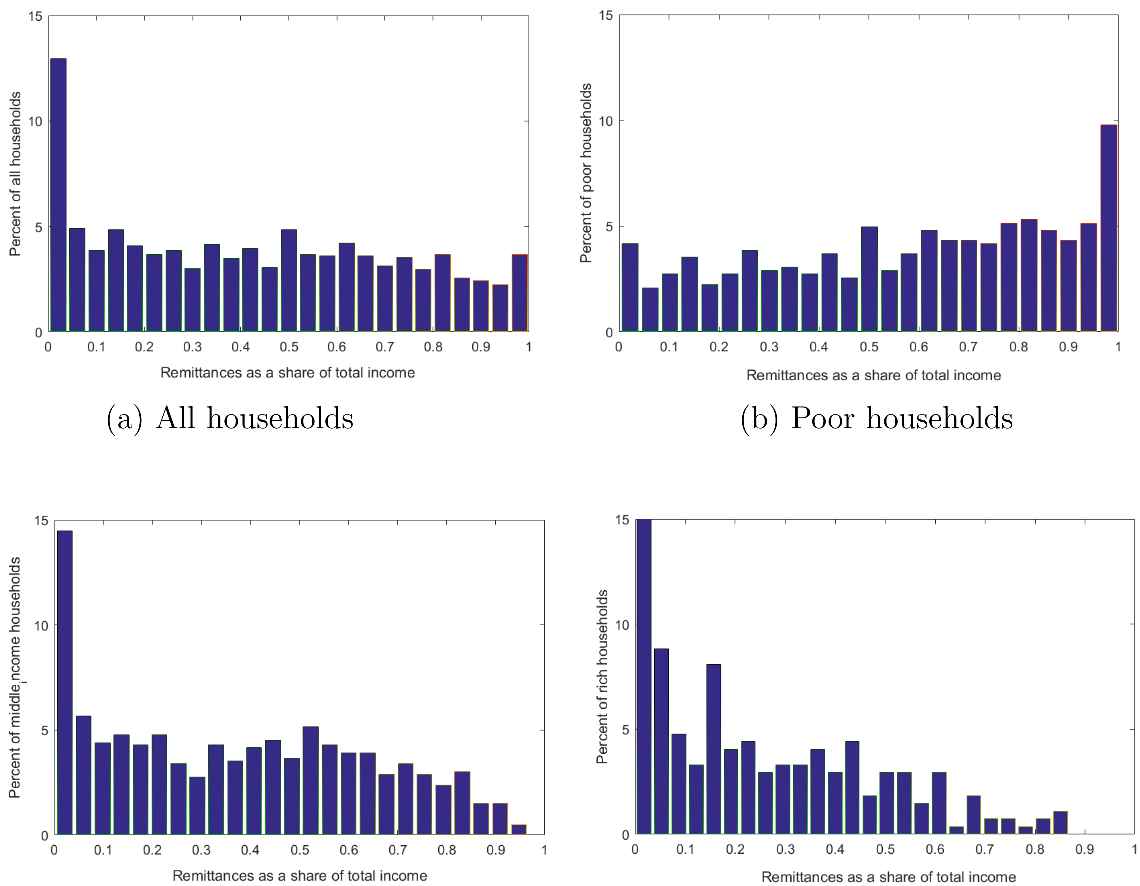
Country (Year)	No. of HHs	Size of population	Income group (j)	**Income share**† Domestic (ξ^j)	Remittances ($\Re^j$)	Fraction of HHs' receiving remittances	Average remittances‡
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1,791	10,038	Poor	0.05	0.41	0.11	2,491
Guatemala	3,583	19,646	Middle	0.37	0.41	0.08	1,460
(2000)	1,791	7,787	Rich	0.58	0.18	0.08	1,546
	7,165	37,471	All	1.00	1.00	0.09	1,777
	10,254	53,479	Poor	0.05	0.42	0.03	23,193
India	20,508	101,377	Middle	0.36	0.33	0.01	17,854
(2011)	10,254	45,220	Rich	0.59	0.25	0.01	25,761
	40,914	200,076	All	1.00	1.00	0.01	21,653
	1,467	7,609	Poor	0.05	0.31	0.43	17,963
Nepal	2,936	14,459	Middle	0.35	0.46	0.27	23,493
(2011)	1,467	6,065	Rich	0.60	0.23	0.19	38,629
	5,870	28,133	All	1.00	1.00	0.29	23,414
	1,142	7,320	Poor	0.06	0.28	0.20	501
Tajikistan	2,287	15,108	Middle	0.42	0.50	0.17	483
(2007)	1,142	6,134	Rich	0.52	0.22	0.16	605
	4,571	28,562	All	1.00	1.00	0.18	512
	694	3,929	Poor	0.04	0.16	0.03	118,722
Uganda	1,389	7,749	Middle	0.27	0.50	0.02	479,382
(2011)	694	3,055	Rich	0.69	0.34	0.03	232,963
	2,777	14,733	All	1.00	1.00	0.02	267,652

Note: Income groups are defined by using quartiles of non-remittances income per capita. Households in the first quartile are classified as poor-income group, households in the second and third quartiles are classified as middle-income group, and households in the fourth quartile are defined as rich-income group.

† Income share means share of each household group within each type of total income, namely total non-remittances domestic income and total remittances income.

‡ It is average remittances per person (in local currency) within each type of household, conditional on households receive remittances.

Figure 1.6: Distribution of Remittance Shares in Total Income in Nepal, Conditional on Households Receive Remittances



(a) All households

(b) Poor households

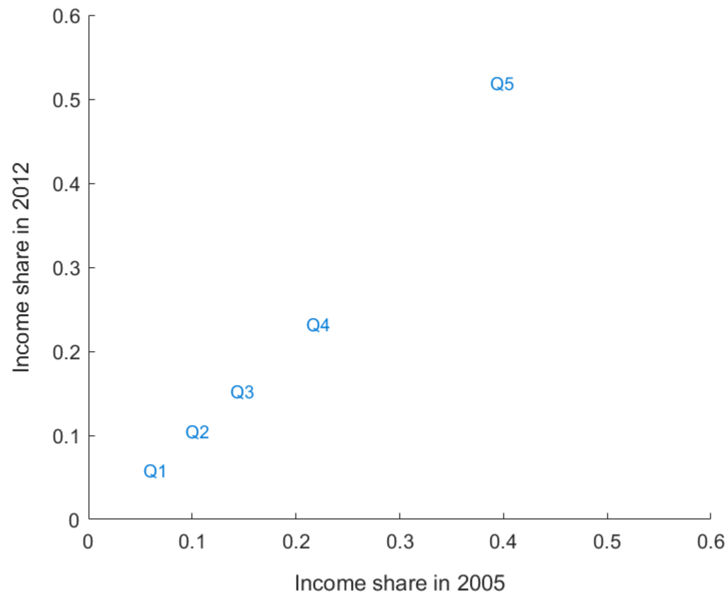
(c) Middle-income households

(d) Rich households

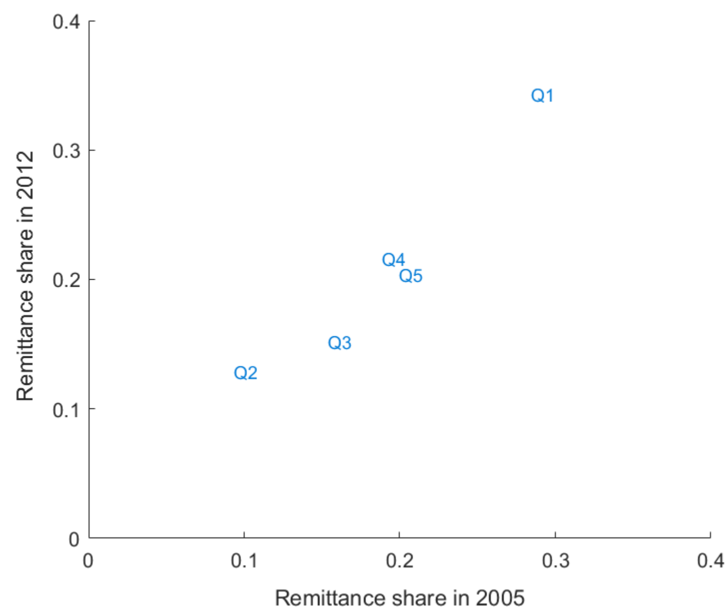
Note: Households in the bottom, middle two, and top quartiles are defined as poor, middle-income, and rich households, respectively.

Source: Nepal Living Standard Survey-III (2010-11).

Figure 1.7: Domestic Income and Remittances Shares by Quintile Income Groups of Households in India



(a) Domestic income share



(a) Remittances income share

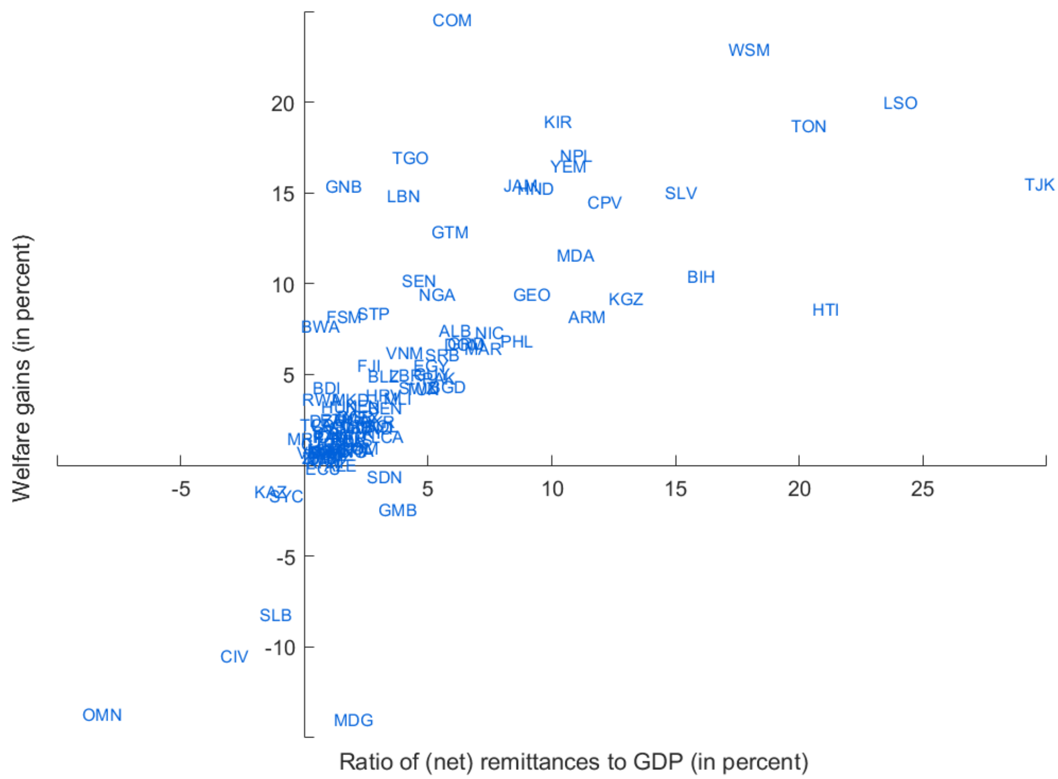
Note: Out of total 38,514 panel households between between 2005 and 2011, about 680 households received international remittances.
Source: India Human Development Survey, 2005 and 2011/12.

Table 1.10: Welfare Gains from Net Remittances, 1975-2013

		Welfare gains (W^i)	
		Sample period	
Sample	No. of countries	1975-2013	1994-2013
All countries	102	1.86	2.54
(without China)		(2.47)	(3.42)
By geographic regions			
Africa	37	3.17	3.73
Asia	22	1.56	2.36
(wthout China)		(2.39)	(3.73)
Europe†	21	2.24	2.23
America	22	1.78	2.13
By income groups			
Low-income countries	51	2.71	3.92
Middle-income countries	51	0.76	0.77
By depth of financial market			
Countries with shallow market	51	3.43	4.37
Countries with deep market	51	1.36	1.97

Note: Welfare gains (in percent) are estimated for CRRA utility with risk aversion parameter, $\gamma = 3$ and the discount rate, $\delta = 0.02$. Reported values above are population weighted averages. Countries below and above the median real GDP per capita in 2013 are defined as low- and middle-income countries respectively. Similarly, countries below and above the median value of private credit by banks and financial institutions as a share of GDP in 2013 are defined as countries with shallow and deep financial market respectively.
† Eastern European countries have remittances data only from 1994.

Figure 1.8: Relationship between Welfare Gains and Remittances to GDP Ratio, 1975-2013



Note: Welfare gains are estimated for CRRA utility with risk aversion parameter, $\gamma = 3$ and the discount rate, $\delta = 0.02$..

Table 1.11: Decomposition of Welfare Gains

Sample	Welfare gains	Decomposition of gains		
		Level effect	Growth effect	Volatility effect
All countries	1.86	0.72	0.87	0.27
Africa	3.17	0.73	1.34	1.10
Asia	1.56	0.70	0.77	0.09
Europe	2.24	1.04	1.25	-0.05
America	1.78	0.68	0.90	0.20

Note: Welfare gains (in percent) are estimated for CRRA utility with risk aversion parameter, $\gamma = 3$ and the discount rate, $\delta = 0.02$. Reported values above are population weighted averages. The level effect means the gains from a higher level of income due to remittances in the initial period. The growth effect means the gains from a higher average growth of income due to remittances. Finally, the volatility effect means the gains due to lower volatility of income growth due to remittances.

Table 1.12: Welfare Gains from Remittances in Selected Countries: By Income Groups of Households

	Welfare gains (W^i)				
		Income groups of households (HHs)			
	Representative HH	Poor	Middle	Rich	**All**
Country (k)	(1)	(2)	(3)	(4)	(5)
Guatemala	12.25	47.65	13.32	4.32	**20.69**
India	1.45	7.89	1.55	0.61	**3.06**
Nepal	16.46	46.01	17.60	8.18	**23.29**
Tajikistan	14.75	43.74	16.87	7.13	**22.08**
Uganda	1.92	5.72	3.04	1.37	**3.41**
Average	**1.96**	**9.27**	**2.15**	**0.86**	**3.80**

Note: Welfare gains (in percent) are estimated for CRRA utility with risk aversion parameter, $\gamma = 3$ and the discount rate, $\delta = 0.02$. Column (1) reports the gains for a country representative agent. Welfare gains for each income group are calculated using the income and remittances shares in each country k reported in Table 9. Households in the bottom and top quartiles are classified as poor and rich households respectively. Households in the middle two quartiles are classified as middle-income households. Welfare gains for all households in column (5) is calculated as $W{=}\sum_j \varkappa^j W^j$ for $j = p$, m, and r, where $j = p$, m, and r refer to poor, middle-income, and rich households, respectively. Population shares ($\varkappa^j$) are derived from population size of each income group in each country in Table 9. The last row reports the population-weighted average of the gains in all five countries. The average remittances-to-GDP ratios (in percent) in Guatemala, India, Nepal, Tajikistan, and Uganda are 5.27, 2.38, 13.82, 37.48, and 1.69 respectively.

Table 1.13: Welfare Gains from Remittances in all Countries: By Income Groups of Households

Income groups	Population share ($\varkappa^j$) (1)	Welfare gains (W^j) (2)	Aggregate welfare gains (W) (3)
A. No group			
Representative agent	1.00	1.86	**1.86**
B. Quartile groups†			
Poor	0.27	7.56	
Middle	0.52	2.31	**3.43**
Rich	0.21	0.88	
C. Quintile groups			
Q1	0.21	8.66	
Q2	0.22	3.49	
Q3	0.21	2.51	**3.55**
Q4	0.19	1.69	
Q5	0.17	0.68	
D. Decile groups			
D1	0.10	12.02	
D2	0.11	6.89	
D3	0.11	4.29	
D4	0.11	2.91	
D5	0.11	2.75	**3.80**
D6	0.10	2.63	
D7	0.10	2.30	
D8	0.09	1.33	
D9	0.09	1.07	
D10	0.08	0.45	

Note: I use income shares from Guatemala to countries in Latin America, from India and Nepal to countries in Asia, from Tajikistan to countries in Eastern Europe, and from Uganda to countries in Africa to extrapolate the GDP and remittances by various income groups of households. Welfare gains (in percent) are estimated for CRRA utility with risk aversion parameter, $\gamma = 3$ and the discount rate, $\delta = 0.02$. Reported values above are population weighted averages. Welfare gains at aggregate household level (W) is calculated as $W=\sum_j \varkappa^j W^j$ for each income group j.

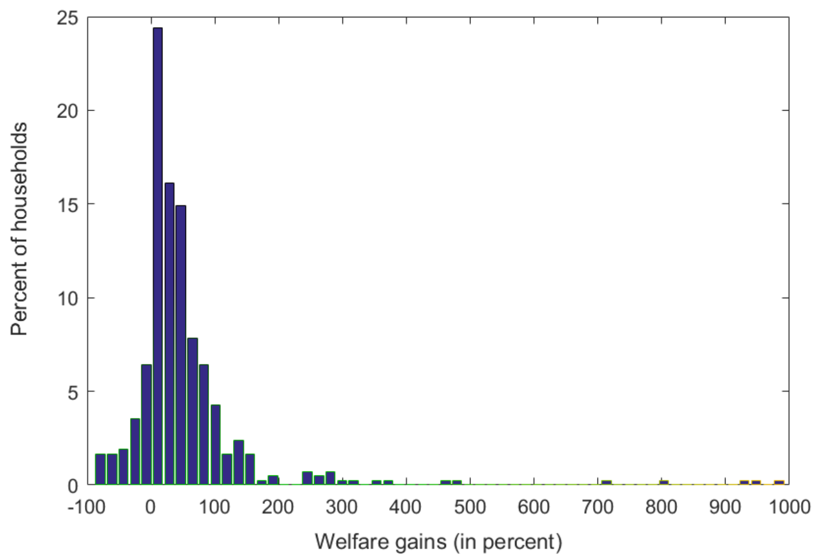
† Households in the bottom and top quartiles are classified as poor and rich households respectively. Households in the middle two quartiles are classified as middle-income households.

