RESEARCH ARTICLE

The Impact of Remittances on the Youth's Human Resource Development, Employment, and Entrepreneurship: Evidence from Philippine CBMS Data

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Abstract: International migration has been a significant avenue for many Filipinos to make use of interspatial differences in purchasing power, to send home remittances, and to maximize household income. However, migration has had a stigma of being disruptive to children's educational outcomes, and remittances have been noted to cause dependence among working age members. This study estimates the impact of remittances on the human resource development, employment, and entrepreneurial outcomes and choices of the Philippine youth, individuals aged fifteen to thirty, using CBMS data census of selected De La Salle school communities. I employ an instrumental variable multinomial logistic regression to look at the impact of remittances on human resource development outcomes, that is, whether a young person is working, studying, both, or neither, and find that those in households receiving remittances are more likely to end up studying than working or being idle. This serves as evidence against the stigma that remittances cause dependency or idleness. I employ the same empirical strategy to look at the impact of remittances on employment outcomes, that is, whether a young person is working in a private household, a public/private establishment, self-employed, working in a family-run business, or not working. I find that they are most likely to work for a private household or a public/private establishment rather than be self-employed, which paints a sad picture for entrepreneurship. I calculate the average treatment effect on the treated (ATT) of remittances on households' propensity to be engaged in entrepreneurial activity, and find that remittances have little to no impact (and at times negative) on the likelihood of households and individuals being engaged in entrepreneurship. Overall, though the impact of remittances may be lackluster for employment and entrepreneurship, it encourages the accumulation of human capital.

Keywords: International Migration, Remittances, Human Resource Development, Entrepreneurship, Community-Based Monitoring System

JEL Classification Codes: F22, F24, I20, J22

Since the mid 1970's, international migration has become a major avenue for Filipinos to take advantage of differences in wage and living standards across countries in the hopes of raising the welfare of their families at home and maximizing their income across time. The total stock of Filipinos overseas have increased in the past decade with around 7.383 million in 2000, to 9.452 million in 2010, and approximately 10.238 million in 2013 (Commission of Filipinos Overseas [CFO], 2016). It may be noted further that during this period, the stock of permanent migrants increased from approximately 2.551 million in 2000 to 4.869 million in 2013, whereas the stock of temporary migrants, though fluctuating, increased immensely from 2.991 million in 2000 to 4.207 million in 2013 (CFO, 2016). Temporary labor migration has been a strong motivation for many Filipino families to invest in their human capital and maximize their income across time and space. Due to this, the phenomenon that is the "Overseas Filipino Workers" (OFWs) or overseas contract workers (OCWs) has spread across the world. Among the top destinations of OFWs in 2014 are Saudi Arabia, United Arab Emirates, Singapore, Qatar, and Hong Kong (Philippine Overseas Employment Administration [POEA], 2016).

To maximize the benefits of international migration, particularly to take advantage of the interspatial differences in purchasing power, migrants send remittances to their families in the home country that usually has lower wages. Remittance inflows to the Philippines have grown significantly in the past few years, increasing from USD 18.762 billion in 2010 to USD 25.606 billion in 2015 (Bangko Sentral ng Pilipinas [BSP], 2016). In 2015, the largest inflows of remittances come from Saudi Arabia (USD 2.844 billion), United Arab Emirates (USD 2.030 billion), United Kingdom (USD 1.515 billion), Singapore (USD 1.505 billion), and Japan (USD 1.222 billion).

In the light of this phenomenon, how families make use of remittances remains an issue. Tabuga (2007) found that remittances decrease the proportion of expenses spent by families on food, and increases that for education, health services, housing and repairs, consumer durables, leisure, and gifts. This partially makes up the criticism for remittances that they are being misused. Studies (Orbeta, 2008; Tullao, Cortez, & See, 2007; Tabuga, 2007) found that remittances enhance human capital accumulation through additional spending on education. There are still, however, conflicting views on the impacts of remittances. Tullao et al. (2007) and Rodriguez and Tiongson, (2001) found that households that receive remittances have a lower labor force participation rate, which may imply that remittances induce dependency. However, Ducanes and Abella, (2007) and Cabegin, (2006) found that remittances may reduce labor force participation, but this may not necessarily imply dependency or idleness in part of the recipients, but an avenue to improve self-employment.

Remittances play a role in financing the basic necessities of the household, as well as improvements of their dwelling, acquisition of electronics, and other luxuries. A significant point of interest in this study is how remittances affect the outcomes of the youth when it comes to human resource development and employment, and how it affects the decision of households to engage in entrepreneurial activity.

The objectives of the study are as follows:

1. Using the 2015 Philippine CBMS data, trace the impact of remittances on human resource development decisions of the youth using a multinomial logistic regression.
2. Using the 2015 Philippine CBMS data, trace the impact of remittances on the employment decisions of the youth using a multinomial logistic regression.
3. Using the 2015 Philippine CBMS data, trace the impact of remittances on the propensity of households to engage in specific entrepreneurial activity using propensity score matching.

Review of Literature

Migration, Remittances, Schooling and Employment

Temporary international migration and remittances (M&R) are two concepts that are intertwined. Temporary migration is a move that enables households to take advantage of differentials in wages. In their interest of maximizing income over time and taking advantage of interspatial differences in purchasing power, they send remittances to their families for their basic necessities and other expenses.

Bouoiyour and Miftah (2015) investigated the impact of migration and remittances on the probability of completing higher and post-secondary education, as well as the probability of attaining higher years of education. They used a sample from Morocco wherein most migrants are the adult children of households aged 18–20 and 21–24. They found that left-behind children from remittance receiving households attain higher years of schooling as compared to those with migrants but receive no remittances, especially males. They found, however, that the likelihood of completing higher education is lower. What may be noted about this study is that migrant self-selection is not explicitly captured in the model which only uses migration status to represent M&R. Theoharides (2014) utilized a provincial level panel data model controlling for province-level fixed effects to estimate the impact of the demand for migration on secondary enrollment rates for the Philippines. She developed an instrument that predicts the number of migrants for each province-year by getting the average of the number of national emigrants according to destination weighted according to the proportion of total migrants contributed by the province for a base year. The weight is constant across time however, which may cause problems of measurement if it turns out that the contributions of the different provinces to national migration have changed significantly over time. She found that migration demand generally improves total secondary private enrollment a lot more than public enrollment, and that female migration demand improves female enrollment most of all.

A longstanding issue that is highlighted in the literature of M&R and human capital formation is brain gain/brain drain. The migration of workers has consequences on the labor market. There will usually be an emigration of low skilled and professional workers. The loss of professional workers is equivalent to a brain drain in the home country. However, the prospect of migration can help increase schooling rates that can lead to brain gain. This has been suggested by Stark and Dorn (2013) and Stark, Helmenstein, and Prskawetz (1997). Stark et al. (1997) suggested that although migrants take along more human capital than if there was no prospect of migration, workers that stay will also have more human capital because of the prospect and aspiration to migrate. This was extended by Stark and Dorn (2013) who showed that in the presence of savings, with a low degree of relative risk aversion, a worker who saves when there is a prospect of migration will acquire more human capital than without the prospect of migration. Since M&R are intertwined, remittances plays a crucial role in increasing the demand for better education, and hence, investment in human capital (Tullao & Cabuay, 2012). Receiving remittances imply that a household has sent a member to work or has relatives in foreign countries. The brain drain and the complementary brain gain may facilitate human capital accumulation because members of remittance-receiving tend to have an inclination to increase their labor productivity in the home country in hopes of overseas migration in the future (Tullao & Cabuay, 2012). Wang (2012) suggested that given the case of parental migration, schooling may be disrupted due to the absence of the parents, but there is also a possibility that it may be enhanced when remittances are sent, or that children exhibit the aspiration to migrate.

On the other hand, there is much debate about the link between remittances and employment. The prospect of labor migration (which is a form of brain drain) induces the remaining household members to increase their labor productivity (Stark & Dorn 2013; Stark et al., 1997), which enhances employability (brain gain) in spite of aspirations to migrate in the future (Tullao & Cabuay, 2012). Using a descriptive analysis, Tullao et al. (2007) found that labor participation is lower in remittance-receiving households. Rodriguez and Tiongson (2001) attributed this to increased demand for leisure. Ducanes and Abella (2007) have found otherwise, particularly in a case where there are OFWs present in the household. Cabegin (2006) found that the labor supply decision of households vary between men and women depending on the presence of school-age children. In general, remittances decrease labor participation for both, although depending on the presence of work-age children, it increases self-employment work hours for women, which is the entrepreneurial option when receiving remittances. Yang (2008) looked into international data and found that remittances do not affect the number of work hours, but increases the work hours under self-employment which is consistent with Cabegin (2006). Drinkwater, Levine, Lotti, and Pearlman (2003) also looked into international data and found that remittances has decreasing, albeit insignificant effect, on unemployment. Empirical studies in the literature are inconsistent potentially because of the endogenous nature of migration, which is highly dependent for a household's motivation to send a migrant (Tullao & Cabuay, 2012).

Migration, Remittances, Employment and Entrepreneurship

The discussion on the impact of remittances on youth employment paints a picture similar to the debate on the impact of remittances on the decision of households and its members to participate in the labor force. In their study in Kyrgyzstan, Karymshakov, Abdieva, Sulaimanova, and Sultakeev (2015) found that remittances have no impact on the propensity of youth to be self-employed or to be employed by an institution, but impact positively to contributing to a family-run establishment. This reinforces hypotheses that members have a higher likelihood of contributing to a family-run establishment so as to replace the migrant member. In addition, they find that young males have higher propensity to be engaged in self-employment.

On the other hand, the study of Petreski, Maojsoska-Blazevski, Ristovska, and Smokvarski (2014) reported mixed findings regarding the impact of remittances on the propensity of remittance-receiving households for youth self-employment. Using OLS and Probit regressions, their findings suggested that remittance receiving households exhibit higher propensities to engage in youth employment, but taking into account the potential endogeneity of remittances using IV regressions, they find that remittance-receiving households have lower propensities to engage in youth self-employment. They found as well that young households' members from remittance-receiving households have significantly higher probabilities of setting up their own businesses as compared to non-young counterparts, which suggests that young persons recognize remittances as a way to finance long-term productive ventures. Similarly, Yang (2008) found that given favourable exchange rate shocks, household with migrants experience more work hours put into self-employment and higher entrepreneurial income. Chalise (2014) concluded that migrant remittances are not strong enough factor to encourage entrepreneurial activities although only descriptive statistics were generated from the survey of households. Using a probit model while accounting for potential endogeneity with respect to the receipt of remittances in a sample from Ecuador, Vasco (2013) concluded that M&R have no impact on the likelihood of a household owning a business, rather, education and access to capital are stronger determinants.

The Phenomenon of Self-Selection in Migration and Remittances

An increasing number of studies on migration and remittances have contributed in addressing the issue of endogeneity. Models that are run using OLS given the presence of endogeneity will end up yielding biased (small-sample) and inconsistent (large-sample) estimators. Selectivity bias occurs when the choice of economic agents based on perceived favorable returns causes a non-random distribution of the outcome (Nakosteen & Zimmer, 1980). In migration (and in many other cases, e.g., labor force participation), this phenomenon is coined self-selection. For example, when in the course of determining who will migrate from the community, those most likely to be selected are those with higher educational attainment, thus causing a reverse causality in the determination of demand for educational attainment which will depend on migration networks and the prospect of migration. One of the earlier works by Nakosteen and Zimmer (1980) used MLE and 2SLS to estimate the impact of migration on income using a probit first stage for migration expressed as a function of wage differentials, age, race, gender, and other factors. They recommended the use of human capital investment, wage differential strategies, and locational change as controls for migration. Chiquiar and Hanson (2005) used logit to look at the determinants of migration to the US and found differences in gender affect the selection of migrants, and that there is negative self-selection among migrants since returns to education are higher in Mexico than in the US for Mexican nationals. This causes lower wage, lower education individuals to migrate. McKenzie and Rapoport (2010) looked at the impacts of migration networks on the choice of education with the use of OLS and 2SLS. They instrumented migration using male school attendance and past migration rates. They found that larger networks, though may lead to the ease of migration, causes lower skill accumulation, and hence negative self-selection. Using multinomial logit, Bertoli (2010) estimated the impact of individual, household, county (particularly migration networks), and provincial level characteristics on the four possible outcome of an individual to stay in Ecuador, migrate to the US, Spain, or to other countries.

The transfer of remittances, on the other hand, is a different decision point altogether. Bettin, Lucchetti, and Zazzaro (2011) elaborated that a sample selection phenomenon also occurs in the sending of remittances. They theorized that positive remittances will depend on a positive level of income that must be higher than the cost of sending remittances (constrained sending) and depends on the choice of the migrant, whether or not they are willing to send remittances (unconstrained sending), which is modeled as a latent factor. Respectively, these two factors are what determine the amount to be remitted and the propensity to remit. Bettin et al. (2011) estimated a model of remittances as a function of income and consumption using the Heckman selection model (when only the propensity to remit is considered) and a double-hurdle model (when both underlying factors are considered) via limited information maximum likelihood. Cox, Eser, and Jimenez (1998) utilized logit and tobit to estimate remittances as a function of income, social security income, education, and age. They found that the sending of remittances follow a life cycle—the likelihood of sending remittances are quite high in younger, lower income years, and decrease as the person enters older, higher income years, and increase again when the person enters the age of retirement where they are no longer income generating.

In this study, to simultaneously contribute to the debate on the impact of remittances on both human capital accumulation and employment, I will look at the impact of remittances on the human resource development outcomes of the youth; that is, whether they will end up in a school participation outcome, or that of labor force participation, neither, or both. I will also look at the impact on employment outcomes, whether they will end up working for private households, private/public establishments, self-employment, or family-run businesses. I will also look at the impact of remittances on the likelihood of a person to be engaged in an entrepreneurial activity. However, I cannot take the issue of self-selection lightly. Combining the propositions of Bettin et al. (2011) and Nakosteen and Zimmer (1980), I assume that the choice of sending remittances will also be determined by the factors that determine migration. Mainly, human capital accumulation is what affects the likelihood of a person to migrate. Aside from differences in wages, this same mechanism is what may affect the likelihood that a person can remit. That is, a more educated migrant has a higher likelihood of having income larger than the cost of remittances, and will affect the amount and his propensity to remit. Other factors that may influence the propensity to remit must also be considered, such as the migrant's gender, age, recipient household incomes, home ownership, and access to capital markets.

Methodology

Description of the Data

This study utilizes the 2015 Community-Based Monitoring System (CBMS) data set with the Youth Employment and Entrepreneurship (YEE) and Social Protection and the Informal Sector (SPIS) rider questionnaires. Due to the dataset being very recently collected, purposive complex sampling has been done. Each of the three major island groups of the Philippines is represented (Luzon, Visayas, and Mindanao). The dataset includes four regions: Region 4A (CALABARZON) and National Capital Region (NCR) for Luzon, Region 6 (Western Visayas) for the Visayas, and Region 10 (Northern Mindanao) for Mindanao. NCR includes Manila (with two project sites/barangays) and Marikina (with three barangays). The Region 4A municipalities included are Lipa City in Batangas, and Maragondon and Dasmarinas in Cavite which include one barangay each. For Region 6 in Visayas, Bago City of Negros Occidental constitutes the largest portion of the survey comprised of seven barangays. Region 10 is represented by Ozamiz City of Misamis Occidental and is comprised of two barangays. One limitation that should be noted about the dataset is that there are no sampling weight variables available. To account for the potential distributional biases in the sample, I include province fixed effect dummies. One note that needs to be considered is that during the course of the project (Cabuay, 2016), the 2015 CBMS with YEE and SPIS was still being completed. The dataset used in this study is a more recent version of the dataset with a larger return rate of the survey.

This study focuses on the youth segment of the sample—individuals aged 15 to 30. The reason for this is that the youth segment is the proportion that has the largest incentive to choose among the human resource development outcomes of schooling, employment, and entrepreneurship. Additionally, the youth serves as key targets for human capital accumulation in order to achieve developmental outcomes such as inclusive growth.