Table 1.14: Welfare Gains from Remittances by Income Groups of Households in India between 2005 and 2012

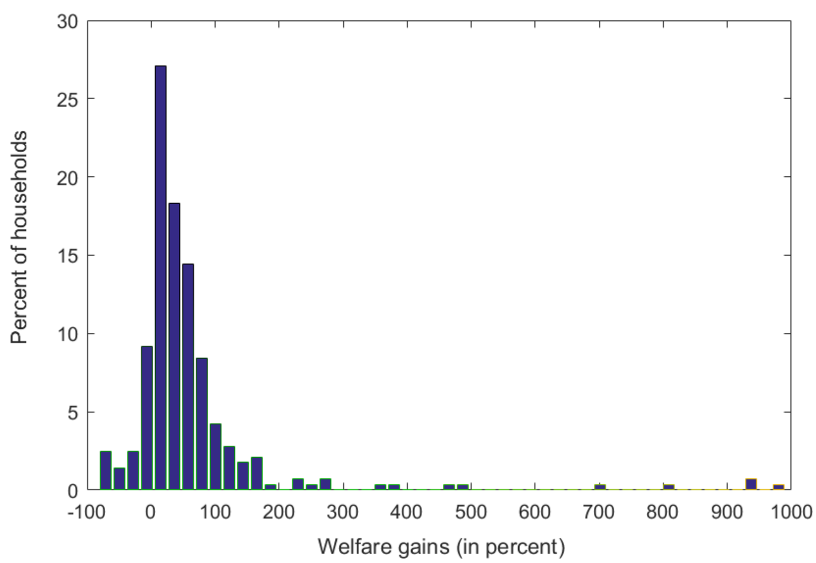
	Household panel		Country aggregate
	All India	Kerala, Punjab, & Rajasthan	All India
Income groups	(1)	(2)	(3)
A. No group			
All households	0.54	2.93	1.45
B. Quartile groups			
Poor	0.98	6.67	7.89
Middle	0.46	2.08	1.55
Rich	0.27	0.91	0.61
C. Quintile groups			
Q1	1.13	7.49	10.48
Q2	0.47	2.74	2.81
Q3	0.48	1.97	1.44
Q4	0.38	1.68	1.19
Q5	0.22	0.80	0.48
Remittances as a share of domestic income			
Year 2005	0.005	0.021	0.025
Year 2012	0.013	0.054	0.034

Note: First two columns report gains (in percent) calculated using household panel data between 2005 and 2012. The last column reports the gains calculated using time series GDP and remittances data from 1975 to 2013 and income shares from household survey, 2012. Welfare gains are estimated for CRRA utility with risk aversion parameter, $\gamma = 3$ and the discount rate, $\delta = 0.02$. Households in the bottom and top quartiles are classified as poor and rich households respectively. Households in the middle two quartiles are classified as middle-income households. As for all panel households in India, 421 out of total 37,291 households receive remittances. In Kerala, Punjab, & Rajasthan states, 283 out of total 5,383 households receive remittances. For country aggregate in column (3), the last two rows report the remittances as a share of GDP.

Figure 1.9: Distribution of Welfare Gains from Remittances in India between 2005 and 2012



(a) 421 households in India.



(b) 283 households in Kerala, Punjab and Rajasthan states.

Note: Figures plot the gains (in percent) for remittances-recipient households only.

Source: India Human Development Survey, 2005 and 2011/12.

1.8 Appendix

Table 1.15: List of Variables and Data Source

Variables	Source
Remittances	World Development Indicators (*WDI*), World Bank
Nominal GDP	*WDI*
Population	*WDI*
CPI 2005 base year	*WDI*
Export	*WDI*
Foreign direct investment	*WDI*
Nominal exchange rate	International Financial Statistics (*IFS*), International Monetary Fund (IMF)
Stock of migrants	Global Bilateral Migration Database, World Bank & Global Migration Database, United Nations
Private credit as a share of GDP	Global Financial Development Database (*GFDD*), World Bank
Bank accounts per 1,000 adults	*GFDD*
Value of collateral needed for a loan (percent of loan amount)	*GFDD*
Short-term interest rates	*OECD.Stat* & *WDI*

Table 1.16: List of 102 Countries

No	Country	No	Country	No	Country
1	Albania	35	Grenada	69	Nepal
2	Algeria	36	Guatemala	70	Nicaragua
3	Armenia	37	Guinea-Bissau	71	Nigeria
4	Azerbaijan	38	Guyana	72	Oman
5	Bangladesh	39	Haiti	73	Pakistan
6	Belize	40	Honduras	74	Panama
7	Benin	41	Hungary	75	Paraguay
8	Bolivia	42	India	76	Peru
9	Bosnia and Herzegovina	43	Indonesia	77	Philippines
10	Botswana	44	Jamaica	78	Poland
11	Brazil	45	Kazakhstan	79	Romania
12	Bulgaria	46	Kenya	80	Rwanda
13	Burkina Faso	47	Kiribati	81	Samoa
14	Burundi	48	Korea, Rep.	82	Sao Tome and Principe
15	Cabo Verde	49	Kyrgyz Republic	83	Senegal
16	Cambodia	50	Lao PDR	84	Serbia
17	Chad	51	Latvia	85	Seychelles
18	China	52	Lebanon	86	Slovak Republic
19	Colombia	53	Lesotho	87	Solomon Islands
20	Comoros	54	Liberia	88	Sri Lanka
21	Costa Rica	55	Lithuania	89	Sudan
22	Cote d'Ivoire	56	Macedonia, FYR	90	Swaziland
23	Croatia	57	Madagascar	91	Syrian Arab Republic
24	Czech Republic	58	Malawi	92	Tajikistan
25	Djibouti	59	Mali	93	Togo
26	Dominican Republic	60	Mauritania	94	Tonga
27	Ecuador	61	Mauritius	95	Tunisia
28	Egypt, Arab Rep.	62	Mexico	96	Uganda
29	El Salvador	63	Micronesia, Fed. Sts.	97	Ukraine
30	Ethiopia	64	Moldova	98	Uruguay
31	Fiji	65	Mongolia	99	Venezuela, RB
32	Gambia, The	66	Morocco	100	Vietnam
33	Georgia	67	Mozambique	101	Yemen, Rep.
34	Ghana	68	Namibia	102	Zambia

Table 1.17: List of Household Survey Data

Country	Survey	Year
Guatemala	Encuesta Nacional sobre Condiciones de Vida (ENCOVI)	2000
India	India Human Development Survey (IHDS)	2005
India	India Human Development Survey-II (IHDS-II)	2011-12
Nepal	Nepal Living Standard Survey (NLSS)	2010-11
Tajikistan	Tajikistan Living Standards Measurement Survey (TLSS)	2007
Uganda	The Uganda National Panel Survey (UNPS)	2011-12

1.8.1 Construction of Non-remittances Income from Household Survey

Non-remittances income of a typical household includes the following flows of resources in the past 12 months from the year the household survey is conducted:

1. **Farm income**: Total value of crops produced (net of share paid to landlord) plus value of crop by-products plus net income from renting farm assets plus income from non-crop farm products plus earning from the sale of livestock plus value of home-produced non-crop consumption. Then, cultivation costs, maintenance expenditures on farm machinery and buildings, fodder and other livestock expenditure, expenditure for the purchase of livestock, and cash rent paid to landlord are substracted.

2. **Wage income**: Total cash and in-kind earning in agriculture and non-agriculture sectors.

3. **Enterprise income**: Total income from non-agriculture enterprises. Wages paid both cash and in-kind, energy expenditure, expenditure on raw materials, other operating expenditure, and share of net revenue paid to partners are substracted.

4. **Rental income**: Income from renting out non-agriculture property and assets.

5. **Housing income**: Imputed rental value of own-occupied housings.

6. **Other income**: Interest, dividends, profit earnings from shares and savings/deposit accounts plus social security payment plus pension income plus commission fees and royalties, and other incomes.

7. Domestic remittances (both cash and in-kind) are excluded from the calculation of non-remittances domestic income.

Table 1.18: System GMM Estimation. Dependent Variable is Remittances per Migrant

Variable	By income group		By depth of financial market	
	Low-income	Middle-income	Shallow market	Deep market
	(1)	(2)	(3)	(4)
Home GDP per capita	-0.376**	-0.027	-0.442**	-0.079
	(0.182)	(0.185)	(0.224)	(0.167)
Host GDP per capita	0.145**	0.070	0.069	0.156*
	(0.066)	(0.139)	(0.103)	(0.087)
Real exchange rate	0.805***	0.727***	0.816***	0.627***
	(0.110)	(0.139)	(0.108)	(0.130)
Real interest rate	0.000	-0.001	-0.002	0.001
	(0.002)	(0.004)	(0.004)	(0.002)
Control variables	Yes	Yes	Yes	Yes
Time fixed effets	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Observations	1134	1171	1136	1169
No. of countries	51	51	51	51
p-value for Sargan test	0.583	0.918	0.478	0.928
p-value for 2nd order autocorrelation	0.607	0.423	0.902	0.759

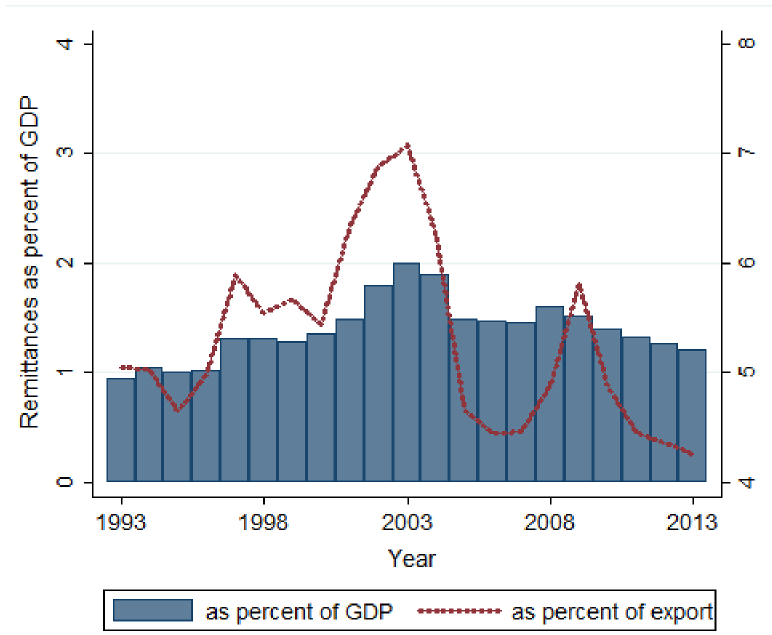
Note: Variables in the estimations are first-difference of logs of real values, except real interest rate. Variable real interest rate represents the first difference of real deposit rate in percent. To compute the AB dynamic system estimator, variables in difference in difference are instrumented with lags of variables in difference (two and higher), while variables in difference are instrumented with lags of their own differences (two and higher). Included control variables are growth in migrant stock abroad and foreign direct investment inflows to home country. Countries below and above the median real GDP per capita in 2013 are defined as low- and middle-income countries respectively. Similarly, countries below and above the median value of private credit by banks and financial institutions as a share of GDP in 2013 are defined as countries with shallow and deep financial market respectively. Standard errors clustered at country level are in parentheses. ***, ** and * denote significance at the 1, 5, and 10 percent levels respectively. All regressions include lag of dependent variable as a regressor

Table 1.19: Means and Variances of Real GDP per capita and Real GDPRMT per capita by Regions

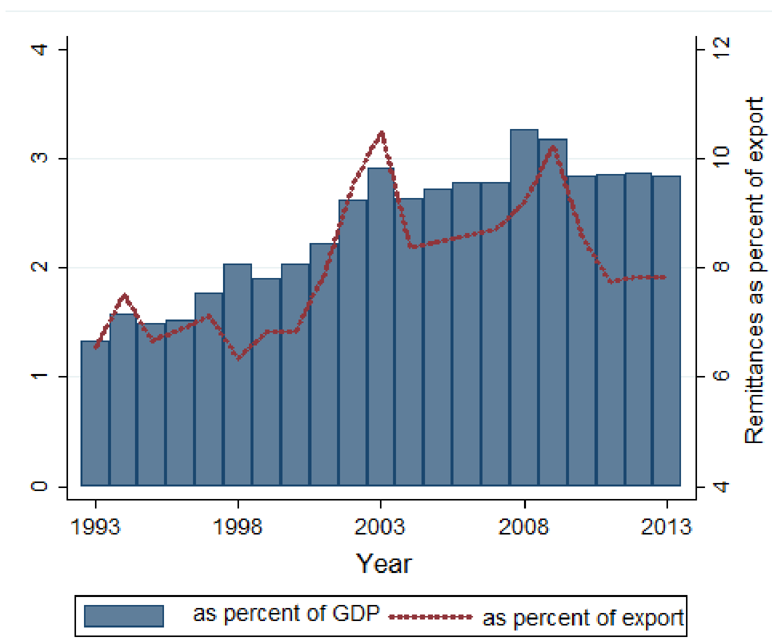
	GDP		GDPRMT	
	Mean	Variance	Mean	Variance
Region	(1)	(2)	(3)	(4)
All	3.01	6.46	3.14	6.44
Africa	2.27	7.68	2.29	7.59
Asia	3.30	4.56	3.42	4.38
Eastern Europe	4.23	4.19	4.54	4.76
Latin America	1.85	8.48	2.00	8.20

Note: GDPRMT is the sum of GDP and remittances. Mean of GDP is $10^2 * \mu_i$ where μ_i = mean(Δlog GDP$_i$) and mean of GDPRMT is $10^2 * \mu_i^r$ where μ_i^r = mean(Δlog GDPRMT$_i$). Similarly, variance of GDP is $10^4 * \sigma_i^2$ where σ_i^2 = var(Δlog GDP$_i$) and variance of GDPRMT is $10^4 * \sigma_i^{r2}$ where σ_i^{r2} = var(Δlog GDPRMT$_i$). Reported values are the averages at the region level.

Figure 1.10: Remittances as Percent of Gross Domestic Product and Export



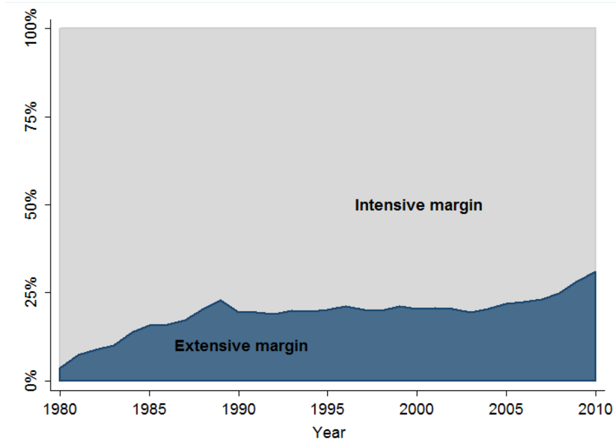
(a) 22 Asian countries



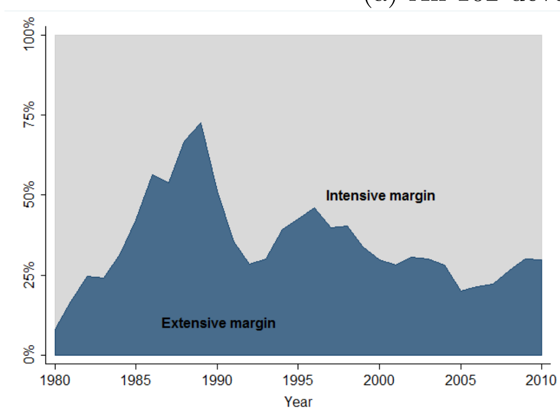
(b) 21 Asian countries (without China)

Note: All variables are measured in current US dollar term. *Source*: World Development Indicators, World Bank.

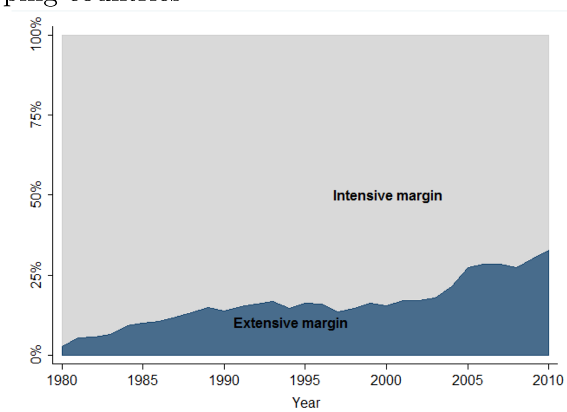
Figure 1.11: Percent Share of Extensive and Intensive Margins in Increase in Real Remittances from 1975