First, we look at the key intervention which is remittances. Table 1 is taken directly from Cabuay (2016) and reports the proportion of the youth sample in households that receive remittances. Across all project sites, only about 8.52% of the sample belongs to households that receive remittances. It may be

Table 1. *Frequency of Youth Individuals in Households that Receive Remittances*

Sites by Province	Frequency	% of Sample	# of Observations
Manila (Code 39)	92	8.49	1,083
Marikina (Code 74)	1,383	9.27	13,920
Batangas (Code 10)	103	23.52	438
Cavite (Code 21)	31	3.86	803
Negros Occidental (Code 42)	891	7.12	12,514
Misamis Occidental (Code 45)	126	12.01	1,049
Total	2,626	8.52	30,807

Source: Table 3 from Cabuay (2016)

Table 2. *Human Resource Development Outcomes According to School and Job Indicators in CBMS Data of Youth Ages 15 to 30, per Province Site*

Sites by Province	School	Working	Idle	Part-timing
Manila (Code 39)	322	420	307	15
Marikina (Code 74)	5,024	5,576	4,008	134
Batangas (Code 10)	142	175	108	2
Cavite (Code 21)	171	316	293	10
Negros Occidental (Code 42)	3,466	4,416	4,167	57
Misamis Occidental (Code 45)	280	349	390	12
All sites	9,405	11,252	9,273	230

Source: Table 4 from Cabuay (2016).

seen that across subsamples, only a small part of the youth reside in households that receive remittances. The highest incidence would be in Batangas (23.52% of the youth sample). Marikina, though it registers a frequency of 1,383, only has 9.27% incidence in the youth sample.

Looking at the human resource development outcomes of the sample (Table 2), I find that across all sites, the largest portion of the sample are in a state of working and not in school (11,252 or 37.31%). This is consistent across all project sites. How these outcomes are computed is elaborated in the empirical strategy section. The proportion of in school and not working is 31.18%, idle (neither in a working nor schooling state) is 30.75%, and part-timing (both working and schooling) is 0.76%.

Table 3 presents the youth employment outcomes according to worker classification. Across all sites, 64.88% are not working as this includes all youth in the sites whether unemployed or not part of the labor force. In terms of those that are working, the largest proportion are made up of those that are working in a public/private establishment (around 78.91% of the working portion), followed by those working in private household (13.38%), and only 5.42% are self-employed and 2.28% are working for a family-run business.

Table 4 reports the incidence of youths that are engaged in entrepreneurial activity. Only about 2.25% across the entire sample are engaged in entrepreneurial activity, and the highest incidence are those from Misamis Occidental (4.58% of the subsample), Negros Occidental (4.58%), and Manila (3.60%).

Empirical Strategy

In estimating the impact of remittances on the human resource development outcomes of youths, I employ a multinomial regression with the following specification:

Table 3. *Youth Employment Outcomes According to Worker Classification in CBMS Data of Youth Ages 15 to 30, per Province Site*

Sites by Province	Private Household	Public/Private Establishment	Self-Employed	Family-Run Business	Not Working
Manila (Code 39)	55	329	35	9	655
Marikina (Code 74)	815	4,216	89	148	9,652
Batangas (Code 10)	39	134	3	3	259
Cavite (Code 21)	49	223	19	17	495
Negros Occidental (Code 42)	396	3,418	392	59	8,228
Misamis Occidental (Code 45)	91	200	47	11	700
All sites	1,445	8,520	585	247	19,989

Source: Table 5 from Cabuay (2016).

Table 4. *Frequency of Youth Aged 15 to 30 in Households With Entrepreneurial Activity*

Sites by Province	Frequency	% of Sample	# of Observations
Manila (Code 39)	39	3.60	1,083
Marikina (Code 74)	111	0.74	14,920
Batangas (Code 10)	4	0.91	438
Cavite (Code 21)	24	2.99	803
Negros Occidental (Code 42)	466	3.72	12,514
Misamis Occidental (Code 45)	48	4.58	1,049
All sites	692	2.25	30,807

Source: Table 6 from Cabuay (2016).

$$HRDdecision_i = \beta_0 + \beta_1 Remittances_i + \sum_{j=1}^{5} \gamma_j Province_j + u_i \quad (1)$$

$HRDdecision_i \in [1,2,3,4]$ which represent human resource development decisions: 1 if the individual is in school and not working, 2 if the individual is working and not in school, 3 if the individual is neither, and 4 if the individual is part-timing both in school and working. This specification exhausts all possible mutually-exclusive outcomes for every individual so as to meet independence from irrelevant alternatives. $Remittances_i \in [0,1]$ which represents whether or not the individual comes from a household that receives remittances: 1 if the household receives remittances and 0 otherwise. $Province_j$ represents the province-level fixed-effect dummies to account for heterogeneities coming from the individuals' provinces of residence, and to account for differences in the sampling. Since there are six provinces in the sample, five province dummies will be added to avoid perfect collinearity.

In estimating the impact of remittances on the youth employment decisions of youths, I employ a multinomial regression with the following specification:

$$YEDecision_i = \beta_0 + \beta_1 Remittances_i + \sum_{j=1}^{5} \gamma_j Province_j + u_i \quad (2)$$

$YEDecision_i$ will be presented in two variations. The first variation will be: $YouthEmploymentDecision_{ij} \in [1,2,3,4,5]$ which represents the kind of employment the *i*th individual: 1 if employed in private household, 2 if employed in an institution/establishment whether public or private, 3 if self-employed, 4 if contributing to a family-run business, or 5 if he is not working.

The second variation will be: $YouthEmploymentDecision_{ij} \in [1, 2, 3, 4]$ which takes up the same specification as the first variation but drops outcome 5. This forces the outcomes to be purely working outcomes, implying that if an individual will end up in a work state, we can find which working state he will most likely be in given the receipt of remittances. This is similar to the setup of Karymshakov et al. (2015).

However, as mentioned previously, remittances may be endogenous to the same factors that induce self-selection among migrants. The amount remitted and the propensity to remit will therefore be estimated using the following specification:

$$\begin{aligned} Remittances_i = {} & \delta_0 + \delta_1 OFWindicator_i + \delta_2 Sex_i + \delta_3 Age_i \\ & + \delta_4 WealthIndex_i + \mu_j HomeOwnership_{ji} \\ & + \theta_l EducationalAttainment_{li} + u_i \end{aligned} \quad (3)$$

$Remittances_i$ is binary: 1 if the individual is in a household that receives remittances, 0 otherwise. $OFWindicator_i$ is a binary dummy variable indicating the presence of an OFW in the household. Sex_i is a binary dummy variable with value 1 if the observation is male and 0 if female. Age_i indicates the age of the observation. $WealthIndex_i$ follows Borromeo (2012), Acosta (2011) and Antón's (2010) measure for wealth. It the serves as the household's indicator of wealth, computed as $WI_i = \sum_j f_j \frac{a_{ij}-m_j}{s_j}$ where a_{ij} is a binary dummy indicating ownership of asset j, m_j is the mean and s_j is the standard deviation of the jth asset, and f_j is the weight assigned to the jth asset by using the first principal component via principal components analysis. $WealthIndex_i$ is a normalized measure of asset ownership with values ranging from negative to positive. $HomeOwnership_{ji}$ is a vector of binary dummies indicating the state of ownership of the household excluding one outcome to avoid perfect collinearity, and $EducationalAttainment_{li}$ is a vector of binary dummies indicating the highest educational attainment of the individual excluding one outcome.

The modeling strategy I undertake is a somewhat ad hoc estimation of Heckman's model of sample selection wherein the first stage equation is equation (3) determining the probability of receiving remittances. The predicted probabilities in (3) are then used to substitute the remittance variable in (1) and (2). I look at the correlation of remittances and its determinants, perform an F-test of joint significance for the first stage regression, and perform a Wald's test to check for the strength of instruments. Equations (1), (2), and (3) are estimated using MLE. Specifically, (3) is estimated using logit, whereas (1) and (2) are estimated using multinomial logit.

In estimating the impact of remittances on the entrepreneurial decisions of households, studies (Karymshakov et al., 2015; Petreski et al., 2014) have made use of multinomial logit, binary probit, and instrumental variable regression techniques to determine the inclination of households and individuals to engage in specific entrepreneurial ventures. Alternatively, remittances may be viewed as a treatment administered to different households, and so we can approach the problem in the light of impact evaluation methods. Particularly, I will test the impact of remittances on the decision to be engaged in entrepreneurship (whether or not the individual is engaged in any entrepreneurial activity) using Propensity Score Matching (PSM). This is similar to the study of Tan and Gibson (2013) where they looked at the impact of foreign maids on female labor force participation, wherein female labor force participation is binary, and so the observed outcome becomes the likelihood of being in the labor force. The various kinds of entrepreneurial activity are measured in binary values (either they are engaged in an activity or they are not), hence the observed outcome will be the likelihood that they will be engaged in a particular activity. The ad hoc technique used to estimate the first stage regression for equations (1) and (2) is likened to the step in matching that estimates the p-score, or in the case stated previously, as the probability of receiving remittances.