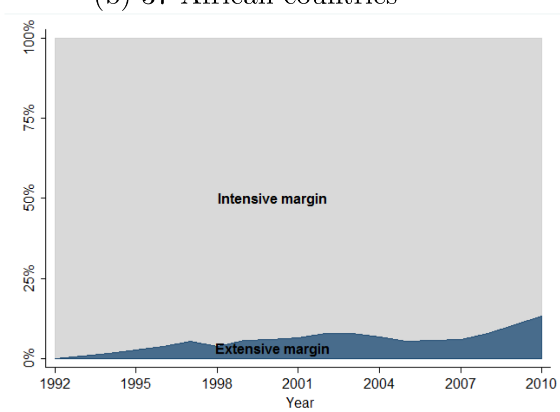
(a) All 102 developing countries



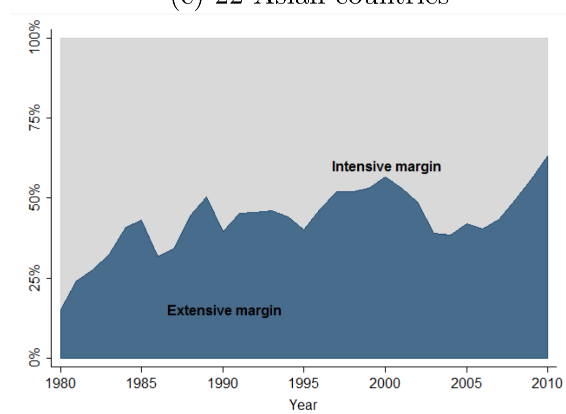
(b) 37 African countries



(c) 22 Asian countries



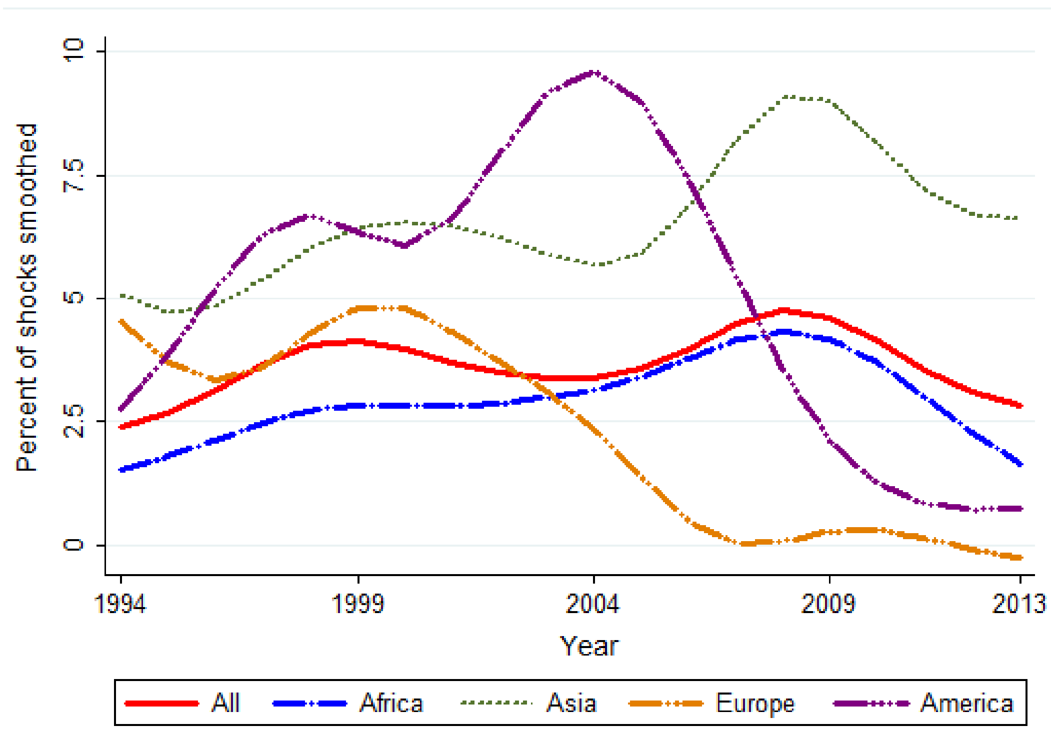
(d) 21 European countries



(e) 22 American countries

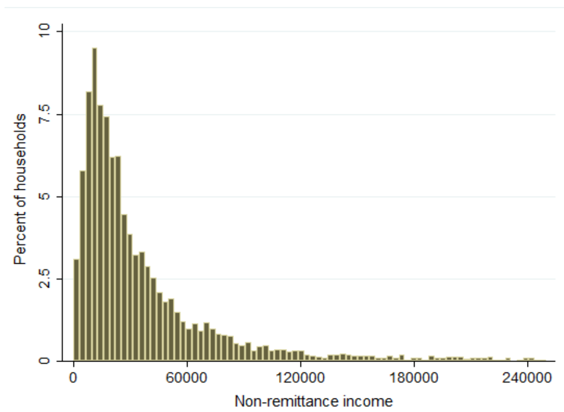
Note: Extensive margin ($margin^R_{ext}$) and intensive margin ($margin^R_{int}$) of remittances are defined as, $margin^R_{ext} = \Delta M_{it} \times rmt_{it-1}$ and $margin^R_{int} = \Delta RMT_{it} - margin^R_{ext}$, where rmt_{it-1}, ΔM_{it}, and ΔRMT_{it} represent remittances per migrant at time $t-1$, changes in migrant stock abroad of country i from time $t-1$ to t, and changes in remittance inflows to country i from time $t-1$ to t respectively. Percent share of extensive and intensive margins explain the dollar importance of the intensive and extensive margins of migrant workers in change in remittances. All changes are in cumulative terms from year 1975.

Figure 1.12: Year by Year Measures of Income Smoothing via Remittances: By Regions (1994-2013)

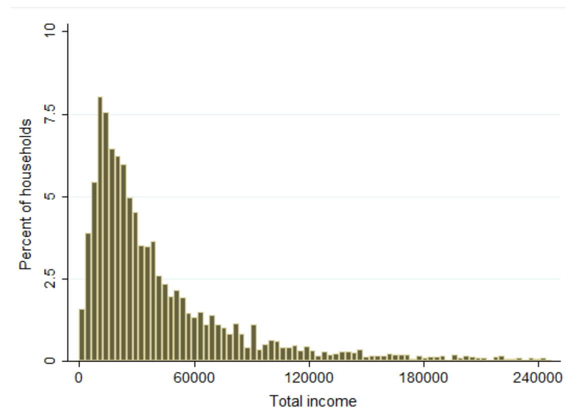


Note: Income smoothing is estimated cross-sectionally in each year and is smoothed by using a Normal kernel with bandwidth equal to 2.

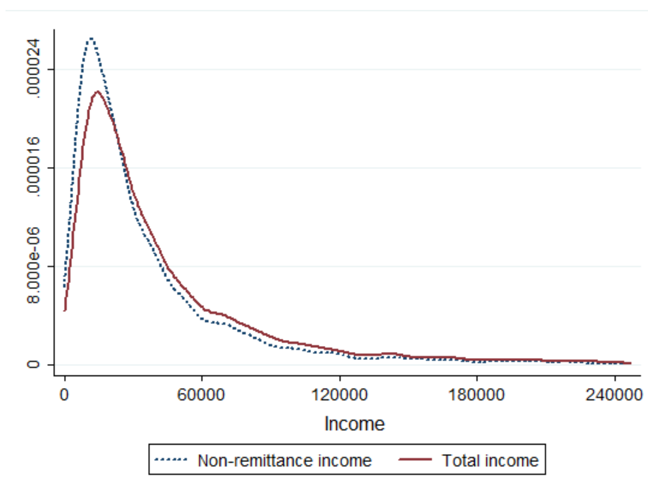
Figure 1.13: Distribution of Non-remittances Income and Total Income in Nepal



(a) Non-remittances income



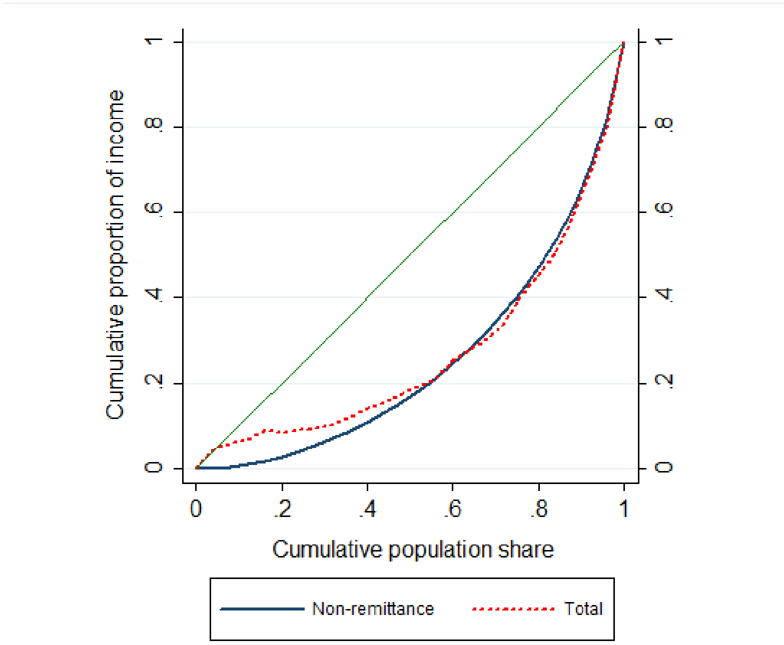
(b) Total income



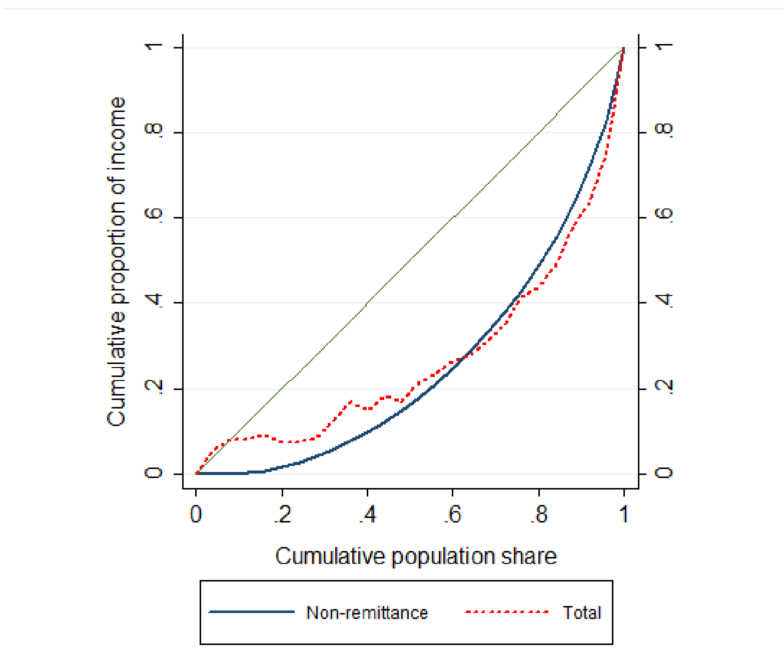
(c) Kernel density (Gaussian) of non-remittances income and total income.

Note: Total income is the sum of non-remittances domestic income and remittances from abroad. Source: Nepal Living Standard Survey-III (2010-11).

Figure 1.14: Lorenz Curve of Non-remittances Income and Total Income in Nepal and Tajikistan



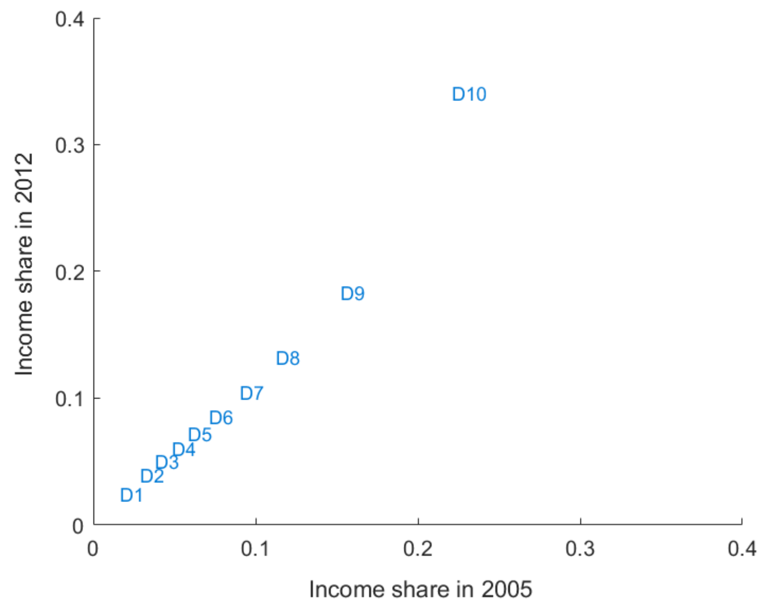
(a) Nepal



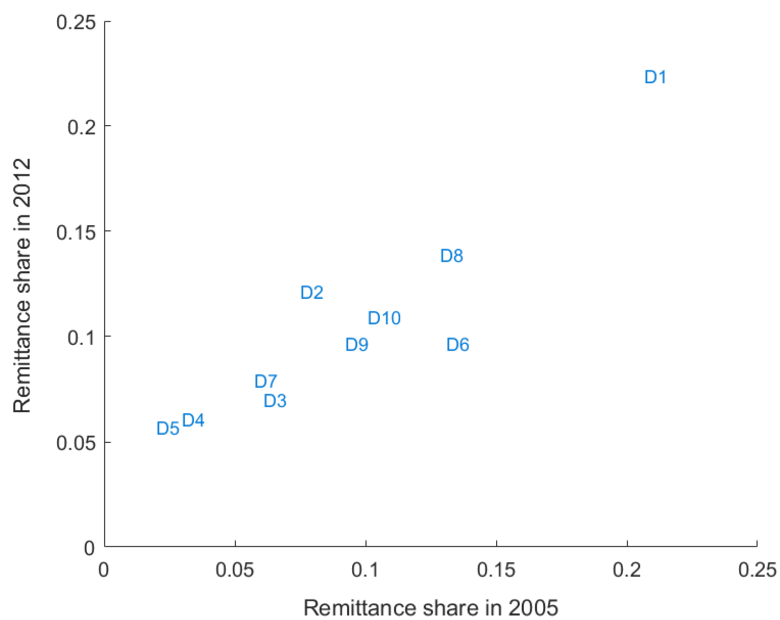
(b) Tajikistan

Note: Total income is the sum of non-remittances domestic income and remittances income from abroad. The construction of non-remittances income is explained in Section 1.8.1 in Appendix.
Source: Nepal Living Standard Survey-III (2010-11), and Tajikistan Living Standards Measurement Survey, 2007.

Figure 1.15: Domestic Income and Remittance Shares by Decile Income Groups of Households in India



(a) Domestic income share

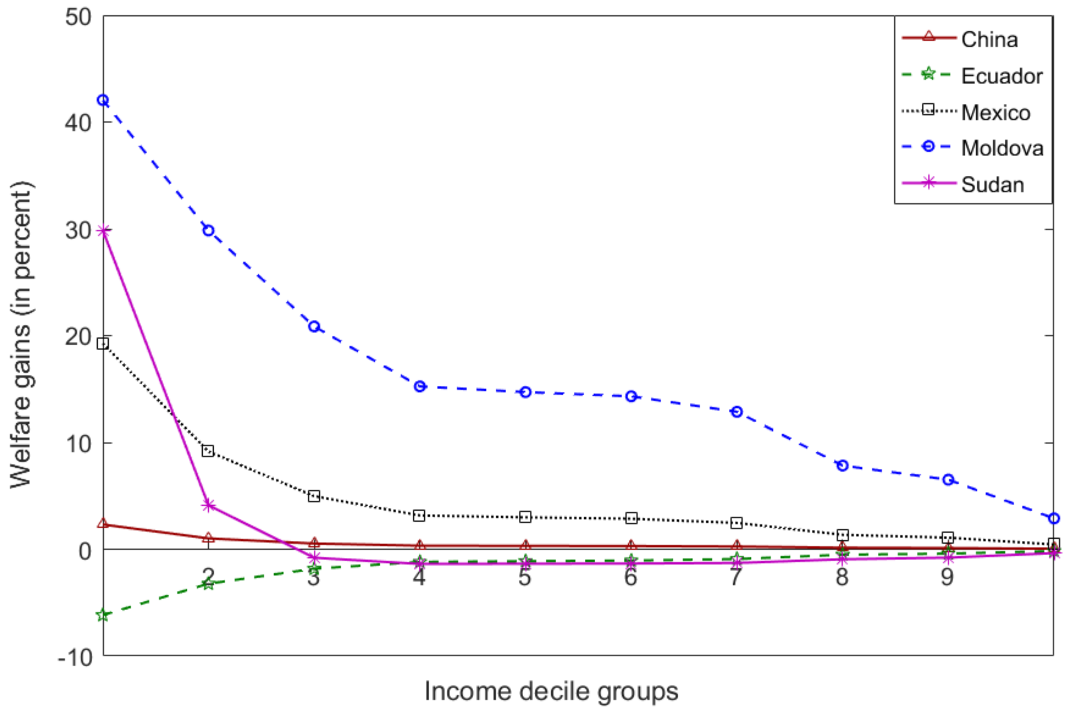


(b) Remittances income share

Note: Out of total 38,514 panel households between between 2005 and 2012, about 680 households received international remittances.

Source: India Human Development Survey, 2005 and 2011/12.

Figure 1.16: Welfare Gains by Income Decile Groups in Selected Countries, 1975-2013



Note: Welfare gains (in percent) are estimated for CRRA utility with risk aversion parameter, $\gamma = 3$ and the discount rate, $\delta = 0.02$..

Chapter 2

Effects of Immigration on Wages: A Reappraisal

2.1 Introduction

Does immigration reduce the real wage of native workers? Are immigrant and native workers imperfectly substitutable in jobs? This paper investigates the effects of immigration on the wages of U.S. native workers at the national level. This is an important topic with lots of policy interest because the share of foreign-born workers in the U.S. labor force has increased significantly from 5.2 percent in 1960 to 16.5 percent in 2014. While a large proportion of these additional foreign-born workers belongs to unskilled group, the real wage of unskilled U.S.-born workers has been stagnated (see Fig. 2.2).[1] Consequently, a large number of studies have examined the effects of immigration on the wages of U.S. native workers over the past two decades, but the existing empirical evidence is mixed and confusing.

Recently, an influential paper by George Borjas (2003), hereafter GB, emphasized the importance of estimating the effects of immigration at the national level. GB

[1] Author's own calculation using U.S. Decennial Censuses from 1960 to 2000 and American Community Surveys 2006 and 2014.

argues that the factor price equalization in the local labor market can pose a serious problem in the cross-city and cross-state analysis of the effects of immigration. Using education and experience skill groups of workers in aggregate production function and the general equilibrium framework, GB finds large negative effects of immigration on the wages. By extending GB framework, Ottaviano and Peri (2012), OP hereafter, show that immigrant and native workers within an education-experience group are imperfectly substitutable and, thus, the effects of immigration on wages are positive but small. However, Borjas, Grogger, and Hanson (2012), BGH hereafter, claim that OP finding of imperfect substitutability between immigrant and native workers is sensitive to the way wages are calculated and the weights used in the regression model, and is, therefore, fragile.

In this paper, I use richly defined skill groups of workers by considering industry- and occupation-specific characteristics of workers in addition to conventionally used education- and experience-specific characteristics of workers. It is quite reasonable to assume that skills are acquired both before and after a person enters the labor market. Since the size of local labor market effects of immigration depends on the degree of elasticity of substitution between immigrant and native workers, it is important to examine the degree of substitutability between immigrant and native workers within a rich set of skill groups of workers based on industry/occupation in addition to education and experience. I make two important plausible assumptions in the paper. First, workers with similar education and experience are more substitutable within an industry/occupation than across industries/occupations due to industry/occupation-specific skills. Second, immigrant and native workers have different language/culture specific skills and different quantitative skills, which may make them imperfectly substitutable. The main contribution of the paper is to provide a new evidence on the substitutability between immigrant and native workers and the wage effects of immigration using better skill groups of workers based on industry, education, experience, and nativity.

Using the data from the U.S. Censuses between 1960 and 2000 and the American Community Survey (ACS) 2006 and 2014, I estimate the elasticity of substitution between immigrant and native workers within the same industry, education, and experience group in contrast to within the same education and experience group in OP.[2] This approach also helps to exploit the variation in labor supply shifts across industries over the study period.[3] My estimation shows that immigrant and native workers are indeed imperfect substitutes. I conduct the sensitivity test of my estimates to different weighting structures and construction of wage earnings under which GBH show that OP finding of imperfect substitutability between immigrant and native workers in OP is fragile. Starting with OP weight, I find that immigrant and native workers are less substitutable within industry-education-experience groups but more substitutable within occupation-education-experience groups. This finding is consistent with the results in Peri and Sparber (2009) in that immigrants specialize in manual-physical intensive occupations whereas natives specialize in communication-language intensive occupations. Depending on wage samples for Male and Female workers and industry or occupation groups considered, the estimated degree of substitution between immigrant and native workers vary between 12 and 33.

I then examine BGH critics on OP finding of imperfect substitutability. BGH argue that if use appropriate regression weights and define the earnings of a skill group as the mean log wage of the group instead of log mean wage, the OP data

[2]Both U.S. Censuses and ACS data are downloaded from IPUMS (Ruggles et al. 2015). Excluding ACS 2014, this is the same data as in BGH and OP.

[3]A close look at the data shows that the inflows of immigrants to the U.S. in recent decades has concentrated in Agriculture, Mining, Construction, and Business Service industries than in Transport and Communication, Wholesale and Retail Trade, and Manufacturing industries (see Table 2.2 and 2.3).

reveal an infinite substitution elasticity between immigrants and natives.[4] When I use BGH weights, the estimated substitution elasticity increases from about 16.9 to 22.2 in the Male sample and from 15.4 to 19.2 in the Male and Female combined sample. Using BGH weight and defining the earnings as the mean log wage (but not including fixed effects), the estimated substitution elasticity increases to about 23.8 in Male sample and 28.6 in Male and Female combined sample. More importantly, all the estimated coefficients are statistically significant at 5 percent level, with most of them significant at the 1 percent level. The corresponding estimates of substitution elasticity in BGH while using education-experience skill groups are 125 in the Male sample and 500 in the Male and Female combined sample, and the coefficients are also not statistically significant, meaning that immigrant and native workers are perfectly substitutable. These results clearly show that industry-specific groups in addition to education-experience groups of workers provide extra variation in the wages and labor supply shifts and allow a better estimate of the substitution elasticity.

The results in this paper show that workers with different experiences are more substitutable within an industry-education group than within an education group with no industry consideration. Similarly, workers across education groups are more substitutable within an industry than across industries. These findings are reasonable because industry and/or occupation choices are often limited by workers' qualifications and skills as opposed to location choices by workers at least in the short run as argued by Friedberg (2001). In contrast to the implicit assumption of perfect substitution between workers with similar education and experience across industries, I find that they are imperfectly substitutable.

Using the estimates of substitution elasticities between different workers by

[4] OP weigh the regression by total employment in each skill group. To BGH, the appropriate weight is the inverse of the sampling variance of the dependent variable, which is the ratio of immigrant-native wages.

industry, education, experience, and nativity from the full sample of data between 1960 and 2014, I calculate the wage effects of immigration over the most recent 1990-2014 period. Similar to OP, I compute both short-run partial direct wage effects and long-run total wage effects of immigration. The partial wage effects capture the elasticity of native wages to immigration within the same skill group, keeping all other variables constant. In other words, it does not take into account the cross-group effects of immigration. Immigration supply shocks in one skill group may increase the productivity and hence the wages of another skill group of workers. I find that the partial direct effects of immigration are about –0.4 percent against –1.1 percent reported in OP during the 1990-2006 period and about –0.7 percent during the 1990-2014 period. Finally, I calculate the long-run total wage effects of immigration by adding all cross-group wage effects and the within group direct partial effects over the 1990-2014 period. One important difference emerges from my estimates comparing to the results in OP. My estimates of long-run negative wage effects on the wage of U.S. unskilled workers are significantly lower than OP's estimates. For example, I find that immigration during 1990-2006 period decreased the wage of U.S. native workers with no high school by about 1.0 percent against 2.0 percent decrease reported in OP. In addition, if one considers the 1990-2014 period, such negative effect are almost not in existence. I find that the immigration during the 1990-2014 has decreased the wage of native workers with no high school by only 0.3 percent.

Looking separately at the industry level, I find that immigration during the 1990-2014 had adverse effects on the wages of native workers in Business and Repair Service, Personal Service, and Agriculture, Mining, & Construction industries. These are the industries that experienced a high growth in immigration inflows over the same period. These are also the sectors that offer jobs which are more manual- and physical-intensive in nature. Immigration over the same period, however, increased the wages of native workers in Manufacturing, Finance and Insurance, and Transportation and Communication industries. Immigration over the 1990-2014 period increased the wages of an average U.S native worker by about 0.6 percent. Overall, I find that immigrant and native workers are indeed imperfect substitutes and the long-run total wage effects of immigration are small but positive.

The rest of the paper is organized as follows: Section 2 develops a theoretical framework, where I introduce the aggregate production function to derive the equations used to estimate the elasticity of substitution between workers. Section 3 discusses the data. In Section 4, I estimate the elasticity of substitution among different groups of workers by industry, education, experience, and nativity. Section 5 discusses the wage effects of immigration, and Section 6 concludes.

2.2 Theoretical Framework

In order to examine the effects of immigration on the wages of U.S. native workers at disaggregated levels, one needs to know the substitutability between different types of workers and the size of inflow of immigrant workers. It is because an influx of immigrants of a certain type may not only cause a downward pressure on the wages of a similar type of native workers but may also create an upward pressure on the wages of other types of native workers. For this purpose, I use the standard structural approach adopted in GB and OP. This approach assumes that the aggregate production function can be represented in terms of a nested CES technology of different types of labor. This production function is widely used in the literature to evaluate how the marginal productivity of a certain type of worker responds to changes in the supply of other types at the national level (see Borjas, 2003; Borjas and Katz, 2007; Katz and Murphy, 1992; Ottaviano and Peri, 2006 & 2012).

While GB uses level of education and years of experience at work to classify worker types, OP added nativity of workers to further categorize workers into different types based on education, experience, and nativity. OP assume that immigrant and native workers within an education-experience group are imperfect substitutes due to different language skills and quantitative skills. In this paper, I define richer skill groups of workers by considering industry- and occupation-specific characteristics of workers in addition to education- and experience-specific characteristics of workers used in GB and OP. I assume that immigrants are a select group with the different language- and culture-specific skills and different quantitative skills due to different schooling system. This makes immigrant and native workers imperfect substitutes even within the same industry and occupation. Similarly, I assume that workers acquire industry- and/or occupation-specific skills after they enter the labor market. This makes workers with same education and experience but across different industry and occupation imperfect substitutes of each other.

2.2.1 Production Function

To begin with, I assume that the U.S. aggregate production is a constant-returns-to-scale Cobb-Douglas combination of capital and aggregate labor:

$$Q_t = A_t L_t^{\alpha} K_t^{1-\alpha}, \tag{2.1}$$

where Q is output, A is exogenous total factor productivity (TFP), K is capital, L is the aggregate labor and $\alpha \in (0, 1)$ is the income share of labor. The subscript t implies that all variables are relative to year t. I argue that the assumption of Cobb-Douglas production function is reasonable because OP have shown in section 2.1 that the implications of this functional form for the real return to capital and the capital-output ratio in the long run have actually been supported by the U.S. data.

In addition, the income share of labor in the long run and across countries has been found reasonably constant (for example, Gollin, 2002).

The aggregate labor L includes the contributions of workers who differ in industry (or occupation), education, experience, and nativity as follows.[5] First, I assume that the labor aggregate L is a CES aggregate of 8 industry-groups of workers:

$$L_t = \left[\sum_{i=1}^{8} \theta_{it} L_{it}^{\frac{\sigma_S - 1}{\sigma_S}} \right]^{\frac{\sigma_S}{\sigma_S - 1}}, \tag{2.2}$$

where L_{it} measures aggregate workers in industry group i at time t, $\sigma_S>0$ is the elasticity of substitution across industry groups of workers, and θ_{it} are time-variant industry-specific productivity levels with $\sum_i \theta_{it} = 1$. Any common factors that affect the productivity of workers in all industries are absorbed in the TFP term A_t. For industrial groups of workers, I consider 8 different industries, namely, Agriculture, mining, and construction, Transportation, communication, and utilities, Wholesale and retail trade, Manufacturing, Finance, insurance, and real estate, Business services, Personal services, and Educational and health services, using the 1-digit industry classification.

The consideration of industry- and/or occupation-specific characteristics of workers while defining skill groups is one of the main contributions of the paper. Both GB and OP assume that workers with a similar level of education and experience are perfectly substitutable across industries. However, it is plausible to argue that skills are acquired both before and after a person enters the labor market. Workers may, therefore, accumulate industry-specific skills over time which makes them

[5] I consider either industry or occupation skill groups, but not both industry and occupation skill groups in order to be parsimonious in the parameter estimates. In addition, this also avoids a large set of missing values. Since all industry and occupation do not have workers of every education and experience skill set, consideration of both industry and occupation groups at the same time results in a large number of missing values.

imperfectly substitutable across industries. As a result, it is hard to argue that workers with similar education are perfectly substitutable across industries. In fact, a study by Blankenau and Cassou (2011) shows that elasticity of substitution between skilled and unskilled workers are considerably different across industries in the U.S., suggesting that industry-specific skill differences affect the extent to which workers substitute each other. I also consider occupation groups of workers to examine the robustness of the measure of elasticity of substitution between immigrant and native workers. Using detail occupation classification 2010 used in U.S. Decennial Census and American Community Survey, I redefine the total 493 occupational categories into 15 broad occupations.[6] In this case, σ_S is the elasticity of substitution across occupation groups of workers and the aggregate labor L_t in Eq. (2.2) is the CES aggregate of 15 occupational groups of workers.

Next, the supply of workers in each industry (L_{it}) is the aggregate of four types of workers based on educational achievements:

$$L_{it} = \left[\sum_{j=1}^{4} \theta_{ijt} L_{ijt}^{\frac{\sigma_E - 1}{\sigma_E}} \right]^{\frac{\sigma_E}{\sigma_E - 1}}, \tag{2.3}$$

where j is an index for educational categories of workers. As in the labor literature, I group workers into four categories so that $j = 1$ denotes high school dropouts, $j = 2$ denotes high school graduates, $j = 3$ denotes college dropouts, and $j = 4$ college graduates. The parameter $\sigma_E > 0$ measures the elasticity of substitution between workers with a different level of education within an industry. I assume that workers with different educational achievements are imperfect substitutes within an industry. Similarly, θ_{ij} represent the industry-education specific productivity level with $\sum_j \theta_{ij} = 1$

[6]The 15 broad occupation groups used in the paper are Management, Business and financial specialist, Computer and mathematical, Engineering, Scientist, researchers and educators, Community and protective services, Legal services, Art and design, Health-care services, Production, Building, maintenance and personal care, Office and administration, Farming, construction and extraction, Installation and repair, and Transportation.

for each i. Any change in θ_{ij} would imply a shift in the relative productivity of education groups of workers within an industry. One of the advantages of the framework used in this paper is while GB and OP allow education-specific technology parameter θ_j to vary over time, I allow industry-education-specific technology parameter θ_{ij} to vary over time. Since I expect workers within an industry group to be closer substitutes than workers across different industry groups, my prior is that $\sigma_E > \sigma_S$.

Similarly, following Card and Lemieux (2001), Borjas (2003), and Ottaviano and Peri (2012), I define the supply of workers in each education group within an industry, L_{ijt}, as a CES aggregate of workers with different experience levels:

$$L_{ijt} = \left[\sum_{k=1}^{8} \theta_{ijk} L_{ijkt}^{\frac{\sigma_X - 1}{\sigma_X}} \right]^{\frac{\sigma_X}{\sigma_X - 1}}, \tag{2.4}$$

where k is an index for experience levels of workers within each industry and education group. Similar to GB and OP, I use experience intervals of five years between 0 and 40, so that $k = 1$ indicates workers with $0-4$ years of experience, $k = 2$ indicates workers with $5-9$ years of experience, and so on. The parameter $\sigma_X > 0$ measures the elasticity of substitution between workers in the same industry and education group but with different experience levels. The technological parameter θ_{ijk} that shifts the relative productivity of experience groups within an industry and education group is assumed to be time invariant. This is richer assumption than the one in GB and OP that education-experience-specific productivity levels are time invariant. Further, θ_{ijk} are standardized so that $\sum_k \theta_{ijk} = 1$ for each j within each i. Workers within an education group are expected to be more substitutable than across different education groups. So, my prior is that $\sigma_X > \sigma_E$, as found in the labor literature.

Finally, similar to OP, I define L_{ijkt} as a CES aggregate of foreign- and U.S.-born workers. Defining the supply of similarly educated and experienced foreign- and U.S.-born workers, respectively, within the same industry by D_{ijkt} and F_{ijkt}, and σ_M

as the elasticity of substitution between them, the CES aggregator at the level of nativity of workers is:

$$L_{ijkt} = \left[\theta^{d}_{ijk} D_{ijkt}^{\frac{\sigma_M - 1}{\sigma_M}} + \theta^{f}_{ijk} F_{ijkt}^{\frac{\sigma_M - 1}{\sigma_M}} \right]^{\frac{\sigma_M}{\sigma_M - 1}}. \tag{2.5}$$

The foreign- and U.S.-born workers-specific productivity levels, denoted by θ^{f}_{ijk} and θ^{d}_{ijk} respectively, are also standardized so that $\sum_{n=d,f} \theta^{n}_{ijk} = 1$. Here again, I follow OP's assumption that foreign-born workers have different language abilities, culture-specific skills, and quantitative skills and hence they are imperfect substitutes for U.S.-born workers in jobs even within an industry or occupation group. A recent study by Fogged and Peri (2015) show that foreign-born workers, in fact, choose a different set of occupations than the native workers in Denmark because of such different productivity characteristics between immigrant and native workers.

In a slightly different context, Borjas, Freeman, and Katz (1997) show that immigrant and native workers seem to concentrate in a different set of industries and the differences in educational attainment are not sufficient to explain this behavior. Table 2.1 also shows that there is a considerable heterogeneity in the ratio of immigrant workers to native workers across industries and occupations. I exploit this variation in the labor supply shift across industries and occupations while estimating the effects of immigration. Similarly, a significant fraction of U.S. immigrants come from Mexico, and countries in Central and South America, and in Asia, which are all developing countries with different industrial mix than in the U.S.[7] It is, therefore, reasonable to consider that these immigrants come not only with different language and quantitative skills as suggested by OP but also with a different set of prior industry-specific skills and experiences. Accordingly, one can expect immigrant and native workers to

[7]For example, the share of immigrants from Mexico, India, China, Philippines, Vietnam, Cuba, Dominican Republic, El Salvador and Guatemala in total immigrants in the U.S. is about 56 percent in 2014 (Auther's own calculation).

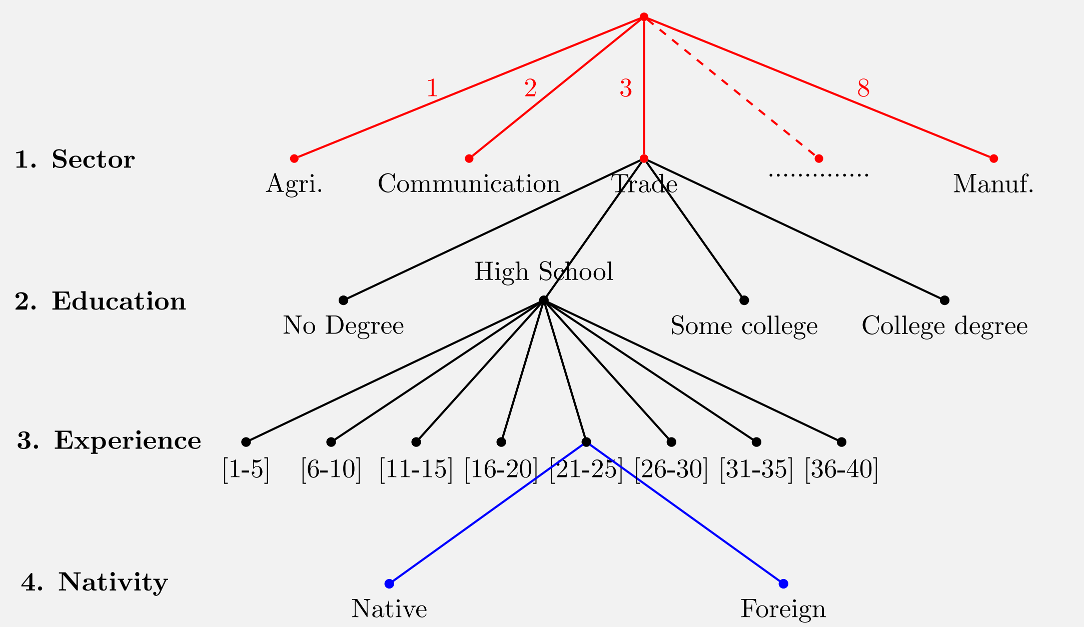


Figure 2.1: CES nesting structure of labor aggregates in the production function.

be less than perfectly substitutable within an industry group. The most important implication of the CES nested structure of industry-groups of workers in Eq. (2.2) is that similarly educated and experienced workers are more substitutable within an industry than across industries.

The complete CES nesting structure of the labor aggregate in the production function (1) is depicted in Figure 2.1. Using the nested structure of labor aggregate in aggregate production function (1), I derive the demand function for each type of worker at a given point of time. The competitive equilibrium wage of each type of worker is then the value of her marginal productivity. Assuming output as the numeraire good, the natural logarithm of the equilibrium wage of U.S.-born workers in industry i with education j and experience k is:

$$\ln w^d_{ijkt} = \ln\left(\alpha A_t \kappa_t^{1-\alpha}\right) + \frac{1}{\sigma_S}\ln L_t + \ln\theta_{it} - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_E}\right)\ln L_{it} + \ln\theta_{ijt}$$
$$- \left(\frac{1}{\sigma_E} - \frac{1}{\sigma_X}\right)\ln L_{ijt} + \ln\theta_{ijk} - \left(\frac{1}{\sigma_X} - \frac{1}{\sigma_M}\right)\ln L_{ijkt} + \ln\theta^d_{ijk} - \frac{1}{\sigma_M}\ln D_{ijkt}. \quad (2.6)$$

where w^d_{ijkt} and D_{ijkt} represent the equilibrium average wage and the total labor input of U.S-born workers, measured in hours worked, respectively. Following GB and OP, I assume that TFP term A_t and parameters θs depend on exogenous technological factors only, meaning that they are independent of the supply of foreign-born workers. Notice that there are 8 skill groups by experience, 4 skill groups by education, and 8 skill groups by industry. All together, there are 256 skill groups by industry, education, and experience.

2.2.2 Effects of Immigration on Wages

The wage equation (2.6) can be used to compute the percentage change in the wage of a certain type of workers due to a percentage change in the supply of another type of workers, given the values of elasticity of substitutions. In other words, I can use this equation to derive the effect of immigration on native wages. The overall impact on wages of natives in group i, j, k depends on the effect of immigration on the marginal productivity of the same group of native workers operating at four different levels as follows.

First, immigration affects the marginal productivity of native workers in group i, j, k by increasing the supply of aggregate labor. This effect operates through $\frac{1}{\sigma_S}\ln L_t$ and is positive due to imperfect substitutability among different types of workers. Second, the supply of immigrants within the same industry also affect the marginal productivity of natives in group i, j, k through the term $-\left(\frac{1}{\sigma_S} - \frac{1}{\sigma_E}\right)\ln L_{it}$.