Remittances in this setting are viewed as a treatment, however, as we have acknowledged previously, the sample selection among migrants and the receipt of remittances prevents the desirable property of having a pure, randomly-assigned treatment available in natural experiments and randomized control trials to isolate the impact of the treatment. Furthermore, as it will be discussed in the succeeding section, it is notable that remittance-receiving households have very different characteristics relative to non-remittance-receiving households. To make up for this, we must provide a model for program selection—a model that determines the likelihood (probability) that a household will receive remittances given a set of observable characteristics. Predicted probabilities (p-scores) are then estimated and matched for treatment and control groups. This stage of the methodology is a bit more liberal than first-stage regressions in terms of specification but still require that the chosen covariates must be independent of the treatment and in estimating the p-scores, the balancing property must be met (Khandker, Koolwal, & Samad, 2010). That is, the set of observable characteristics must be comparable for treatment and control groups so as to simulate two observationally identical observations whose only difference is the receipt of the treatment. At the same time, sufficient common support must be available, that is, the range for matching treatment to control observations must be the same. P-scores are then matched for treatment and control groups using nearest neighbor matching. This step sets together treatment and control observations with approximately same conditional probability of receiving remittances given the characteristics in the model for program selection. After matching, the Average Treatment Effect on the Treated (ATT), which is the average differences in outcomes (in this case the likelihood of entrepreneurial activity) between treatment and control groups. The ATT is computed as

$$ATT = \frac{1}{N_T}\left(\sum_{1}^{N_T}(Y_T - Y_C)\right)$$

Y_T - Y_C represent the difference in outcomes of the matched treatment and control households. N_T represents the matched sample. Standard errors are generated using bootstrapping (Khandkher et al., 2010). The algorithm used to estimate the ATT was that of Becker and Ichino (2002).

However, caution must be exercised when using matching to determine treatment effects. Keele (2010) stresses that computed ATTs will be unbiased as long as covariates in the model of program selection are truly exogenous. This requires that there are no hidden biases that may confound the matching of p-scores (Rosenbaum, 2005). To test for this, I perform the Rosenbaum Sensitivity Analysis which tests the sensitivity of the impact estimates to the presence of hidden confounders.

Results and Discussion

Initially, I check for the strength of the instruments for the remittances variable using pairwise correlation and find that remittances is strongly correlated to the presence of an OFW as expected, the wealth index, owning a house and lot, and being a college graduate. I proceed to run the logit equation (3) using maximum likelihood estimation (Appendix A). I find that regressor groups generally have consistent coefficients. The presence of OFWs greatly increases the odds of receiving remittances, males have lower odds, older individuals have a higher chance of receiving remittances, and higher wealth indices have higher odds. Chi-square tests and Wald's tests reveal that each major regressor group has a significant joint impact on the odds of receiving remittances.

Table 5 reports the marginal effects and the relative risk ratios (RRR) of the probability of receiving remittances (note that the variable becomes the probability to receive remittances after being estimated from the first stage equation which uses logit) to the four mutually exclusive human resource development outcomes. Looking at marginal effects, it may be said that individuals in households with higher probability to receive remittances have a higher likelihood of being in school. This confirms the findings and suggestions of Theoharides (2014), Stark and Dorn (2013), Tullao and Cabuay (2012), Tullao et al. (2007), Tabuga (2007), and Stark et al. (1997). At the same time, youth that belong to households that receive remittances have lower likelihood to be in the labor force, idleness, and part-timing outcomes. This confirms the proposition of Tullao et al. (2007) and Rodriguez and Tiongson (2001) that remittance receiving households may have lower labor participation rates, but this indicates that they do not turn to idleness. The results here are slightly different from Cabuay (2016) such that the coefficient for the part-timing outcome is insignificant whereas in Cabuay (2016) it was negative. Looking at the RRR of remittances for the labor force, idle, and part-timing outcomes, it may be seen that the RRRs are less than one. This indicates that the probability

Table 5. *Marginal Effects and RRR of the Impact of Remittances on Human Resource Development Outcomes*

School Participation	Labor Force Participation	Idle	Part-timing
0.1154439	- 0.0737378	- 0.044155	0.0024492
(0.0134874)***	(0.152966)***	(0.148952) ***	(0.0023692)
	^0.5615303	^0.5994304	^0.9558093

*Note: School participation outcome is used as base category. Standard errors in parenthesis. *,**,*** denote 10%, 5% and 1% level of significance, respectively. ^ represents RRR.*

change in the ith outcome (any one of the three) is less than the probability change in the base outcome which is schooling. This implies that a higher probability of receiving remittances will more likely go into the base outcome schooling than the other outcomes of labor force participation and idleness.

This may serve as an indication that individuals, particularly the youth, who drop from the labor force upon receiving remittances may not purely be due to leisure spending, dependence or idleness, but may perhaps be a shift towards stronger human capital accumulation outcomes. This supports the suggestions of Theoharides (2014) which suggests a liquidity effect and relative-wage effect of migration and remittances. Migration, and now with the receipt of remittances, will encourage participation in school since a household's liquidity constraint is relaxed (liquidity effect), but will discourage those working school-aged members to work since their current wage given their current level of education is surely lower compared to their potential earnings if they invest further in their human capital or when they face the prospect of migration to a country with higher earning (relative-wage effect). This relative-wage effect also confirms the theoretical suggestions of Stark and Dorn (2013) and Stark et al. (1997).

Table 6 reports the marginal effects and the RRRs of the probability of receiving remittances on youth employment decisions. The first half of the table (part A) reports the impacts of remittances on the likelihood that the individual will end up in the five outcomes of no work, working in private household, working in private/public establishment, self-employed, and working in family-owned business. The result here is quite different than that in Cabuay (2016) where the result is that individuals are more likely to work (and potentially attend school). Looking at both marginal effects and RRRs, I find that when the prospect of schooling is removed (an additional parameter was set in defining these work outcomes, restricting only to individuals that are employed rather than employed or seeking), individuals in households with higher propensity to remit are more likely to work for private households and public/private establishments, and less likely to be self-employed and not work.

Part B re-runs equation 2 but excludes the "not working" outcome. The results for this model are quite different from Cabuay (2016) and Karymshakov et al. (2015) where they find that households that receive remittances are more likely to work for a family-run business. The result here is that when the sample is made up of those fully employed, they are less-likely to be self-employed, no impact with respect to working in family businesses, and more likely to work for private households and public/private establishments. This may imply that when individuals are working, remittances give little motivation for them to engage in self-employment, which may be attributed to the growth of human capital as highlighted in the previous model.

Furthermore, the results in Table 6 paint quite the sad picture for individual entrepreneurship. The findings in Cabuay (2016) are quite different when using PSM to estimate the impact of remittances on the likelihood of households to be engaged in entrepreneurship potentially due to differences in the variables used for determining sample selection. Cabuay (2016) used indices of wealth, domestic wages, and job indicators. The criteria used for determining program selection in this study are the presence of OFWs in the household, an index of wealth, and total wage earnings across all members per household.

Table 7 presents raw comparisons of the various entrepreneurial activity outcomes as well as the set of observable characteristics. Most notably, it may be seen that individuals in households that receive remittances generally post a lower entrepreneurial incidence (around 1.64%) than those that do not receive remittances (around 1.96%). Note that the statistics

Table 6. *Marginal Effects and RRR of the Impact of Remittances on Youth Employment Decision*

Private Household	Public/Private Establishment	Self-Employed	Family-Run Business	Not Working
A. Given all outcomes				
0.0258416 (0.0052324)*** ^1.83841	0.0450033 (0.0126663)*** ^1.239865	-0.034791 (0.0027669)*** ^0.1647934	-0.0031405 (0.0027669) ^0.7165678	-0.0329084 (0.0140459)**
B. Excluding "Not Working" outcome				
0.0624953 (0.0141963)*** ^12.79064	0.0555772 (0.0229092)** ^8.457901	-0.1077998 (0.0198387)***	-0.0102755 (0.0076991) ^5.118579	--

*Note: Not working outcome is used as base category for A. Self-employed used as base category for B. Standard errors in parenthesis. *,**,*** denote 10%, 5% and 1% level of significance, respectively. ^ represents RRR.*

presented for entrepreneurial activity are based on entrepreneurial indicators that have binary values so the value presented represents the proportion of the subsample that that is engaged in entrepreneurship. This is also the case for crop farming, poultry raising, fishery, forestry, services, transportation, mining, and construction. Individuals in remittance-receiving households have only a slightly higher incidence for retail trade (9.9% compared to 9.6%) and manufacturing, which is a bit more contrasting (0.83% vs 0.67%). In terms of the other covariates, remittance-receiving households also vary greatly in contrast to non-remittance-receiving ones. Remittances receiving households generally have a higher wealth index (1.8 in general versus – 0.0105, which implies that those with remittances have a larger accumulation of assets), and more of the subsample own their own house and lot (63.59% versus 49.9%). Those that do not receive remittances tend to have a larger proportion of the subsample that rent their house, or own a house with free rent with owner's consent. In terms of education attainment, it may be noticed that there are larger proportions of the individuals in non-remittance-receiving households that have finished only up until a certain grade level and is not a graduate of a cohort. There are more grade school and high school graduates among those in non-remittance-receiving households (2.44% and 23.79%, respectively versus 0.46% and 16.79% for remittance-receiving households), but there are more post-secondary graduates and college graduates among individuals from remittance receiving households (4.15% and 25.93%, respectively) than those from non-remittance-receiving households (3.2% and 13.42%, respectively). The same may be said when comparing treatment and control groups given the various ranges of common support (model 2 to 6 in table 7).

Table 8 reports the ATT of remittances on the likelihood of a household being engaged in a particular entrepreneurial activity. As may be expected from the results of equation 2, the impact of remittances is quite uninspiring. Across models (a)-(d) of program selection, remittances have limited impact on the propensity of households being engaged in all activities. An exception is model (e) which controls for total household wage income. This is quite different from Cabuay (2016) who looks at the individual level propensity. This coincides with the findings of Chalise (2014) and Vasco (2013) who conclude that migration and remittances have little to no impact on entrepreneurship. A few exceptions may be noted, however. In model (a), the impact of remittances on the propensity of engaging in a service based activity (e.g., restaurants, health and wellness establishments) is negative (-0.9%). In model (c), this is the only instance where remittances has a positive impact (1.8%) on the propensity to engage in a retail trade activity (*sari-sari stores* and convenience stores). In model (d), a negative impact may be seen for poultry farming (-0.6%) and mining (-0.1%), and although significant, the ATTs are quite minute. In model (e), there are more significant impacts. For crop farming, poultry, fishery, retail trade, services, transportation, and construction, the impact of remittances is negative. The largest impact is that on retail trade (-5.8%), transportation (-3.3%), and construction (-1.7%). Furthermore, I redo the

Table 7. *Means of individual and household entrepreneurial indicators and observable characteristics of individuals that are aged 15 to 30, by receipt of remittances, before and after common support given various combinations of covariates used for determining p-scores*

		With Remittances	Without Remittances					
			(1)	(2)	(3)	(4)	(5)	(6)
Entrepreneurial Activity	Entrepreneurship	0.016432	0.019664	0.019664	0.019544	0.019664	0.019679	0.01965
	Crop	0.016375	0.022817	0.022817	0.02295	0.022817	0.022697	0.022868
	Poultry	0.012186	0.021362	0.021362	0.021486	0.021362	0.021382	0.02141
	Fishery	0.005712	0.009829	0.009829	0.009887	0.009829	0.009839	0.009851
	Forestry	0.002285	0.002626	0.002626	0.002463	0.002626	0.002628	0.002632
	Retail Trade	0.099772	0.096519	0.096519	0.096795	0.096519	0.096612	0.096735
	Manufacturing	0.008378	0.006707	0.006707	0.006746	0.006707	0.006571	0.006722
	Service	0.006474	0.007452	0.007452	0.007352	0.007452	0.007459	0.007326
	Transportation	0.035034	0.040488	0.040488	0.040545	0.040488	0.040527	0.040579
	Mining	0	0.001278	0.001278	0.001106	0.001278	0.001279	0.00128
	Construction	0.010663	0.020581	0.020581	0.020701	0.020581	0.020459	0.020627
	Age	22.87597	22.64549	22.64549	22.64479	22.64549	22.64585	22.64748
	Household Wealth Index	1.803009	-0.10501	-0.10501	-0.12406	-0.10501	-0.11286	-0.11325
Tenure	Own or owner-like possession of house and lot	0.635948	0.499131	0.499131	0.497609	0.499131	0.498934	0.498115
	Rent house/room including lot	0.140137	0.148433	0.148433	0.148619	0.148433	0.148576	0.148659
	Own house, rent lot	0.009139	0.010007	0.010007	0.00953	0.010007	0.010016	0.010029
	Own house, rent-free lot with consent of owner	0.154227	0.268692	0.268692	0.270076	0.268692	0.268843	0.269294
	Own house, rent-free lot without consent of owner	0.007616	0.016146	0.016146	0.01624	0.016146	0.016161	0.016182
	Rent-free house and lot with consent of owner	0.0377	0.033285	0.033285	0.033479	0.033285	0.033139	0.033359
	Rent-free house and lot without consent of owner	0.000381	0.003336	0.003336	0.003355	0.003336	0.003339	0.003343
	Living in a public space with rent	0	0.001561	0.001561	0.00157	0.001561	0.001563	0.001565
	Living in a public space without rent	0.013328	0.017033	0.017033	0.017132	0.017033	0.017049	0.017071
	Other tenure status	0.001523	0.002378	0.002378	0.002391	0.002378	0.00238	0.002383
Highest Educational	No Grade	0.003427	0.004684	0.004684	0.004676	0.004684	0.004689	0.004695
	Day Care	0.000762	0.00039	0.00039	0.000393	0.00039	0.000391	0.000391
	Nursery/Kindergarten/Preparatory	0.000762	0.000319	0.000319	0.000321	0.000319	0.00032	0.00032
	Grade 1	0.000381	0.003087	0.003087	0.003105	0.003087	0.00309	0.003094
	Grade 2	0.001523	0.005287	0.005287	0.005318	0.005287	0.005292	0.005299
	Grade 3	0.002285	0.006636	0.006636	0.006674	0.006636	0.006642	0.006651

Table 7. *Means of individual and household entrepreneurial indicators and observable characteristics of individuals that are aged 15 to 30, by receipt of remittances, before and after common support given various combinations of covariates used for determining p-scores*

Highest Educational	Grade 4	0.001904	0.009829	0.009829	0.009887	0.009829	0.009839	0.009851
	Grade 5	0.004189	0.014726	0.014726	0.014812	0.014726	0.01474	0.014759
	Grade 6	0.008378	0.021397	0.021397	0.021451	0.021397	0.021418	0.021445
	Grade 7	0.01409	0.032646	0.032646	0.032836	0.032646	0.032642	0.032719
	Grade 8	0.039985	0.063412	0.063412	0.063602	0.063412	0.063437	0.063447
	Grade 9/3rd Year HS	0.063214	0.084915	0.084915	0.085017	0.084915	0.084997	0.084999
	Grade 10/4th Year HS	0.054075	0.053263	0.053263	0.053323	0.053263	0.053243	0.053311
	Grade 11	0.000762	0.000887	0.000887	0.000892	0.000887	0.000888	0.000889
	Grade 12	0.001142	0.001278	0.001278	0.001285	0.001278	0.001279	0.00128
	1st Year Technical Vocational	0.004189	0.004755	0.004755	0.004783	0.004755	0.004724	0.004766
	2nd Year Technical Vocational	0.006855	0.008304	0.008304	0.008316	0.008304	0.008276	0.008287
	3rd Year Technical Vocational	0.000381	0.001952	0.001952	0.001927	0.001952	0.001954	0.001921
	1st Year College	0.091775	0.081864	0.081864	0.081912	0.081864	0.081907	0.081834
	2nd Year College	0.103199	0.077357	0.077357	0.077415	0.077357	0.077289	0.077424
	3rd Year College	0.070069	0.051347	0.051347	0.051324	0.051347	0.051289	0.051284
	4th Year College or higher	0.040746	0.029878	0.029878	0.029552	0.029878	0.029836	0.029661
	Post Grad with Units	0.006855	0.006458	0.006458	0.006424	0.006458	0.006464	0.006402
	ALS Elementary	0	0.000994	0.000994	0.000999	0.000994	0.000995	0.000996
	ALS Secondary	0.003808	0.004081	0.004081	0.004105	0.004081	0.004085	0.00409
	SPED Elementary	0.000381	0.000603	0.000603	0.000607	0.000603	0.000568	0.000605
	SPED Secondary	0	0.000284	0.000284	0.000286	0.000284	0.000284	0.000285
	Grade school Graduate	0.00457	0.024449	0.024449	0.024591	0.024449	0.024437	0.024504
	High School Graduate	0.167936	0.237855	0.237855	0.23799	0.237855	0.238012	0.237961
	Post-secondary Graduate	0.041508	0.032007	0.032007	0.032051	0.032007	0.032038	0.032044
	College Graduate	0.25933	0.134168	0.134168	0.133236	0.134168	0.134084	0.1339
	Master's PhD Graduate	0.001523	0.000887	0.000887	0.000892	0.000887	0.000853	0.000889
	Number of Observations	2626	28181	28181	28018	28181	28154	28118

Note: The means of the characteristics of the individuals in households that receive remittances are the same for all combinations of covariates chosen to estimate the p-score. The means of the characteristics for individuals in non-remittance-receiving households vary slightly across the combinations of covariates. (1) represent the means prior to taking common support. (2) represents means of observations within common support given the OFW indicator and the wealth index. That for (3) are for those observations within the common support given the OFW indicator and domestic wage, (4) is given the OFW indicator only, (5) is given the wealth index only, and (6) is given domestic wage only. All five sets of combinations of covariates used for calculating p-scores satisfy the balancing property.