This is negative if workers with different education within an industry are closer substitutes than workers in a different industry. Third, there is the effect on marginal productivity generated by the supply of immigrants within the same education group in industry i. This effect operates through $-\left(\frac{1}{\sigma_E} - \frac{1}{\sigma_X}\right) \ln L_{ijt}$ and is negative if workers with different experiences within the same industry-education group are closer substitutes than workers with different education group within an industry. Fourth, the supply of immigrants within the same industry-education-experience group directly affects the marginal productivity of workers in group i, j, k by affecting the term $-\left(\frac{1}{\sigma_X} - \frac{1}{\sigma_M}\right) \ln L_{ijkt}$. This effect is negative if foreign-born and U.S.-born workers within the same industry-education-experience group are closed substitutes than workers with different experiences within an industry-education group. Finally, there is an additional effect on the marginal productivity through the term $\ln\left(\alpha A_t \kappa_t^{1-\alpha}\right)$ because the capital-labor ratio may adjust to immigration in the short-run. The total wage effect of immigration on wages of native workers is obtained by aggregating all these effects.[8]

Most of the studies that examine effects of immigration on wage using an area approach often report the effect of immigration on the wages of natives within same education-experience group (and in the same industry), keeping all other aggregates L_{ijt}, L_{it}, L_t, and κ constant (e.g. Borjas, 2003, except section VII).[9] OP call this a *partial effect*, which is different than the total effect on wages. It is obtained by regressing the wage of natives $\ln(w^d_{ijkt})$ on the total supply of foreign-born workers (F_{ijkt}) in the same group i, j, k and controlling for year and education-by-year effects. Denoting the change in the supply of foreign-born due to immigration between two censuses in group i, j, k as $\Delta F_{ijkt} = F_{ijkt+10} - F_{ijkt}$, the partial effects of immigration,

[8]The derivation of each of the effects is presented in Appendix A.
[9]Earlier studies did not consider industry-specific skills of workers.

expressed in terms of percentage variation of native wages ($\Delta w_{ijkt}/w_{ijkt}$), is given by,

$$\Big(\frac{\Delta w_{ijkt}}{w_{ijkt}}\Big)^{partial} = \Big[\Big(\frac{1}{\sigma_M} - \frac{1}{\sigma_X}\Big)\Big(\frac{\mathfrak{s}^f_{ijkt}}{\mathfrak{s}_{ijkt}}\Big)\Big(\frac{\Delta F_{ijkt}}{F_{ijkt}}\Big)\Big], \tag{2.7}$$

where the variables $\mathfrak{s}^f_{ijkt}$ and $\mathfrak{s}_{ijkt}$ are the shares of total wage bill in year t paid to foreign-born workers and all workers in group i, j, k, respectively, such that $\mathfrak{s}^f_{ijkt} = \frac{w^f_{ijkt}F_{ijkt}}{\sum_i\sum_j\sum_k(w^f_{ijkt}F_{ijkt}+w^d_{ijk}D_{ijkt})}$ and $\mathfrak{s}_{ijkt} = \frac{w^f_{ijkt}F_{ijkt}+w^d_{ijk}D_{ijkt}}{\sum_i\sum_j\sum_k(w^f_{ijkt}F_{ijkt}+w^d_{ijk}D_{ijkt})}$.

However, the partial effect in Eq. (2.7) does not capture the cross-group effects of immigration on the wages of native workers in the group i, j, k. Immigration also changes the labor supply of workers in other industry-education-experience groups that affects the productivity and wages of native workers in the group i, j, k. Aggregating all these effects and accounting for the response of capital-labor ratio to immigration as in OP, the total effect of immigration on the wages of U.S.-born workers in group i, j, k is given by the following expression:

$$\begin{aligned}\Big(\frac{\Delta w_{ijkt}}{w_{ijkt}}\Big)^{total} &= \frac{1}{\sigma_S}\sum_{m\in i}\sum_{e\in j}\sum_{x\in k}\Big(\mathfrak{s}^f_{mext}.\frac{\Delta F_{mext}}{F_{mext}}\Big)+\Big(\frac{1}{\sigma_E}-\frac{1}{\sigma_S}\Big)\sum_{e\in j}\sum_{x\in k}\Big(\frac{\mathfrak{s}^f_{iext}}{\mathfrak{s}_{it}}.\frac{\Delta F_{iext}}{F_{iext}}\Big)\\ &+\Big(\frac{1}{\sigma_X}-\frac{1}{\sigma_E}\Big)\sum_{x\in k}\Big(\frac{\mathfrak{s}^f_{ijxt}}{\mathfrak{s}_{ijt}}.\frac{\Delta F_{ijxt}}{F_{ijxt}}\Big)+\Big(\frac{1}{\sigma_M}-\frac{1}{\sigma_X}\Big)\Big(\frac{\mathfrak{s}^f_{ijkt}}{\mathfrak{s}_{ijkt}}.\frac{\Delta F_{ijkt}}{F_{ijkt}}\Big)+(1-\alpha)\frac{\Delta\kappa_t}{\kappa_t}.\end{aligned} \tag{2.8}$$

Notice that there are total 296 cross-group effects produced by immigrants in other groups and a capital-adjustment term that affect the wages of natives in the group i, j, k in Eq. (2.8). There are 8 cross-effects in the single summation that takes into account the fact the supply shocks in all 8 experience groups of workers due to immigration affect the marginal productivity and hence wages of workers in the group i, j, k. Similarly, there are 32 cross-effects in the double summation implying that supply shocks in all 32 education-experience groups due to immigration affect the marginal productivity and hence wages of workers in industry group i. Finally, there are 256 cross-effects in the triple summation capturing the positive effects on the productivity of native workers in the group i, j, k due to the increase in the supply of all types of labor due to immigration.[10]

In addition to the direct partial effects and the cross-group effects, adjustment of capital to immigration also affect wages of workers in the group i, j, k=. OP provide a detail discussion on physical capital adjustment to immigration. They show that aggregate capital-output ratio did not exhibit any trend but the capital-labor ratio grew at a constant rate over the 1960-2004 period in the United States meaning that the U.S. economy follows a balanced growth path in the long run. This implies that immigration does not affect the capital stock of the economy in the long-run due to immediate full adjustment of capital-stock which restores the capital-labor ratio at the pre-immigration level. However, as argued by OP, investors may respond continuously to inflows of labor in the short run. This means immigration may also affect wages of native workers by changing the marginal productivity of capital in the short run. Therefore, the calculation of short-run effects of immigration on wages of native workers should also take into account the possibility of partial capital adjustment to immigration in the short run. Since the focus of this paper is to answer whether foreign-born and U.S.-born workers are imperfectly substitutable or not and if they are substitutable how the consideration of industry-specific skills affect the signs and magnitudes of effects of immigration on wages of native workers in the long-run, this paper will not incorporate the physical capital adjustment to immigration.

[10]See Ottaviano and Peri (2006 & 2012) for a detail on the response of capital-labor ratio to immigration.

2.3 Data

I use the same sources of data and the same rules for defining the variables as OP and BGH. However, I extend the sample period to 2014 and also add industry (occupation) specific skills in the skill set of workers. I, therefore, use data drawn from the 1960-2000 decennial Censuses, and the 2006 and 2014 American Community Surveys. Similar to OP and BGH, I also construct a more restricted wage sample including only full-time workers. A person working at least 40 weeks in the year and at least 35 hours in the usual workweek is defined as a full-time worker. Using 1-digit industry classification 1990 used in U.S. Decennial Census and American Community Survey, I consider 8 broad industry groups of workers, namely, Agriculture, mining, and construction, Transportation, communication, and utilities, Wholesale and retail trade, Manufacturing, Finance, insurance, and real estate, Business services, Personal services, and Educational and health services. Similarly, using detail occupation classification 2010, I redefine the total 493 occupational categories into 15 broad occupations, namely, Management, Business and financial specialist, Computer and mathematical, Engineering, Scientist, researchers and educators, Community and protective services, Legal services, Art and design, Health-care services, Production, Building, maintenance and personal care, Office and administration, Farming, construction and extraction, Installation and repair, and Transportation.

I estimate the parameters of elasticity of substitution using the entire repeated cross-sectional data, 1960-2014. I then use these estimates to compute the effects of immigration on the real wages during the most recent period, 1990-2014. This enhances the comparability of my results with that of OP, who focus on the 1990-2006 period.

Table 2.1 presents the summary statistics of the mean weekly real wage of natives (column 2) and mean relative employment of immigrants to native workers (column 4) during the 1960-2014 period. One can clearly observe that the relative employment of immigrants is uneven not only across education groups but also across industry and occupation groups. The education and health related industry have the lowest relative employment of immigrants whereas the personal service industry provides the highest relative employment to immigrants. Similarly, the relative employment of immigrants is significantly different across various occupations. However, the mean weekly real wage of natives is not necessarily the lowest in the sector with the highest relative employment of immigrants.

Table 2.2 and 2.3 report the percentage change in labor supply due to new immigrants, measured in hours worked, (column 3) and the percentage change in weekly wages of natives (column 4) for each industry-education group over the period 1990-2014.[11] The column 3 shows that there is a wide variation in the labor supply shifts due to immigration across different industry-education groups. Workers with no high school degree experienced the largest percentage increase in labor supply (21.5 percent to 40.3 percent) due to immigration irrespective of the groups of workers by industry. Similarly, agriculture, mining, and construction industry experienced the largest percentage increase in the labor supply (14.4 percent) due to immigration while manufacturing industry experienced the smallest percentage increase in the labor supply (5.4 percent) due to immigration over the period 1990-2014. Similarly, column 4 of Table 2.2 and 2.3 show the percentage change in the weekly real wages of native workers within each industry-education group over the period 1990-2014. While comparing columns 3 and 4, one can see that there is no strong negative correlation between an increase in the share of immigrants in the U.S. labor force and the changes in the real wages of U.S. native workers. While workers in some

[11] Table 2.2 and 2.3 here are similar to the Table 1 in OP which presents immigration and changes in native wages by education-experience groups over the period 1990-2006.

industry-education groups experience negative wage growth, workers in other groups experience positive wage growth. The negative wage growth is concentrated typically among low-skilled workers. In the following sections, I estimate the elasticity of substitution between workers of different types by industry, occupation, education, experience, and nativity to formally examine how immigration affects the wages of U.S. native workers.

2.4 Estimates of Elasticity of Substitution

2.4.1 Place of Birth

I first estimate the elasticity of substitution between equally skilled immigrants and natives. For this, I proceed as follows. Using the assumption that wage equals the value of marginal product, the nested CES production function framework in Section 2 also enables to derive the equilibrium wage for immigrants in industry i with education j and experience k. The natural logarithm of the ratio of the wages of foreign-born workers to U.S.-born workers is then,

$$\ln\Big(\frac{w^f_{ijkt}}{w^d_{ijkt}}\Big) = \ln\Big(\frac{\theta^f_{ijkt}}{\theta^d_{ijkt}}\Big) - \frac{1}{\sigma_M}\ln\Big(\frac{F_{ijkt}}{D_{ijkt}}\Big), \tag{2.9}$$

where Eq. (2.9) defines the relative labor demand for immigrants and natives in group i,j,k in Census year t. Here, w^f_{ijkt} and w^d_{ijkt} are the average wages of immigrants and natives in group i,j,k and F_{ijkt} and D_{ijkt} are the corresponding hours worked. I assume that the relative productivity, $\ln(\theta^f_{ijkt}/\theta^d_{ijkt})$, can be represented as $\psi_{ijk} + \psi_t + \epsilon_{ijkt}$, where ψ_{ijk} is a set of 256 industry-education-experience effects, ψ_t is a set of seven year effects, and ϵ_{ijk} is the mean-zero random variables. I can then estimate the elasticity of substitution between immigrants and natives by running the following regression equation:

$$\ln\left(\frac{w^f_{ijkt}}{w^d_{ijkt}}\right) = \psi_{ijk} + \psi_t - \frac{1}{\sigma_M}\ln\left(\frac{F_{ijkt}}{D_{ijkt}}\right) + \epsilon_{ijkt}. \tag{2.10}$$

I assume that after allowing the relative productivity term to have 256 industry-education-experience effects and a common component of variation over time, the remaining time variation in relative productivity represented by ϵ_{ijkt} is independent of relative labor supply. Under this assumption, the estimates of $1/\sigma_M$ are consistent. As argued by OP, these assumptions seem reasonable because any group specific variation in efficiency is canceled out since I am using ratios of wages and labor supply within industry-education-experience groups. For example, any biased technological change affecting the productivity of workers in manufacturing industry (or more educated workers) relative to agriculture and construction industry (or to less educated workers) are washed out in the ratios. In addition, my framework allows for a richer set of fixed effects to control for unobserved differences in relative productivity by industry-education-education skill groups.

Table 2.4 reports the estimated values of $-1/\sigma_M$ under different specifications. The method of estimation is Least Squares. In all specifications, I weigh each cell by OP's original weights, i.e., total employment of each (industry-)education-experience cell. The weighted least square help down-weigh the cells with large sampling errors because of their small sample size (Ottaviano and Peri, 2012, p.170). I first estimate $-1/\sigma_M$ using education-experience skill groups between 1960 and 2006 to replicate OP's estimates reported in column 2 of Table 2. Column 1 of Table 2.4 presents my estimates which are very similar to OP's estimates. For example, OP's estimate of $-1/\sigma_M$ using wage sample for male workers is –0.033 while my estimate for the same wage sample is –0.030. This small discrepancy arises because OP failed to exclude self-employed in the calculation of average weekly wage of the group as highlighted by BGH (p. 201). The robust standard errors, clustered by education-experience cells, are also very similar. The rest columns in Table 2.4 shows how the parameter estimates of $-1/\sigma_M$ changes when one extends study period to most recent period 2014 and adds industry and occupation skill groups. The estimated coefficients reported in column 2 of Table 2.4 are about 50 percent larger in magnitude than the ones reported in column 1. This might suggest that natives are specializing in a different set of skills and occupations over time to mitigate the adverse impacts of immigration. As a result, immigrants and natives become more imperfect substitutes over time. The estimated coefficients are even larger by about 20 percent in column 3 when I add industry groups of workers. It is important to note that the standard errors are significantly smaller when adding industry group, suggesting that coefficients are better estimated while adding industry groups. These results suggest that immigrants and natives are less substitutable when one extends the sample to include the longer time period and adds industry groups of workers.

I also use 14 occupation groups of workers instead of industry groups to check the robustness of my estimates of $-1/\sigma_M$. The estimated coefficients reported in column 4 are now smaller than the ones reported in column 3. This finding suggests that immigrants and natives are more substitutable within the same occupation than within the same industry. This is a reasonable finding because immigrants and natives may choose different occupations within an industry. It is important to note that the estimates of $-1/\sigma_M$ are all significant within 1 percent level of significance with much lower standard errors than in the case of OP. The estimates are robust across different wage samples, for example, male wage sample, female wage sample, the pool of male and female wage sample, and for male wage sample but labor supply measured as employment, as reported in Table 2.4. Moreover, the estimates are robust and statistically significant with and without fixed effects and also with and without using weights (see columns 1 through 3 in Table 2.5). Similarly, the estimates are also robust while using wage sample that consists of only full-time workers as reported in column 4 through 6 in Table 2.5.

However, BGH argued that OP's estimates of imperfect substitution between immigrants and natives are fragile on four grounds (see Section 3 of Borjas, Grogger, and Hanson, 2012 for a detail on it). First, OP fail to exclude the self-employed while calculating the average weekly wage of the group. Correcting for this results in an increase in the estimate of the elasticity of substitution between immigrants and natives by about 15 percent. However, my estimates reported in Table 2.4 and 2.5 are already corrected for it. Second, BGH argue that the appropriate weight is the inverse of the sampling variance of the dependent variable, i.e. wage ratio (BGH weight, hereafter), not the total employment in an education-experience cell (OP weight, hereafter). BGH shows that the use of BGH weight causes the estimates of $-1/\sigma_M$ to fall from –0.033 and –0.024 (see column 2 of panel A of Table 2 in OP) to –0.013 and –0.011 (see row 2 of column 3 of Table 1 of BGH) in the samples of male and the combined sample of male and female respectively. In addition, these coefficients are no longer significant. As a result, the implied elasticity of substitution increased from 30 to 77 for male and from 42 to 91 for the combined sample of male and female. Note that these estimations include education-by-experience and time fixed effects. I estimate $-1/\sigma_M$ using both BGH weights and OP weights using industry-education-experience cells over the period 1960-2014 and my results are quite different. The estimated coefficients are presented in Table 2.6. In the sample of all workers in row 1 and column 2 and 3, the estimated coefficient decreases from –0.059 to –0.045 for male and from –0.065 to –0.052 for the combined sample of male and female when using BGH weights instead of OP weights. That means, the implied elasticity of substitution increases from 17 to only 22 for male and from 15 to 19 for the combined sample of male and female. My estimated coefficients are significant within 1 percent level in column 3 even when I use BGH weights in contrast to BGH findings of insignificant coefficients. Note that my estimation includes industry-education-experience and time fixed effects.

Third, BGH argues that the standard approach in the literature is to use the mean of log weekly earnings instead of the log of mean weekly earnings as in OP. When the dependent variable is the difference in mean log immigrant wages and mean log native wages and using the corrected appropriate BGH weights, the estimated coefficients with no fixed effects in BGH are –0.008 for male and –0.002 for the combined sample of male and female (see row 3 of column 1 of Table 1 in BGH). These coefficients are no longer significant. Similarly, the implied elasticity of substitution is now 125 for male and 500 in the combined sample of male and female. In contrast to BGH findings, my estimated coefficients for the same sample, as reported in row 2 of column 1 in Table 2.6, are –0.029 and –0.040 respectively and both coefficients are statistically significant at 1percent level. The implied elasticity of substitution is now 35 for male and 25 for the combined sample of male and female.

Forth comment by BGH regarding the fragility of OP findings hinges on controlling for skill-group and period fixed effects. Since the dependent variable is the log of relative wages in OP setting and the difference in immigrant-native log wages in BGH setting, any factor that affects both immigrant and native labor demand equally is automatically washed out. However, any systematic differences in the composition of natives and immigrants within skill groups and any such differences that evolve over time may affect the relative wages, leading to a spurious correlation between relative wages and relative employment. As argued by BGH, one solution to this problem is to control for skill-group and period fixed effects. When controlling for education by experience and period fixed effects in combination with the mean of log wages and BGH weights, the estimated coefficients turned out to be 0.008 for male and 0.001 for combined sample of male and female in row 3 of column 3 in Table 1 in BGH. This implies that the elasticity of substitution is effectively infinite. In my estimations where I control for industry-by-education-by-experience and period fixed effects, these coefficients are –0.057 and –0.056 respectively (see row 2 of column 3 in Table 2.6), where the later coefficient for combined male and female sample is still significant at 5 percent level. These estimated parameters still suggest an imperfect elasticity of substitution between immigrants and natives. In addition, BGH argue that there can be ample statistical grounds for including education-year and experience-year fixed effects. Including these additional fixed effects also makes OP findings of imperfect elasticity fragile. However, including a full set of fixed effects results in a significant loss of the degree of freedom, for example, there will be 122 dummies for 192 total observations. In other words, too many fixed effects may eat up most of the variations in data.