Table 8. *ATT of Remittances on the Likelihood of Household Entrepreneurial Activities for All Sites*

Activity	Control	OFW, WI (a)	OFW, Wage (b)	OFW (c)	WI (d)	Wage (e)
Crop		0.006 (0.006) [0.915]	-0.006 (0.006) [-1.004]	-0.008 (0.005) [-1.479]	-0.003 (0.004) [-0.706]	**-0.008** **(0.003)** **-2.498**
Poultry		0.002 (0.006) [0.266]	-0.005 (0.005) [-1.004]	-0.008 (0.005) [-1.604]	**-0.006** **(0.003)** **[-1.819]**	**-0.006** **(0.003)** **[-2.188]**
Fishery		-0.003 (0.005) [-0.610]	-0.003 (0.004) [-0.740]	-0.003 (0.003) [-0.976]	-0.001 (0.002) [-0.266]	**-0.006** **(0.002)** **[-3.560]**
Forestry		0.002 (0.002) [0.819]	0.000 (0.002) [0.190]	0.000 (0.002) [0.052]	0.001 (0.001) [0.606]	-0.000 (0.001) [-0.125]
Retail Trade		0.013 (0.014) [0.909]	-0.003 (0.013) [-0.234]	**0.018** **(0.011)** **1.697**	-0.009 (0.008) [-1.158]	**-0.058** **(0.007)** **[-8.361]**
Manufacturing		-0.003 (0.003) [-0.861]	-0.000 (0.003) [-0.086]	0.001 (0.003) [0.274]	-0.001 (0.002) [0.520]	-0.002 (0.002) [-1.226]
Service		**-0.009** **(0.004)** **[-2.466]**	-0.005 (0.003) [-1.387]	-0.004 (0.003) [-1.314]	-0.003 (0.002) [1.510]	**-0.004** **(0.002)** **[-2.478**]
Transportation		0.009 (0.009) [1.050]	-0.001 (0.009) [-0.150]	0.007 (0.007) [0.998]	-0.008 (0.005) [-1.565]	**-0.033** **(0.004)** **[-7.402]**
Mining		0.000 (0.001) [0.329]	-0.002 (0.001) [-1.565]	-0.001 (0.001) [-1.001]	**-0.001** **(0.001)** **[-1.970]**	-0.000 (0.001) [-0.463]
Construction		-0.007 (0.007) [-1.089]	-0.009 (0.006) [-1.585]	-0.003 (0.005) [-0.707]	-0.004 (0.003) [-1.368]	**-0.017** **(0.003)** **[-6.517]**

Note: Standard errors in ( ), t-ratios in [ ]. Highlighted cells represent significant findings at 5%.

estimation of the ATTs using Leuven and Sianesi's (2003) *psmatch2* algorithm (results in Appendix E). Much like using the ATT algorithm of Becker and Ichino (2002), the impact of remittances on the likelihood of household entrepreneurial activity is quite lackluster. Households that receive remittances only have about 0.29% higher likelihood of engaging in a forestry-related activity, about 2.93% higher likelihood of engaging in a retail trade-related activity and 1.17% higher likelihood of engaging in transportation-related activity. All other activities appear to be unaffected by the receipt of remittances. Checking for the robustness of the treatment effects to hidden biases using the Rosenbaum bounds sensitivity analysis, I find that the treatment effects on forestry, retail trade, and transportation activities are robust to hidden biases up to a gamma of 1.5 which indicates that there is a reasonable allowance for our inference. That is, the odds of a person being considered in the treatment due to unobserved bias can go up to 1.5 times before inference becomes invalid.

As a check for robustness, I repeat the same empirical strategy I performed for the models on human resource development and youth employment decisions for the propensity of being engaged in entrepreneurship using a logit model (Appendix D). Similar to what is reported in Table 8, higher probabilities of receiving remittances have no impact on the likelihood of being engaged in an entrepreneurial activity as evidenced by insignificant logit coefficients and marginal effects.

At first glance, these results may seem quite pessimistic from an entrepreneurial perspective. But, it may not be so bad that remittances discourage entrepreneurship in this sample. What remittances can potentially encourage is retail trade, which in this country is made up primarily of small stores and microenterprises that are low income and low value-adding. In this case, investing remittances in retail trade, though is ideal, may be an indication that domestic income and remittances may not be sufficient to finance basic necessities, and that entrepreneurship here may be to ensure subsistence. Discouraging entrepreneurship may have a brighter side to it as evidenced by the impact of remittances to encourage the youth to invest in their human capital which not only increases their earnings, but their contributions and value added to society as well. Remittances may not be enough to encourage higher value-adding entrepreneurial activities which may depend more on education and the access to capital markets (Vasco, 2013).

Conclusion

The phenomenon of migration has been placed under a negative light because of the brain drain, the erosion of family ties as members become immersed in very different cultures, and disruptive effects on the schooling of children left behind especially in the case of parental migration (Wang, 2012). Similarly, remittances has been perceived to discourage labor force participation, inducing dependence or idleness among working age members of households (Tullao et al., 2007), and although overall beneficial, households that receive remittances have been noted to use it primarily on consumption and leisure spending (Tullao et al., 2007; Tabuga, 2007).

In this study however, I find direct evidence to put migration and remittances in a relatively better light. Despite these known negative impacts, migration and remittances' greatest contribution may not be the consumption spending or the maximization of income, but rather the greater human capital accumulation (Stark & Dorn, 2013; Stark et al., 1997). In this light, though remittances discourage the engagement of individuals and households in self-employment and entrepreneurship (especially low value-adding, subsistence entrepreneurship), since these activities may depend more on education and availability of capital markets (Vasco, 2013), its impact on raising human capital not only increases overall productivity, but may open opportunities in the future for households and individuals to start up higher value-adding, innovative forms of businesses.

Migration and remittances can serve as a strong avenue to strengthen a country's work force, relaxing liquidity constraints and fueling aspirations to migrate in the future (Theoharides, 2014). Migration and remittances enables us to reach higher levels of human capital accumulation which may be beyond our reach given domestic incomes and wages, and a lot higher than when there is no prospect to migrate (Stark & Dorn, 2013; Stark et al., 1997).

Future extensions of this research may look into other factors that may determine migrant selection or the probability of receiving remittances. Non-labor income may play a large role in labor market decisions. In terms of entrepreneurship, it may also be useful to consider the impact of remittances while considering imperfections in credit markets. Policy-wise, learning to channel the fruits of migration and remittances into more productive outcomes is what will allow us to find more socially well-off solutions.