The results in this section indicate that all of the four arguments put forward by BGH to show OP's finding of imperfect elasticity of substitution between immigrants and natives as fragile do not hold true in my estimation when I use industry-education-experience groups of workers. I also use 14 broad occupation groups instead of 8 industry groups to check the robustness of my findings of imperfect elasticity of substitution. The estimated coefficients are presented in Table 2.7, which also provide a clear evidence of imperfect substitution between immigrants and natives within occupation-education-experience cells as well.

Finally, Tables 2.8 and 2.9 shows how the elasticity of substitution between immigrants and natives varies across industry, education, and experience groups. The estimated coefficients of $-1/\sigma_M$ when all workers are used to construct the wage sample are presented in columns 1 through 2 while the estimated coefficients obtained from using only full-time workers are presented in column 3 through 4. Results in panel 1 show that immigrant and native workers are less substitutable in agriculture, mining, and construction than in other industries. Immigrant and native workers are perfectly substitutable in education and health and finance, insurance, and, real estate sectors. Panel 2 shows that immigrant and native workers are imperfectly substitutable in all education groups except college graduates. For different experience groups also, immigrants and natives are imperfectly substitutable (see panel 3).

To sum up, four important results emerge from the estimates reported in Table 2.6 through 2.9. First, immigrants and natives appear to be more substitutable when using BGH weights than using OP weights. Second, the estimated coefficients $-1/\sigma_M$ are significantly negative at the 1 percent level in most of the cases irrespective of the BGH and OP weights used. Third, immigrants and natives with similar education and experience within an industry are imperfectly substitutable in all industries except education and health service related industry and finance, insurance, and real estate related industry. Fourth, the estimated values range between –0.014 to –0.057 in Table 2.6 and 2.7 while using BGH weights and considering industry-education-experience and occupation-education-experience skill groups of workers. Most of them cluster around –0.04 implying estimates of σ_M in the vicinity of 25. So, I find that immigrants and natives are about 1/4th more substitutable when considering industry-education-experience skill groups and applying appropriate weights as suggested by BGH. I, therefore, conclude that immigrants and natives are indeed imperfect substitutes. My results suggest that the consideration of industry and/or occupation groups of workers is important while estimating the elasticity of substitution between immigrants and natives, and hence evaluating the effects of immigration on the wages of natives.

2.4.2 Industry, Education, and Experience

The rest of the sections in this paper is directed towards evaluating the long run impact of immigration on the wages of U.S. native workers. Moreover, the empirical framework of my analysis is similar to OP. Now, I use the estimated value of the fixed effects ψ_{ijk} to get the estimated value of the systematic, time-invariant, components of the efficiency terms θ^f_{ijk} and θ^d_{ijk}as follows:

$$\hat{\theta}^f_{ijk} = \frac{exp(\hat{\psi}_{ijk})}{1 + exp(\hat{\psi}_{ijk})}, \qquad \hat{\theta}^d_{ijk} = 1 - \hat{\theta}^f_{ijk}.$$

Then, using the estimated values $\hat{\theta}^f_{ijk}$, $\hat{\theta}^d_{ijk}$, and $\hat{\sigma}_M$, I construct the aggregate labor input in Eq. (2.5) as $\hat{L}_{ijkt} = \left[\hat{\theta}^d_{ijk} D_{ijkt}^{\frac{\hat{\sigma}_M - 1}{\hat{\sigma}_M}} + \hat{\theta}^f_{ijk} F_{ijkt}^{\frac{\hat{\sigma}_M - 1}{\hat{\sigma}_M}}\right]^{\frac{\hat{\sigma}_M}{\hat{\sigma}_M - 1}}$. I can then calculate the corresponding equilibrium average wage for each industry-education-experience group i, j, k,

$$\ln \overline{W}_{ijkt} = \ln\left(\alpha A_t \kappa_t^{1-\alpha}\right) + \frac{1}{\sigma_S} \ln L_t + \ln \theta_{it} - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_E}\right) \ln L_{it} + \ln \theta_{ijt} - \left(\frac{1}{\sigma_E} - \frac{1}{\sigma_X}\right) \ln L_{ijt} + \ln \theta_{ijk} - \frac{1}{\sigma_X} \ln L_{ijkt}, \quad (2.11)$$

where $\overline{W}_{ijkt}$ is the average wage paid to workers in the industry-education-experience group i, j, k and $\overline{W}_{ijkt} = w^f_{ijkt}(F_{ijkt}/L_{ijkt}) + w^d_{ijkt}(D_{ijkt}/L_{ijkt})$. I then use Eq. (2.11) to estimate the parameter $-1/\sigma_X$. In the empirical estimation, I include period fixed effects ϕ_t to control for the variation in the common aggregate terms $\ln\left(\alpha A_t \kappa_t^{1-\alpha}\right) + \frac{1}{\sigma_S} \ln L_t$. Similarly, I use industry by period fixed effects to control for the variation in the term $\ln \theta_{it} - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_E}\right) \ln L_{it}$, industry by education by period fixed effects to control for the variation in the term $\ln \theta_{ijt} - \left(\frac{1}{\sigma_E} - \frac{1}{\sigma_X}\right) \ln L_{ijt}$, and industry by education by experience to control for the variation in the term $\ln \theta_{ijk}$. I, therefore, estimate $-1/\sigma_X$ by implementing the following Eq.,

$$\ln \overline{W}_{ijkt} = \phi_t + \phi_{it} + \phi_{ijt} + \phi_{ijk} - \frac{1}{\sigma_X} \ln \hat{L}_{ijkt} + \epsilon_{ijkt}, \tag{2.12}$$

where the term ϵ_{ijkt} represents industry-education-experience specific random disturbance. I assume that industry-education-experience specific productivity terms are constant over time, which is similar to the assumption of constant education-experience specific productivity terms in GB, OP and Borjas and Katz (2007). However, the nested-CES structure in this paper allows for a richer set of group-specific productivities than in GB and OP. For example, the framework in GB and OP allows for 32 systematic variations in education-experience specific productivities. My framework allows for 256 systematic variations in industry-education-experience specific productivities. One needs to control for these systematic variations in group-specific productivities because they might be correlated with group specific measures of labor hours worked. Failures to do so result in inconsistent estimates. In contrast to GB and OP, I also control for the experience by period effects in estimating $-1/\sigma_X$. The identifying assumption here is that after controlling for systematic shifts in demand due to variation in TFP, capita-labor ratio, and group specific productivities, the remaining variation in the employment of immigrant worker is due to supply shifts. So, a number of immigrants in each group i, j, k (i.e. F_{ijk}) is an instrument for the size of the workforce ($\hat{L}_{ijk}$) in that group and the method of estimation is 2SLS.

OP consider four different nesting structures in the CES production function (see p. 163 in OP) and document that a nesting structure with four narrowly defined education groups (no degree, high school, some college, and college degree) within two broadly defined education group, namely low-skilled and high-skilled group, should be adopted in the immigration literature. In OP paper, the positive effects of immigration during 1990-2006 on the wages of U.S. native workers even with less than high school arises due to this particular nesting structure. It is because of this nesting structure, following Card (2009, p.2), assumes that workers with no school degree are perfect substitutes for those with a high school degree. As a result, as argued by BGH, the impact of low-skilled immigrants will be diffused across a broad segment of the labor market and thus the estimated effects of immigration on wages will be small. However, the existing literature provides less evidence on the degree of elasticity of substitution between these two skill groups of workers. BGH also suggest that one needs to take more caution while making this assumption because empirical results are sensitive on how the changes in demand that affect workers with no degree and high school degree differently are controlled for. I, therefore, use only four narrowly defined education skill groups of workers throughout this paper. Similarly, two broad experience groups, namely Young (with potential years of experience less than 20) and Old (with potential years of experience between 21 and 40) used in OP are also not considered as they are already shown not preferred by the data in OP.

Table 2.10 presents the estimates of substitution elasticity between workers with different experiences, $-1/\sigma_X$, using 2SLS estimation for the sample of male only, female only, male and female pooled, and male employment instead of hours worked respectively. The estimates using OP weights are reported in column 1 and those using BGH weights are reported in column 2. The estimated coefficients of $-1/\sigma_X$ are significant at the 1percent level in all samples except in the case of female sample. The female wage samples are found to be noisy in both OP and BGH. While comparing the estimates in Table 2.10 to the estimates in column 1 of Table 3 (p.178) in OP, one can see that the estimated values of $-1/\sigma_X$ with industry-education-experience groups of workers are about one-third to one-half of the estimates with only education-experience groups. This means that workers with similar education within an industry but with different experiences are about 30percent to 50percent more substitutable than in the case when one does not consider industry specific skill groups. The estimated value of $-1/\sigma_X$ is about –0.09 when I use OP weight and about –0.07 when I use BGH weight. When I take the average of these estimates (i.e. –0.08), the implied σ_X is about 12. This apparently seems too high estimate compared to existing available estimates in the literature. However, it is important to note that most of the existing studies consider only education-experience skill groups. Yet, my estimates of σ_X are close to a lower limit of several studies, for example, –0.080 in Welch (1979, Table 7) and –0.107 in Card and Lemieux (2001, Table V).

Now using the estimate of σ_X and obtaining the estimates θ_{ijk} from the industry-education-experience fixed effects in regression (12), I construct the CES composite $\hat{L}_{ijt}$ as:

$$\hat{L}_{ijt} = \left[\sum_{k=1}^{8} \hat{\theta}_{ijk} L_{ijkt}^{\frac{\hat{\sigma}_X - 1}{\hat{\sigma}_X}} \right]^{\frac{\hat{\sigma}_X}{\hat{\sigma}_X - 1}}, \tag{2.13}$$

where $\hat{\theta}_{ijk} = \frac{exp(\hat{\phi}_{ijk})}{\sum_k exp(\hat{\phi}_{ijk})}$. The equilibrium average wage for industry-education group i, j (i.e. $\overline{W}_{ijt}$) is then:

$$\ln \overline{W}_{ijt} = \ln\left(\alpha A_t \kappa_t^{1-\alpha}\right) + \frac{1}{\sigma_S} \ln L_t + \ln \theta_{it} - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_E}\right) \ln L_{it} + \ln \theta_{ijt} - \frac{1}{\sigma_E} \ln L_{ijt}, \tag{2.14}$$

where $\overline{W}_{ijt} = \sum_k \overline{W}_{ijkt} \left(\frac{L_{ijkt}}{L_{ijt}}\right)$. I follow the same strategy as before to control for TFP, capital-labor ratio, labor aggregates, and group specific productivity terms. In particular, I use period fixed effects δ_t to absorb the variation in the common aggregate terms $\ln\left(\alpha A_t \kappa_t^{1-\alpha}\right) + \frac{1}{\sigma_S} \ln L_t$, industry by period fixed effects δ_{it} to control for the variation in the term $\ln \theta_{it} - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_E}\right) \ln L_{it}$, and industry-education time trends $(TimeTrend)_{ij}$ to control for the systematic variation in the industry-education specific productivity term $\ln \theta_{ijt}$. Having controlled for those systematic components, I assume that the rest of the variation in the employment of immigrant worker within a group is due to supply shifts. Under this identifying assumption, $\ln F_{ijt}$ (where $F_{ijt} = \sum_k F_{ijkt}$) is the instrument for $\hat{L}_{ijt}$. In other words, I estimate -1/σ_E by running the following regression by 2SLS:

$$\ln \overline{W}_{ijt} = \delta_t + \delta_{it} + (TimeTrend)_{ij} - \frac{1}{\sigma_E} \ln \hat{L}_{ijt} + \epsilon_{ijt}. \tag{2.15}$$

Both OP ad BGH provide estimates of –1/σ_E using data from Census (including ACS) and Current Population Survey (CPS) data. However, I estimate σ_E using Census (including ACS) data only. Table 2.11 reports the estimates of –1/σ_E using OP weights in column 1 and using BGH weights in column 2. I estimate –1/σ_E using the sample of male only, female only, male and female pooled, and male employment instead of hours worked respectively as in OP. Using OP weights in column 1, the estimated coefficients vary between –0.13 and –0.19, with most of them significant at the 5percent level. When using BGH weights, the estimated coefficients vary between –0.14 and –0.16 in the case when they are significant. However, most them are in the neighborhood of –0.17 with implied σ_E of about 5.88. The implied estimate of σ_E in this paper is obviously larger than the ones in OP (see column 2 and 3 in Table 4 in OP, where the estimated value of σ_E ranges between 4.5 and 2.3). Accordingly, it is also higher than the estimate of 1.3 in GB and the estimate of 2.4 in Borjas and Katz (2007). One should remember that the estimates of σ_E in this paper are the elasticity of substitution between workers with a similar level of education but within an industry. Intuitively, this implies that workers with a similar level of education are more substitutable within an industry than across industries. The only comparable results that exist in the literature is by Blankenau and Cassou (2011). They examined the elasticity of substitution between skilled and unskilled labor across 13 different industries, where the estimated values range between 2.2 to 500, with the median value of 7.98.

Following the same procedure as before, I finally construct the CES labor aggregate at the industry level, $\hat{L}_{it}$, by using the estimate of σ_E and the estimates of θ_{ij} from industry-specific fixed effects in regression (15). That is,

$$\hat{L}_{it} = \left[\sum_{j=1}^{4} \hat{\theta}_{ij} L_{ijt}^{\frac{\hat{\sigma}_E - 1}{\hat{\sigma}_E}} \right]^{\frac{\hat{\sigma}_E}{\hat{\sigma}_E - 1}}, \tag{2.16}$$

where $\hat{\theta}_{ij} = \frac{exp(\hat{\delta}_{ij})}{\sum_j exp(\hat{\delta}_{ij})}$ and $\overline{W}_{it} = \sum_j \overline{W}_{ijt} \left(\frac{L_{ijt}}{L_{it}} \right)$. Using the marginal cost pricing condition, the equilibrium average wage for industry group of worker ($\overline{W}_{it}$) is:

$$\ln \overline{W}_{it} = \ln \left(\alpha A_t \kappa_t^{1-\alpha} \right) + \frac{1}{\sigma_S} \ln L_t + \ln \theta_{it} - \frac{1}{\sigma_S} \ln L_{it}. \tag{2.17}$$

In the empirical estimation, I run the following regression equation

$$\ln \overline{W}_{it} = \vartheta_t + (TimeTrend)_i - \frac{1}{\sigma_S} \ln \hat{L}_{it} + \epsilon_{it}, \tag{2.18}$$

where the period fixed effects ϑ_t absorb the variation in the term $\ln \left(\alpha A_t \kappa_t^{1-\alpha} \right) + \frac{1}{\sigma_S} \ln L_t$ and industry-specific time trends $(TimeTrend)_i$ absorb the systematic variation in the efficiency term $\ln \theta_{it}$. Having controlled for these potential systematic shifts in demand due to TFP, capital-labor ratio, and industry-time specific productivity level, I again assume that the remaining change in the employment of immigrant within an industry group is due to a supply shift. This means $\ln F_{it}$ can be an instrument for $\ln L_{it}$ and I estimate Eq. (2.18) by 2SLS. Table 2.12 reports the estimates of values of $-1/\sigma_S$ using both OP and BGH weights and across the sample of male only, female only, male and female pooled, and male employment instead of hours worked respectively. The estimates are all significant and vary between –0.32 and –0.44, with the average value of –0.38. The implied value of elasticity of substitution between workers of different industries is, therefore, about 2.63. This suggests that workers across different industries are slightly more substitutable than the workers across different education level when one does not consider industry groups of workers. It is because the estimated value of σ_E in most commonly cited papers, for example, Katz and Murphy (1992), Angrist (1995), Johnson (1997), and Krusell et al. (2000), ranges between 1.5 and 2.5.

2.5 Effects of Immigration on Wages: 1990-2014

2.5.1 Short-run Partial Effects on Wage

As highlighted in OP, the nested-CES model developed in Section 2 allows distinguishing between partial and total wage effects of immigration. Section 2.2 provides a detail explanation on this. The partial wage effects capture the elasticity of native wages to immigration within the same skill group i, j, k, keeping all other variables, for example, TFP, capital-labor ratio, aggregate labor composites in other skill groups as well as in skill groups at the higher ladder of CES nesting structure, constant. In other words, it does not take into account the cross-group effects of immigration on the wages of native workers in the group i, j, k. Most of the empirical findings on cross-city and cross-state evidence are only the partial wage effects of immigration.

Using the expression (7) in Section 2.2 and since $\left(\frac{\mathfrak{s}^f_{ijkt}}{\mathfrak{s}_{ijkt}}\right)\left(\frac{\Delta F_{ijkt}}{F_{ijkt}}\right) = \frac{\Delta F_{ijkt}}{(D_{ijks}+F_{ijkt})}$ when the share of immigrant in employment in i, j, k is similar to its share of wages in group, the partial effect $\left(\frac{\Delta w_{ijkt}}{w_{ijkt}}\right)^{partial}$ is given by $\left(\frac{1}{\sigma_M} - \frac{1}{\sigma_X}\right)\frac{\Delta F_{ijkt}}{(D_{ijks}+F_{ijkt})}$. Here, $\frac{\Delta F_{ijkt}}{(D_{ijks}+F_{ijkt})}$ measures the percentage increase in the inflow of immigrants relative to the total initial employment of all workers. Focusing on the 1990-2014 period, the inflow of immigrants in this period increased by about 19percent relative to total initial employment in 1990. Now, looking at the estimated values of $-1/\sigma_M$ and $-1/\sigma_X$ in Tables 2.6 and 2.10 for the sample of Male only and Male and Female pool, the values of $\left(\frac{1}{\sigma_M} - \frac{1}{\sigma_X}\right)$ vary between –0.012 and –0.028. This suggests that partial effects of immigration on wages of average U.S. native workers would be between

–0.23percent and –0.53percent. These values are only about one-fourth of the partial negative effects reported in OP. Therefore, the consideration of industry-education-experience skill groups of workers results in a lower negative partial direct effect of immigration on wages of average U.S. native workers. So, my finding of negative but very small partial direct effects of immigration on wages is consistent with that of Card (2001 and 2009), Friedberg (2001) and Lewis (2005). However, this partial effect does not reflect the true overall effect of immigration on wages. In addition, this partial effect is almost always negative as long as immigrants are more substitutable with natives within the same skill groups than with natives in other skill groups.