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Appendix A. Logit Regression of First Stage Remittances Model

Logistic regression Number of obs = 105288
Wald chi2(42) = 21621.06
Prob > chi2 = 0.0000
Log pseudolikelihood = -16508.679 Pseudo R2 = 0.4803

remit	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
ofwindicator	4.419485	.0320355	137.96	0.000	4.356696	4.482273
sex1	-.0779898	.0310894	-2.51	0.012	-.1389239	-.0170557
age	.0070561	.0010212	6.91	0.000	.0050544	.0090577
wealthindexnatl	.175165	.0069407	25.24	0.000	.1615616	.1887685
tenur1	-.5621361	.3073023	-1.83	0.067	-1.164438	.0401654
tenur2	-.7132817	.3097059	-2.30	0.021	-1.320294	-.1062692
tenur3	-1.069605	.3842801	-2.78	0.005	-1.822781	-.3164303
tenur4	-.4821878	.3082812	-1.56	0.118	-1.086408	.1220323
tenur5	-.7602736	.3579658	-2.12	0.034	-1.461874	-.0586735
tenur6	-.4171059	.314179	-1.33	0.184	-1.032885	.1986735
tenur7	-.8869065	.4700366	-1.89	0.059	-1.808161	.0343482
tenur9	-1.03521	.3327156	-3.11	0.002	-1.68732	-.3830989
educal2	.2591939	.1256413	2.06	0.039	.0129414	.5054464
educal3	.2246304	.1114534	2.02	0.044	.0061857	.4430751
educal4	-.0595864	.122943	-0.48	0.628	-.3005503	.1813775
educal5	-.0743555	.1095782	-0.68	0.497	-.2891248	.1404139
educal6	-.03189	.1051511	-0.30	0.762	-.2379825	.1742024
educal7	-.0063945	.1066793	-0.06	0.952	-.215482	.2026931
educal8	-.0913422	.106512	-0.86	0.391	-.300102	.1174176
educal9	-.0847473	.1090428	-0.78	0.437	-.2984673	.1289726
educal10	-.0291391	.1135066	-0.26	0.797	-.2516078	.1933297
educal11	-.1856944	.1045742	-1.78	0.076	-.390656	.0192672
educal12	-.3209018	.1063952	-3.02	0.003	-.5294326	-.112371
educal13	.0244012	.1167045	0.21	0.834	-.2043355	.2531378
educal14	.1452161	.3250678	0.45	0.655	-.4919051	.7823373
educal15	-.9658434	.5642439	-1.71	0.087	-2.071741	.1400542
educal16	-.9228547	.4164147	-2.22	0.027	-1.739013	-.106697
educal17	-.6056845	.2084884	-2.91	0.004	-1.014314	-.1970548
educal18	-.9095093	.4150335	-2.19	0.028	-1.72296	-.0960585
educal19	-.0740435	.0998237	-0.74	0.458	-.2696943	.1216074
educal20	-.2006598	.0928374	-2.16	0.031	-.3826177	-.0187018
educal21	-.2732192	.1075435	-2.54	0.011	-.4840007	-.0624377
educal22	-.3465482	.11695	-2.96	0.003	-.5757659	-.1173305
educal23	-.6522402	.2419991	-2.70	0.007	-1.12655	-.1779307
educal24	.3463685	.7352779	0.47	0.638	-1.09475	1.787487
educal25	.3993342	.4491014	0.89	0.374	-.4808883	1.279557
educal26	.0511192	.7594386	0.07	0.946	-1.437353	1.539592
educal27		0	(omitted)			
educal28	-.1750523	.106488	-1.64	0.100	-.3837649	.0336603
educal29	-.2102231	.0748583	-2.81	0.005	-.3569427	-.0635035
educal30	.1781949	.1084796	1.64	0.100	-.0344211	.390811
educal31	-.1876765	.0768729	-2.44	0.015	-.3383446	-.0370084
educal32	-.4130316	.3312079	-1.25	0.212	-1.062187	.236124
_cons	-3.220254	.3105287	-10.37	0.000	-3.828879	-2.611629

Appendix B. Multinomial Logit Model for Human Resource Development

```
Iteration 0:   log likelihood = -34417.965
Iteration 1:   log likelihood =  -34255.88
Iteration 2:   log likelihood = -34254.515
Iteration 3:   log likelihood = -34254.509
Iteration 4:   log likelihood = -34254.509

Multinomial logistic regression                  Number of obs   =     30381
                                                 LR chi2(18)     =    326.91
                                                 Prob > chi2     =    0.0000
Log likelihood = -34254.509                      Pseudo R2       =    0.0047
```

hrddecision2	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
1	(base outcome)					
2						
premitlogit	-.5770895	.0738752	-7.81	0.000	-.7218822	-.4322968
provi1	-.0239852	.1356315	-0.18	0.860	-.2898181	.2418477
provi2	.3185764	.1212573	2.63	0.009	.0809165	.5562363
provi4	-.0608631	.1098495	-0.55	0.580	-.2761641	.1544379
provi5	-.0741081	.0778834	-0.95	0.341	-.2267568	.0785406
provi6	-.1923169	.0770113	-2.50	0.013	-.3432563	-.0413774
_cons	.3091201	.0748509	4.13	0.000	.162415	.4558253
3						
premitlogit	-.5117753	.0764903	-6.69	0.000	-.6616937	-.361857
provi1	-.2197633	.1502437	-1.46	0.144	-.5142355	.074709
provi2	.5785175	.1245629	4.64	0.000	.3343786	.8226563
provi4	.3638465	.1114451	3.26	0.001	.1454182	.5822748
provi5	.2014505	.0826257	2.44	0.015	.039507	.363394
provi6	-.1471344	.082093	-1.79	0.073	-.3080337	.0137649
_cons	.0290341	.0797974	0.36	0.716	-.127366	.1854342
4						
premitlogit	-.0451968	.3182068	-0.14	0.887	-.6688707	.578477
provi1	-1.194231	.7596044	-1.57	0.116	-2.683028	.2945666
provi2	.2311576	.419374	0.55	0.581	-.5908004	1.053116
provi4	-.0812048	.3959611	-0.21	0.838	-.8572742	.6948646
provi5	-1.070938	.2964446	-3.61	0.000	-1.651958	-.4899169
provi6	-.557848	.2782843	-2.00	0.045	-1.103275	-.0124207
_cons	-3.06117	.2667454	-11.48	0.000	-3.583981	-2.538358

. margins, dydx(premitlogit) predict(outcome(1))

```
Average marginal effects                         Number of obs   =      30381
Model VCE    : OIM

Expression   : Pr(hrddecision2==1), predict(outcome(1))
dy/dx w.r.t. : premitlogit
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
premitlogit	.1154439	.0134874	8.56	0.000	.0890091	.1418786

```
. margins, dydx(premitlogit) predict(outcome(2))

Average marginal effects                         Number of obs   =      30381
Model VCE    : OIM

Expression   : Pr(hrddecision2==2), predict(outcome(2))
dy/dx w.r.t. : premitlogit
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
premitlogit	-.0737378	.0152966	-4.82	0.000	-.1037186	-.043757

```
. margins, dydx(premitlogit) predict(outcome(3))

Average marginal effects                         Number of obs   =      30381
Model VCE    : OIM

Expression   : Pr(hrddecision2==3), predict(outcome(3))
dy/dx w.r.t. : premitlogit
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
premitlogit	-.044155	.0148952	-2.96	0.003	-.0733491	-.0149609

```
. margins, dydx(premitlogit) predict(outcome(4))

Average marginal effects                         Number of obs   =      30381
Model VCE    : OIM

Expression   : Pr(hrddecision2==4), predict(outcome(4))
dy/dx w.r.t. : premitlogit
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf. Interval]	
premitlogit	.0024492	.0023692	1.03	0.301	-.0021943	.0070927

```
. mlogit hrddecision2 premitlogit provi1 provi2 provi4 provi5 provi6 if age15to30==1, baseoutcome(1) rrr
```

Iteration 0: log likelihood = -34417.965
Iteration 1: log likelihood = -34255.88
Iteration 2: log likelihood = -34254.515
Iteration 3: log likelihood = -34254.509
Iteration 4: log likelihood = -34254.509

Multinomial logistic regression	Number of obs = 30381
	LR chi2(18) = 326.91
	Prob > chi2 = 0.0000
Log likelihood = -34254.509	Pseudo R2 = 0.0047

hrddecision2	**RRR**	**Std. Err.**	**z**	**P>|z|**	**[95% Conf.**	**Interval]**
1	(base outcome)					
2						
premitlogit	.5615303	.0414831	-7.81	0.000	.485837	.6490167
provi1	.9763002	.1324171	-0.18	0.860	.7483997	1.2736
provi2	1.375169	.1667492	2.63	0.009	1.08428	1.744096
provi4	.940952	.1033631	-0.55	0.580	.7586884	1.167002
provi5	.9285713	.0723203	-0.95	0.341	.7971146	1.081707
provi6	.8250454	.0635379	-2.50	0.013	.7094563	.9594669
_cons	1.362226	.1019639	4.13	0.000	1.176348	1.577475
3						
premitlogit	.5994304	.0458506	-6.69	0.000	.5159767	.6963819
provi1	.8027088	.1206019	-1.46	0.144	.5979576	1.077571
provi2	1.783393	.2221446	4.64	0.000	1.397072	2.276539
provi4	1.438853	.1603531	3.26	0.001	1.156523	1.790106
provi5	1.223176	.1010658	2.44	0.015	1.040298	1.438202
provi6	.863178	.0708609	-1.79	0.073	.7348906	1.01386
_cons	1.02946	.0821482	0.36	0.716	.8804114	1.203741
4						
premitlogit	.9558093	.304145	-0.14	0.887	.5122868	1.78332
provi1	.3029369	.2301122	-1.57	0.116	.0683559	1.342544
provi2	1.260058	.5284355	0.55	0.581	.5538838	2.866568
provi4	.9220049	.365078	-0.21	0.838	.4243171	2.003438
provi5	.3426871	.1015877	-3.61	0.000	.1916742	.6126773
provi6	.5724396	.159301	-2.00	0.045	.3317826	.9876561
_cons	.0468329	.0124925	-11.48	0.000	.0277649	.078996