2.5.2 Long-run Total Effects on Wages

In this section, I discuss the total wage effects of immigration during the most recent period 1990-2014 in order to increase the comparability of my results with that of OP. As shown in expression (8) in Section 2.2, the total wage effects of immigration include both direct partial within-group wage effects and a set of indirect cross-group wage effects. There are total 296 cross-group effects produced by immigrants in other skill groups. In other words, total wage effects depend on all the cross elasticities of substitution ($\sigma_S, \sigma_E, \sigma_X$, and σ_M) and relative labor supply of all industry, education, and experience groups of workers, where the latter depends on the inflows of immigrants in all skill groups. In the paper, I focus on the total long-run wage effects of immigration by allowing for full adjustment of the capital stock of the economy, i.e. $(\Delta\kappa_t/\kappa_t)_{immigration} = 0$. The capital-labor ratio does not change in the long-run due to the labor supply shock caused by immigration. This implies that immigration does not affect the capital stock of the economy in the long-run.

Table 2.13 and 2.14 reports the simulated “long-run” total wage effects of immigration over the 1990-2014 period. Panel A presents the values of the estimated parameters $\sigma_S, \sigma_E, \sigma_X$, and σ_M used in each simulation. Similar to OP, I make 1,000 draws from the joint normal distribution of these parameters with the specified mean and standard deviation. For each draw of the parameters, I calculate the percentage change in real wages for U.S. native workers in each industry-education-experience skill group i, j, k by using the percentage change in immigrants by skill groups and the simulated parameter values in formula (8). This generates 1,000 simulated effects for each skill group i, j, k. I then calculate the simulated average wage change for each group i, j, k and its simulated standard error. Finally, I obtain the weighted average wage change (and standard error) for each education and industry group separately, where the weights are the corresponding wage-share in the education and industry groups. These percentage changes in the real wages of U.S. native workers due to immigration during 1990-2014 for education group are reported in Panel B and that for industry group are reported in Panel C.

The column 1 in Table 2.13 and 2.14 presents the replicated OP estimates of long-run total wage effects of immigration reported in column 2 of Table 6 in OP. For those estimates, OP use the same nesting-CES structure as I do in this paper. All the calculated values of total wage effects of immigration for U.S. native workers with "no degree", "high school degree", "some college", and "college degree" are exactly same although the standard errors in my calculation are slightly smaller. Column 2 reports the simulated total wage effects of immigration once I add industry-specific skill groups of workers in the nesting-CES structure of aggregate production function. Two important results emerge from a close comparison across column 1 and 2 in Panel B. First, the negative total wage effects of immigration on native workers with no high school degree reduces by about 50 percent when we consider industry-education-experience skill groups of workers instead of education-experience groups only. OP find that immigration over the 1990-2006 period decreases the wage of natives with no high school decreased by about 2 percent. My calculation suggests that the immigration during the same period decreases the wage of those workers by only about 1 percent. Second, the positive wage effects of immigration for natives with high school degree and some college degree also seem to be much lower than the ones calculated by OP. For example, the total positive wage effects of immigration for natives with high school degree and college degree reduce from 1.1 percent to 0.4 percent and from 1.9 percent to 1.4 percent when adding industry specific groups of workers in the nested-CES structure of aggregate production function. Closer values of parameter estimates of $\sigma_S, \sigma_E, \sigma_X$, and σ_M and a much lower partial negative effect of immigration, i.e. a lower value of $1/\sigma_M$ - $1/\sigma_X$, are the main reasons for this effects.

Panel C in Table 2.14 reports the simulated long-run total wage effects of immigration across different industries. For the period 1990-2006, the negative effects of immigration seem to concentrate in three main industries, namely, Agriculture, mining, & construction, Business service, and Personal service industries.[12] Immigration over the 1990-2006 period reduced the real wages of U.S. native workers by about 3.5 percent in Business service industry, 2.2 percent in Personal service industry, and 1.9 percent in Agriculture, mining, & construction industry. However, immigration during this period increases the wages of natives by about 0.8 percent in Transportation, communication, & utilities, by about 1.0 percent in Finance, insurance, & real estate, and by about 2.5 percent in Manufacturing industries. These findings are apparently consistent with the findings of Foged and Peri (2015), who document that immigrants take jobs that are more manual intensive in nature whereas natives take jobs that are communication intensive. Most of the occupations in Agriculture, mining, & construction, Business service, and Personal service industries are physical-manual intensive and, thus, natives in those industries face a fierce competition from

[12]Business services includes services to dwellings, personnel supply services, automotive rental and leasing, electrical repair, and others.

immigrants. Accordingly, real wages of native workers in those industries decrease.

The column 3 in Table 2.13 and 2.14 presents the simulated long-run total wage effects of immigration during the 1990-2014 period. Panel B reports the wage effects for four education groups of native workers and Panel C reports the those for eight industry groups of native workers. The calculated total wage effects for the 1990-2014 period are broadly similar to those for 1990-2006, except one important difference. For native workers with no high school degree in Panel B, the negative total wage effects reduce by about two-third from –1.0 percent to –0.3 percent and the coefficient is no longer significant. Therefore, in contrast to a large negative wage effect of immigration during 1980-2000 period reported in GB and relatively mild negative wage effect of immigration during the 1990-2006 period reported in OP, I find that immigration during 1990-2014 period has negligible and statistically insignificant negative wage effects for native workers with no high school degree. The positive wage effects for natives with high school degree and some college degree over 1990-2014 are slightly larger than over the 1990-2006 period. The wage effects for natives with a college degree –0.2 percent but not significant.

For industry groups of workers also in Panel C, the total wage effects of immigration over the 1990-2014 period are broadly similar to those over the 1990-2006 period. Immigration during the 1990-2014 period reduced the wages of native workers in Agriculture, mining, & construction, Business service, and Personal service industries but increased the wages of native workers in Transportation, communication, & utilities, Wholesale & retail trade industry, Finance, insurance, & real estate, and Manufacturing industries. Immigration during this period has no significant effects on the wages of native workers in Education & health service industries.

Finally, the last row labeled "Average U.S.-born" in Table 2.14 reports the average total wage effects of immigration across all education groups or industry groups of U.S. native workers. As one can see, the average total wage effect is about 0.5 percent over the 1990-2006 period and about 0.6 percent over the 1990-2014 period. Both values are statistically significant at the 1 percent level. It is important to note here that the estimated direct partial effect during the 1990-2014 period in Section 5.1 vary between –0.23 percent and –0.53 percent. This clearly suggests that although the within group direct wage effects of immigration are negative, the total wage effects, after taking into account the indirect cross-group effects, are positive. In addition, my calculated value of average total wage effects across education groups of U.S. native workers is similar to that of OP despite the differences in within education group estimates of wage effects. Overall, I find that immigration over the most recent 1990-2014 period has no negative effects on the wages of U.S. native workers.

2.6 Conclusion

In this paper, I examine the effects of immigration on the wages of U.S. native workers at the national level during the most recent 1990-2014 period. I extend the structural model of production used in Borjas (2003) and Ottaviano and Peri (2012) to consider industry (and occupation) specific skill groups of workers in addition to conventionally used education-experience groups. It is reasonable to argue that skills can be acquired both before and after a person enters the labor market. Such potential industry specific skill differences make workers across different industries imperfectly substitutable. In addition, endogenous choices are also of less concern in the analysis of cross-industry and cross-occupation evidence of effects of immigration than in the analysis of cross-city and cross-state evidence. It is because industry and occupation choices by immigrants are often limited by workers' qualifications and skills at least in the short-run as argued by Friedberg (2001).

Using industry-education-experience skill groups of workers, I find that the immigrant and native workers are indeed imperfect substitutes. The four arguments put forward by Borjas, Grogger, and Hanson (2012) that make the finding of imperfect substitutability between immigrant and native workers of Ottaviano and Peri (2012) fragile does not hold true when I use a richer set of skill groups by industry, education, and experience. The estimated degree of substitution between immigrant and native workers in this paper vary between 12 and 70 against between 22 and 500 reported in Borjas, Grogger, and Hanson (2012). Using my estimates of elasticities of substitution, I find that immigration over the most recent 1990-2014 period had a small negative effect on the wages of native workers with no high school degree (–0.3 percent) against a moderately large negative effect (–2.0 percent) reported in Ottaviano and Peri (2012). However, immigration during the same period had a small positive effect (+0.6 percent) on the wages of average native workers. In the paper, I document the importance of considering the industry (occupation) specific skill groups of workers while estimating the substitutability between immigrant and native workers and thus evaluating the effects of immigration on the wages of native workers.

2.7 References

1. Altonji, Joseph G., and Card, David, 1991. The Effects of Immigration on the Labor Market Outcomes of Less-Skilled Native. In *Immigration, Trade, and the Labor Market*, edited by John M. Abowd and Richard B. Freeman. University of Chicago Press, Chicago.

2. Blankenau, William F., and Cassou, Steven P., 2011. Industry Estimates of the Elasticity of Substitution and the Rate of Biased Technological Change between Skilled and Unskilled Labour. *Applied Economics*, 43, 3129-3142.

3. Borjas, George J., 2003. The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market. *Quarterly Journal of Economics*, 118, 1335-1374.

4. Borjas, George J., Freeman, Richard, and Katz, Larry, 1997. How Much Do Immigration and Trade Affect Labor Market Outcomes? *Brookings Papers on Economic Activity*, 1997(1), 1-90.

5. Borjas, George J., Grogger, Jeffrey, and Hanson, Gordon H., 2012. Comment: On Estimating Elasticities of Substitution. *Journal of European Economic Association*, 10(1), 198-223.

6. Borjas, George J., and Katz, Lawrence, 2007. The Evolution of the Mexican-Born Workforce in the United States. In *Mexican Immigration to the United States*, edited by George Borjas. National Bureau of Economic Conference Report, Cambridge, MA.

7. Card, David, 2001. Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration. *Journal of Labor Economics*, 19, 22-64.

8. Foged, Mette, and Peri, Giovanni, 2015. Immigrants' Effect on Native Workers: New Analysis on Longitudinal Data. *Quarterly Journal of Economics*, 116, 1373-1408.

9. Friedberg, Rachel, 2001. The Impact of Mass Migration on the Israeli Labor Market. Centre for Research & Analysis of Migration Discussion Paper 07/15.

10. Katz, Larry, and, Murphy, Kevin, 1992. Changes in Relative Wages 1963-1987: Supply and Demand Factors. *Quarterly Journal of Economics*, 107, 35-78.

11. Lewis, Ethan, 2005. Immigration, Skill Mix, and the Choice of Technique. *Federal Reserve Bank of Philadelphia Working Paper*, 05-08.

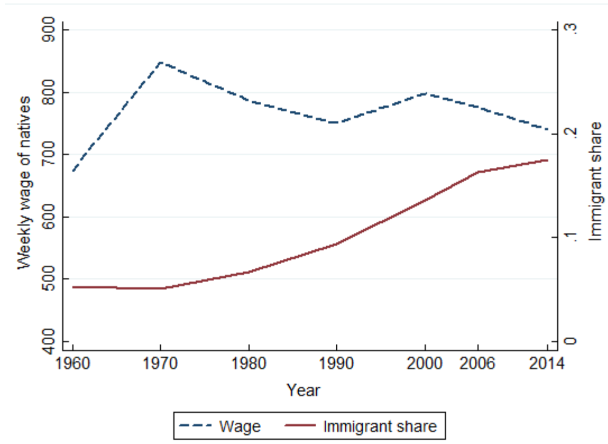
12. Ottaviano, Gianmacro I.P., and Peri, Giovanni, 2006. Rethinking the Effect of Immigration on Wages. National Bureau of Economic Research Working Paper 12496.

13. Ottaviano, Gianmacro I.P., and Peri, Giovanni, 2012. Rethinking the Effect of Immigration on Wages. *Journal of European Economic Association*, 10(1), 152-197.

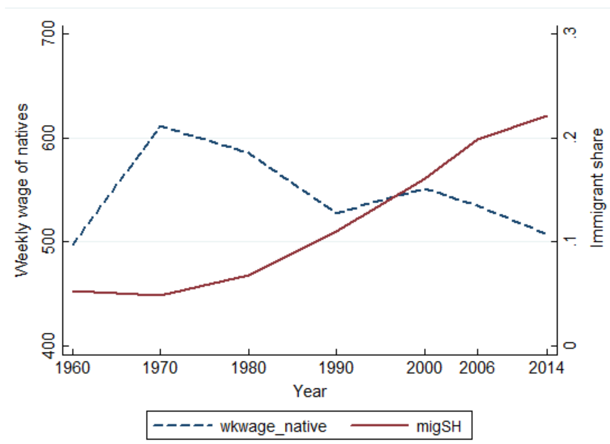
14. Peri, Giovanni, and Sparber, Chad, 2009. Task Specialization, Immigration, and Wages. *American Economic Journal: Applied Economics*, 1(3), 135-169.

15. Ruggles, Steven, Genadek, Katie, Goeken, Ronald, Grover, Josiah, and Sobek, Matthew, 2015. *Integrated Public Use Microdata Series: Version 6.0 [dataset]*. Minneapolis: University of Minnesota, 2015. http://doi.org/10.18128/D010.V6.0.

Figure 2.2: Immigrant Shares and Weekly Real Wages of Native Workersin the U.S., 1960-2014



(a) Full sample



(b) No college degree

(c) No degree

Table 2.1: Mean Weekly Real Wage and Relative Real Wage of Natives, and Relative Employment of Immigrants in the U.S., 1960-2014

Sample	Obs.	Native wage	Immigrant wage / Native wage	Immigrant workers / Native workers
	(1)	(2)	(3)	(4)
Panel A: Full Sample	1767	764	0.95	0.19
Panel B: By education				
No degree	448	486	0.95	0.25
High-school degree	448	604	0.96	0.11
Some college degree	444	757	0.94	0.10
College degree	427	1229	0.89	0.15
Panel C: By industry				
Agriculture, mining, & construction	210	823	0.92	0.18
Transportation, communication, & utilities	221	838	0.91	0.11
Wholesale & retail trade	224	711	0.91	0.15
Manufacturing	224	857	0.90	0.14
Finance, insurance, & real estate	223	844	0.93	0.11
Business services	221	790	0.94	0.19
Personal services	220	596	0.89	0.22
Education & health services	224	652	1.03	0.10
Panel D: By occupation				
Management	220	1018	1.02	0.10
Business & financial specialist	208	837	0.98	0.11
Computer and Mathematical	167	992	1.02	0.25
Engineering	187	967	0.98	0.15
Scientist, researchers, & educators	216	640	1.06	0.09
Community & protective services	200	670	0.90	0.06
Legal services	128	1061	0.93	0.07
Art & design	217	792	1.05	0.12
Healthcare services	220	712	1.07	0.15
Production	224	657	0.84	0.18
Building, maintenance, & perconal care	221	452	0.92	0.26
Office & administration	224	674	0.92	0.10
Farming, construction, & extraction	189	741	0.88	0.22
Installation & repair	182	749	0.92	0.11
Transportation	206	716	0.84	0.13

Table 2.2: Immigration and Changes in Native Wages: By Industry-Education Groups

Industry (1)	Education (2)	Percentage change in labor supply due to new immigrants measured in hours worked, 1990-2014 (3)	Percentage change in weekly wages of Natives, 1990-2014 (4)
Agriculture, mining, & construction	No degree	40.3%	-1.9%
	High-school degree	12.2%	5.8%
	Some college degree	5.4%	2.5%
	College degree	4.2%	7.3%
	All education groups	**14.4%**	**8.5%**
Transportation, communication, & utilities	No degree	28.3%	-14.8%
	High-school degree	8.7%	-6.1%
	Some college degree	6.7%	-2.6%
	College degree	9.6%	11.5%
	All education groups	**9.6%**	**3.6%**
Wholesale & retail retail trade	No degree	28.3%	-15.7%
	High-school degree	8.0%	-9.8%
	Some college degree	4.9%	-17.4%
	College degree	6.9%	-2.9%
	All education groups	**8.3%**	**-5.4%**
Manufacturing	No degree	21.5%	24.4%
	High-school degree	3.8%	17.9%
	Some college degree	2.9%	8.5%
	College degree	6.7%	22.2%
	All education groups	**5.4%**	**33.9%**

Table 2.3: Table 2.2 Continued

Industry (1)	Education (2)	Percentage change in labor supply due to new immigrants measured in hours worked, 1990-2014 (3)	Percentage change in weekly wages of Natives, 1990-2014 (4)
Finance, insurance, & real estate	No degree	32.8%	-8.2%
	High-school degree	8.3%	-0.2%
	Some college degree	4.8%	1.5%
	College degree	13.8%	23.0%
	All education groups	**10.8%**	**22.9%**
Business services	No degree	37.9%	-5.4%
	High-school degree	13.3%	-1.4%
	Some college degree	6.9%	-9.3%
	College degree	7.2%	2.1%
	All education groups	**11.4%**	**7.6%**
Personal services	No degree	22.9%	-1.4%
	High-school degree	6.1%	5.6%
	Some college degree	4.3%	3.8%
	College degree	5.2%	5.7%
	All education groups	**5.6%**	**12.6%**
Educational & health services	No degree	30.3%	-10.1%
	High-school degree	6.5%	-2.4%
	Some college degree	3.9%	-2.9%
	College degree	7.6%	14.1%
	All education groups	**7.4%**	**13.6%**

Table 2.4: Estimates of the Elasticity of Substitution between Natives and Immigrants ($-1/\sigma_M$)

	All workers			
			Add industry or occupation	
	OP (2012)	Add year 2014	Industry	Occupation
	(1)	(2)	(3)	(4)
Male	-0.030**	-0.049***	-0.059***	-0.040***
	(0.015)	(0.014)	(0.009)	(0.007)
Female	-0.056***	-0.072***	-0.083***	-0.048***
	(0.018)	(0.016)	(0.016)	(0.018)
Male and female	-0.019	-0.039**	-0.065***	-0.046***
	(0.016)	(0.016)	(0.009)	(0.007)
Male, Labor supply	-0.034**	-0.054***	-0.065***	-0.044***
measured as employment	(0.014)	(0.014)	(0.009)	(0.007)
Fixed effects:				
Year	Yes	Yes	Yes	Yes
Education×experience	Yes	Yes	Yes	Yes
Industry×education×experience	No	No	Yes	No
Occupation×education×experience	No	No	No	Yes
Observations	192	224	1767	3009

Notes: Heteroskedasticity-robust standard errors, clustered by education-experience cells in column 1 through 2, by industry-education-experience cells in column 3, and by occupation-education-experience cells in column 4 are reported in parentheses. Method of estimation is Least Squares, where I weight each cell by its employment as in OP (2012). ***, **, and * denote significance at the 1, 5, and 10 percent levels respectively.

Table 2.5: Estimates of the Elasticity of Substitution between Natives and Immigrants ($-1/\sigma_M$): All Workers and Full Time Workers

	Industry-education-experience cells					
	All workers			Full time workers		
	No Fixed Effects	With FE	With FE not weighted	No Fixed Effects	With FE	With FE not weighted
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Male	-0.049***	-0.059***	-0.044***	-0.058***	-0.068***	-0.049***
	(0.005)	(0.009)	(0.010)	(0.004)	(0.009)	(0.010)
Female	-0.057***	-0.083***	-0.067***	-0.068***	-0.093***	-0.086***
	(0.006)	(0.018)	(0.018)	(0.007)	(0.019)	(0.017)
Male and female	-0.047***	-0.065***	-0.054***	-0.056***	-0.073***	-0.062***
	(0.005)	(0.009)	(0.010)	(0.004)	(0.008)	(0.010)
Male, Labor supply	-0.054***	-0.065***	-0.050***	-0.061***	-0.079***	-0.069***
measured as employment	(0.004)	(0.009)	(0.010)	(0.004)	(0.009)	(0.009)

Notes: Heteroskedasticity-robust standard errors, clustered over 256 industry-education-experience groups, are reported in parentheses. Method of estimation is Least Squares, where I weight each cell by its employment. FE (fixed effects) include Industry by Education by Experience plus time effects. Total observations are 1767. ***, **, and * denote significance at the 1, 5, and 10 percent levels respectively.

Table 2.6: Robustness of Estimates of the Elasticity of Substitution between Natives and Immigrants ($-1/\sigma_M$)

	Industry-education-experience cells					
	All workers			Full time workers		
	No weight (1)	OP weight (2)	BGH weight (3)	No weight (4)	OP weight (5)	BGH weight (6)
1. Log mean wages (OP)						
Male	-0.044***	-0.059***	-0.045***	-0.049***	-0.068***	-0.036***
	(0.010)	(0.009)	(0.008)	(0.010)	(0.009)	(0.008)
	[0.189]	[0.463]	[0.542]	[0.172]	[0.469]	[0.595]
Male and female	-0.054***	-0.065***	-0.052***	-0.062***	-0.073***	-0.046***
	(0.010)	(0.009)	(0.008)	(0.010)	(0.008)	(0.008)
	[0.338]	[0.583]	[0.652]	[0.318]	[0.578]	[0.704]
2. Mean log wages (BGH)						
Men	-0.029***		-0.057	-0.038***		-0.014
	(0.010)		(0.046)	(0.011)		(0.040)
	[0.223]		[0.570]	[0.187]		[0.584]
Male and female	-0.040***		-0.056**	-0.053***		-0.044*
	(0.010)		(0.028)	(0.010)		(0.026)
	[0.405]		[0.644]	[0.369]		[0.674]

Notes: Heteroskedasticity-robust standard errors, clustered over 256 industry-education-experience groups, are reported in parentheses; adjusted R-squared are reported in brackets. Method of estimation is weighted Least Squares. OP weights are total employment in each cell and BGH weights are the inverse of the sampling variance of the dependent variable. Year and Industry by Education by Experience fixed effects are included. Total number of observations are 1767 for all workers specification and 1745 for full time workers specification. ***, **, and * denote significance at the 1, 5, and 10 percent levels respectively.

Table 2.7: Robustness of Estimates of the Elasticity of Substitution between Natives and Immigrants ($-1/\sigma_M$): By Occupation

	Occupation-education-experience cells					
	All workers			Full time workers		
	No weight	OP weight	BGH weight	No weight	OP weight	BGH weight
1. Log mean wages (OP)						
Male	-0.025**	-0.040***	-0.033***	-0.031***	-0.049***	-0.030***
	(0.012)	(0.007)	(0.006)	(0.014)	(0.007)	(0.006)
	[0.215]	[0.480]	[0.540]	[0.200]	[0.465]	[0.621]
Male and female	-0.025***	-0.046***	-0.035***	-0.035***	-0.054***	-0.032***
	(0.009)	(0.007)	(0.006)	(0.009)	(0.007)	(0.006)
	[0.368]	[0.606]	[0.673]	[0.318]	[0.619]	[0.747]
2. Mean log wages (BGH)						
Men	-0.023**		-0.059	-0.033**		-0.055
	(0.012)		(0.086)	(0.013)		(0.097)
	[0.215]		[0.438]	[0.208]		[0.482]
Male and female	-0.014		-0.052	-0.028***		-0.038
	(0.010)		(0.053)	(0.010)		(0.045)
	[0.357]		[0.394]	[0.345]		[0.469]

Notes: Heteroskedasticity-robust standard errors, clustered over 480 occupation-education-experience groups, are reported in parentheses; adjusted R-squared are reported in brackets. Method of estimation is weighted Least Squares. OP weights are total employment in each cell and BGH weights are the inverse of the sampling variance of the dependent variable. Year and Industry by Education by Experience fixed effects are included. Total number of observations are 3009 for all workers specification and 2912 for full time workers specification. ***, **, and * denote significance at the 1, 5, and 10 percent levels respectively.

Table 2.8: Estimates of the Elasticity of Substitution between Native and Immigrant ($-1/\sigma_M$): Male Workers

	Industry-education-experience cells			
	All workers		Full time workers	
	OP weight **(1)**	BGH weight **(2)**	OP weight **(3)**	BGH weight **(4)**
Panle 1: Industry group				
Agriculture, mining, & construction	-0.102***	-0.087***	-0.106***	-0.080***
	(0.008)	(0.009)	(0.009)	(0.009)
Transportation, communication, & utilities	-0.057***	-0.047***	-0.060***	-0.047***
	(0.010)	(0.011)	(0.010)	(0.009)
Wholesale & retail trade	-0.054***	-0.050***	-0.076***	-0.057***
	(0.018)	(0.012)	(0.012)	(0.009)
Finance, insurance, & real estate	0.025	0.016	0.020	0.026
	(0.038)	(0.031)	(0.039)	(0.037)
Business services	-0.062***	-0.041	-0.073***	-0.036
	(0.019)	(0.026)	(0.018)	(0.026)
Personal services	-0.034***	-0.039***	-0.043***	-0.048***
	(0.012)	(0.012)	(0.012)	(0.015)
Educational & health services	-0.012	-0.015	-0.017	-0.012
	(0.014)	(0.014)	(0.013)	(0.015)
Manufacturing	-0.074***	-0.062***	-0.079***	-0.058***
	(0.008)	(0.010)	(0.009)	(0.010)

Notes: Heteroskedasticity-robust standard errors, clustered over 256 industry-education-experience groups, are reported in parentheses. Method of estimation is weighted Least Squares. OP weights are total employment in each cell and BGH weights are the inverse of the sampling variance of the dependent variable. Industry by Experience fixed effects are included in Panel 1, Industry by Education fixed effects are included in Panel 2, and Education by Experience fixed effects are included in Panel 3. ***, **, and * denote significance at the 1, 5, and 10 percent levels respectively.

Table 2.9: Table 2.8 Continued

	Industry-education-experience cells			
	All workers		Full time workers	
	OP weight **(1)**	BGH weight **(2)**	OP weight **(3)**	BGH weight **(4)**
Panel 2: Education group				
High school dropouts	-0.061***	-0.059***	-0.072***	-0.056***
	(0.007)	(0.005)	(0.005)	(0.005)
High school graduates	-0.086***	-0.085***	-0.092***	-0.074***
	(0.011)	(0.010)	(0.009)	(0.009)
Some college	-0.065***	-0.065***	-0.068***	-0.059***
	(0.020)	(0.016)	(0.020)	(0.015)
College graduates	0.024	0.032	0.017	0.026
	(0.015)	(0.019)	(0.016)	(0.019)
Panel 3: Experience group				
0-10 years	-0.158***	-0.150***	-0.147***	-0.112***
	(0.015)	(0.027)	(0.014)	(0.014)
11-20 years	-0.074***	-0.054***	-0.080***	-0.043**
	(0.015)	(0.016)	(0.015)	(0.017)
21-30 years	-0.062***	-0.052***	-0.069***	-0.044***
	(0.017)	(0.014)	(0.018)	(0.012)
31-40 years	-0.053**	-0.035*	-0.057**	-0.032
	(0.024)	(0.020)	(0.024)	(0.019)

Notes: Heteroskedasticity-robust standard errors, clustered over 256 industry-education-experience groups, are reported in parentheses. Method of estimation is weighted Least Squares. OP weights are total employment in each cell and BGH weights are the inverse of the sampling variance of the dependent variable. Industry by Experience fixed effects are included in Panel 1, Industry by Education fixed effects are included in Panel 2, and Education by Experience fixed effects are included in Panel 3. ***, **, and * denote significance at the 1, 5, and 10 percent levels respectively.

Table 2.10: Estimates of the Elasticity of Substitution between Experience Groups of Workers ($-1/\sigma_X$)

	Industry-education-experience cells	
	OP weight **(1)**	BGH weight **(2)**
Male	-0.087***	-0.070***
	(0.025)	(0.021)
Female	-0.017	0.025
	(0.023)	(0.034)
Male and Female	-0.092***	-0.064***
	(0.022)	(0.020)
Male, Labor supply	-0.087***	-0.069***
measured as employment	(0.024)	(0.022)
Observations	1767	1767
Fixed effects:		
Industry × Year	Yes	Yes
Education × Year	Yes	Yes
Experience × Year	Yes	Yes
Industry × Education × Year	Yes	Yes
Industry × Education × Experience	Yes	Yes

Notes: Heteroskedasticity-robust standard errors, clustered over 256 industry-education-experience groups, are reported in parentheses. Method of estimation is 2SLS using immigrant workers' hours as an instrument for total workers' hours. OP weights are total employment in each cell and BGH weights are the inverse of the sampling variance of the dependent variable. ***, **, and * denote significance at the 1, 5, and 10 percent levels respectively.

Table 2.11: Estimates of the Elasticity of Substitution between Education Groups of Workers ($-1/\sigma_E$)

	Industry-education-experience cells	
	OP weight	BGH weight
	(1)	**(2)**
Male	-0.171**	-0.140**
	(0.063)	(0.061)
Female	-0.129*	-0.080
	(0.071)	(0.058)
Male and Female	-0.187**	-0.159**
	(0.081)	(0.069)
Male, Labor supply measured as employment	-0.172**	-0.148**
	(0.071)	(0.071)
Observations	224	224
Fixed effects:		
Year	Yes	Yes
Industry × Year	Yes	Yes
Education-specific trends	Yes	Yes

Notes: Heteroskedasticity-robust standard errors, clustered over 32 industry-education groups, are reported in parentheses. Method of estimation is 2SLS using immigrant workers' hours as an instrument for total workers' hours. OP weights are total employment in each cell and BGH weights are the inverse of the sampling variance of the dependent variable. ***, **, and * denote significance at the 1, 5, and 10 percent levels respectively.

Table 2.12: Estimates of the Elasticity of Substitution between Industry Groups of Workers ($-1/\sigma_S$)

	Industry-education-experience cells	
	OP weight	BGH weight
	(1)	**(2)**
Male	-0.366**	-0.344**
	(0.129)	(0.138)
Female	-0.328**	-0.320*
	(0.125)	(0.167)
Male and Female	-0.440***	-0.406***
	(0.121)	(0.126)
Male, Labor supply measured as employment	-0.431***	-0.410***
	(0.118)	(0.130)
Observations	56	56
Fixed effects:		
Year	Yes	Yes
Industry	Yes	Yes
Industry-specific trends	Yes	Yes

Notes: Heteroskedasticity-robust standard errors, clustered over 8 industry groups, are reported in parentheses. Method of estimation is 2SLS using immigrant workers' hours as an instrument for total workers' hours. OP weights are total employment in each cell and BGH weights are the inverse of the sampling variance of the dependent variable. ***, **, and * denote significance at the 1, 5, and 10 percent levels respectively.

Table 2.13: Calculated Long-run Wage Effects of Immigration (with Simulated Standard Errors)

	Industry-education-experience cells		
	1990-2006 period		1990-2014 period
	OP (2012)	Add industry	Add industry
	(1)	(2)	(3)
Panel A: Parameter values			
-1/$\sigma_{\mathbf{ind}}$		**–0.38**	**–0.38**
		(0.03)	(0.03)
-1/$\sigma_{\mathbf{edu}}$	**–0.30**	**–0.17**	**–0.17**
	(0.09)	(0.03)	(0.03)
-1/$\sigma_{\mathbf{exp}}$	**–0.16**	**–0.08**	**–0.08**
	(0.05)	(0.01)	(0.01)
-1/$\sigma_{\mathbf{mig}}$	**–0.05**	**–0.04**	**–0.04**
	(0.01)	(0.01)	(0.01)
Panel B: Education group			
High school dropouts	**–2.0**	**–1.0**	**–0.3**
	(0.6)	(0.2)	(0.3)
High school graduates	**1.1**	**0.4**	**0.9**
	(0.2)	(0.1)	(0.2)
Some college	**1.9**	**1.4**	**1.6**
	(0.3)	(0.1)	(0.2)
College graduates	**–0.3**	**0.1**	**–0.2**
	(0.3)	(0.1)	(0.2)
Average U.S.-born	**0.6**	**0.5**	**0.6**
	(0.4)	(0.1)	(0.2)

Notes: The numbers in the table represent the average percentage wage changes for each group within a specific period in each column. The parameters (elasticity of substitutions between workers) used are normally distributed random variables I proceed as follows. I first generate 1000 extractions per each configuration of the parameters from a joint normal distribution. I then calculate the wage effect for each group and then take the average. The average of the 1000 simulated standard errors are reported in the parentheses. The average wage changes and their standard errors are obtained by weighting wage changes and simulated standard errors by each group's share in the total wage bill in the beginning year.

Table 2.14: Table 2.13 Continued

	Industry-education-experience cells		
	1990-2006 period		1990-2014 period
	OP (2012)	Add industry	Add industry
	(1)	(2)	(3)
Panel C: Industry group			
Agriculture, mining, & construction		**–1.9**	**–0.9**
		(0.3)	(0.2)
Transportation, communication,		**0.8**	**0.6**
& utilities		(0.1)	(0.1)
Wholesale & retail trade		**0.2**	**0.8**
		(0.1)	(0.1)
Finance, insurance, & real estate		**1.0**	**1.4**
		(0.1)	(0.2)
Business services		**–3.5**	**–5.2**
		(0.4)	(0.6)
Personal services		**–2.2**	**–3.1**
		(0.3)	(0.3)
Educational & health services		**0.6**	**–0.1**
		(0.1)	(0.1)
Manufacturing		**2.5**	**3.5**
		(0.2)	(0.2)
Average U.S.-born	**0.6**	**0.5**	**0.6**
	(0.4)	(0.1)	(0.2)

Notes: The numbers in the table represent the average percentage wage changes for each group within a specific period in each column. The parameters (elasticity of substitutions between workers) used are normally distributed random variables I proceed as follows. I first generate 1000 extractions per each configuration of the parameters from a joint normal distribution. I then calculate the wage effect for each group and then take the average. The average of the 1000 simulated standard errors are reported in the parentheses. The average wage changes and their standard errors are obtained by weighting wage changes and simulated standard errors by each group's share in the total wage bill in the beginning year.

2.8 Appendix

2.8.1 Wage Effects of Immigration

Following Hamermesh (1993), differentiating Eq (6) with respect to labor input $\ln F_{ijkt}$ and using the expressions $d \ln w = \Delta w/w$ and $d \ln F = \Delta F/F$, the impact of an increase in the supply of foreign workers in industry i, education j and experience k group on the wages of native in the same group i, j, k is:[13]

$$\frac{\Delta w_{ijkt}}{w_{ijkt}} = \Big[\frac{1}{\sigma_S} + \Big(\frac{1}{\sigma_E} - \frac{1}{\sigma_S}\Big)\Big(\frac{1}{\mathfrak{s}_{it}}\Big) + \Big(\frac{1}{\sigma_X} - \frac{1}{\sigma_E}\Big)\Big(\frac{1}{\mathfrak{s}_{ijt}}\Big) + \Big(\frac{1}{\sigma_M} - \frac{1}{\sigma_X}\Big)\Big(\frac{1}{\mathfrak{s}_{ijkt}}\Big)\Big]\mathfrak{s}^f_{ijkt}\frac{\Delta F_{ijkt}}{F_{ijkt}}. \tag{2.19}$$

The wage impact of an increase in the supply of foreign workers in industry i and education j but a different experience group $x \neq k$ on the wages of native in the group is i, j, k is:

$$\frac{\Delta w_{ijkt}}{w_{ijkt}} = \Big[\frac{1}{\sigma_S} + \Big(\frac{1}{\sigma_E} - \frac{1}{\sigma_S}\Big)\Big(\frac{1}{\mathfrak{s}_{it}}\Big) + \Big(\frac{1}{\sigma_X} - \frac{1}{\sigma_E}\Big)\Big(\frac{1}{\mathfrak{s}_{ijt}}\Big)\Big]\mathfrak{s}^f_{ijkt}\frac{\Delta F_{ijxt}}{F_{ijxt}}. \tag{2.20}$$

Similarly, the wage impact of an increase in the supply of foreign workers in industry i but a different education group $e \neq j$ on the wages of native in the group is i, j, k is:

$$\frac{\Delta w_{ijkt}}{w_{ijkt}} = \Big[\frac{1}{\sigma_S} + \Big(\frac{1}{\sigma_E} - \frac{1}{\sigma_S}\Big)\Big(\frac{1}{\mathfrak{s}_{it}}\Big)\Big]\mathfrak{s}^f_{ijkt}\frac{\Delta F_{iext}}{F_{iext}}. \tag{2.21}$$

Finally, the wage impact of an increase in the supply of foreign workers in a different industry $m \neq i$ regardless of education and experience groups on the wages of native in the group is i, j, k is:

$$\frac{\Delta w_{ijkt}}{w_{ijkt}} = \frac{1}{\sigma_S}\mathfrak{s}^f_{ijkt}\frac{\Delta F_{mext}}{F_{mext}}. \tag{2.22}$$

[13] Hamermesh (1993, p.37) derives the expression for the wage elasticity of a factor, say z, for an increase in the supply of a factor, say x, by keeping the quantities of other factors constant. Borjas (2003) and Ottaviano and Peri (2012) use the same technique to evaluate the total wage effects of immigration.

The total wage effect of immigration in the expression (8) in the text is the sum of all these four effects.