Appendix C. Multinomial Logit Model for Youth Employment Decisions

```
. mlogit yeddecision2b premitlogit provi1 provi2 provi4 provi5 provi6 if age15to30==1, baseoutcome(3) vce(robust)

Iteration 0:   log pseudolikelihood = -7562.4585
Iteration 1:   log pseudolikelihood = -7316.4641
Iteration 2:   log pseudolikelihood = -7282.4608
Iteration 3:   log pseudolikelihood = -7281.7892
Iteration 4:   log pseudolikelihood = -7281.7864
Iteration 5:   log pseudolikelihood = -7281.7864

Multinomial logistic regression                 Number of obs   =      10796
                                                Wald chi2(18)   =     452.61
                                                Prob > chi2     =     0.0000
Log pseudolikelihood = -7281.7864               Pseudo R2       =     0.0371
```

yeddecisi~2b	Robust Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
premitlogit	2.548714	.4093531	6.23	0.000	1.746396	3.351031
provi1	2.082383	.6387883	3.26	0.001	.8303808	3.334385
provi2	.5910777	.34805	1.70	0.089	-.0910878	1.273243
provi4	.2479507	.2841342	0.87	0.383	-.3089421	.8048436
provi5	-.3583353	.2289406	-1.57	0.118	-.8070506	.09038
provi6	1.80099	.2444488	7.37	0.000	1.321879	2.280101
_cons	.2248276	.219264	1.03	0.305	-.204922	.6545771
2						
premitlogit	2.135101	.3954854	5.40	0.000	1.359964	2.910238
provi1	1.535248	.6102728	2.52	0.012	.339135	2.731361
provi2	.2918162	.2989551	0.98	0.329	-.294125	.8777574
provi4	-.7642021	.2419247	-3.16	0.002	-1.238366	-.2900384
provi5	-.0139188	.1861809	-0.07	0.940	-.3788266	.350989
provi6	1.644697	.208032	7.91	0.000	1.236961	2.052432
_cons	2.07086	.1797755	11.52	0.000	1.718507	2.423214
3	(base outcome)					
4						
premitlogit	1.632877	.5228607	3.12	0.002	.6080887	2.657665
provi1	1.342302	.8970035	1.50	0.135	-.4157927	3.100396
provi2	1.292419	.5026164	2.57	0.010	.3073086	2.277529
provi4	-.0758148	.5029139	-0.15	0.880	-1.061508	.9098782
provi5	-.495066	.4007588	-1.24	0.217	-1.280539	.2904068
provi6	1.883912	.3979341	4.73	0.000	1.103976	2.663849
_cons	-1.472355	.3786105	-3.89	0.000	-2.214418	-.7302923

```
. margins, dydx(premitlogit) predict(outcome(1))
```

```
Average marginal effects                    Number of obs   =    10796
Model VCE    : Robust

Expression   : Pr(yeddecision2b==1), predict(outcome(1))
dy/dx w.r.t. : premitlogit
------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------------------------------------------------------------------
 premitlogit |   .0624953   .0141963     4.40   0.000      .034671    .0903196
------------------------------------------------------------------------------
. margins, dydx(premitlogit) predict(outcome(2))

Average marginal effects                    Number of obs   =    10796
Model VCE    : Robust

Expression   : Pr(yeddecision2b==2), predict(outcome(2))
dy/dx w.r.t. : premitlogit
------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------------------------------------------------------------------
 premitlogit |   .0555772   .0229092     2.43   0.015      .010676    .1004784
------------------------------------------------------------------------------
. margins, dydx(premitlogit) predict(outcome(3))

Average marginal effects                    Number of obs   =    10796
Model VCE    : Robust

Expression   : Pr(yeddecision2b==3), predict(outcome(3))
dy/dx w.r.t. : premitlogit
------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------------------------------------------------------------------
 premitlogit |  -.1077998   .0198387    -5.43   0.000    -.1466829   -.0689167
------------------------------------------------------------------------------
. margins, dydx(premitlogit) predict(outcome(4))

Average marginal effects                    Number of obs   =    10796
Model VCE    : Robust

Expression   : Pr(yeddecision2b==4), predict(outcome(4))
dy/dx w.r.t. : premitlogit
------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------------------------------------------------------------------
 premitlogit |  -.0102755   .0076991    -1.33   0.182    -.0253655    .0048145
------------------------------------------------------------------------------
```

```
. mlogit yeddecision2b premitlogit provi1 provi2 provi4 provi5 provi6 if age15to30==1, baseoutcome(3) vce(robust) rrr

Iteration 0:   log pseudolikelihood = -7562.4585
Iteration 1:   log pseudolikelihood = -7316.4641
Iteration 2:   log pseudolikelihood = -7282.4608
Iteration 3:   log pseudolikelihood = -7281.7892
Iteration 4:   log pseudolikelihood = -7281.7864
Iteration 5:   log pseudolikelihood = -7281.7864

Multinomial logistic regression                   Number of obs   =     10796
                                                  Wald chi2(18)   =    452.61
                                                  Prob > chi2     =    0.0000
Log pseudolikelihood = -7281.7864                 Pseudo R2       =    0.0371
```

yeddecisi~2b	RRR	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
premitlogit	12.79064	5.235887	6.23	0.000	5.733902	28.53213
provi1	8.023565	5.12536	3.26	0.001	2.294192	28.06112
provi2	1.805934	.6285553	1.70	0.089	.9129375	3.57242
provi4	1.281397	.3640887	0.87	0.383	.7342233	2.236347
provi5	.6988387	.1599925	-1.57	0.118	.4461721	1.09459
provi6	6.055641	1.480294	7.37	0.000	3.750464	9.777668
_cons	1.252107	.2745419	1.03	0.305	.8147109	1.924329
2						
premitlogit	8.457901	3.344976	5.40	0.000	3.896053	18.36117
provi1	4.642476	2.833177	2.52	0.012	1.403733	15.35376
provi2	1.338857	.4002581	0.98	0.329	.7451833	2.405499
provi4	.4657054	.1126656	-3.16	0.002	.2898575	.7482348
provi5	.9861776	.1836074	-0.07	0.940	.6846643	1.420472
provi6	5.179438	1.077489	7.91	0.000	3.445129	7.786814
_cons	7.931644	1.425915	11.52	0.000	5.576196	11.28206
3	(base outcome)					
4						
premitlogit	5.118579	2.676304	3.12	0.002	1.836917	14.26295
provi1	3.827844	3.43359	1.50	0.135	.6598171	22.20675
provi2	3.641583	1.830319	2.57	0.010	1.359761	9.752548
provi4	.9269879	.466195	-0.15	0.880	.3459338	2.48402
provi5	.6095306	.2442748	-1.24	0.217	.2778875	1.336971
provi6	6.579195	2.618086	4.73	0.000	3.016134	14.35142
_cons	.2293846	.0868474	-3.89	0.000	.109217	.4817682

Appendix D. Logit Model for Entrepreneurship to Check the Robustness of Results in Model 3

```
. logit entrepreneur premitlogit provi1 provi2 provi4 provi5 provi6, vce(robust)

Iteration 0:   log pseudolikelihood = -12751.634
Iteration 1:   log pseudolikelihood = -12104.908
Iteration 2:   log pseudolikelihood = -12068.969
Iteration 3:   log pseudolikelihood = -12068.832
Iteration 4:   log pseudolikelihood = -12068.832

Logistic regression                               Number of obs   =     32830
                                                  Wald chi2(6)    =   1213.24
                                                  Prob > chi2     =    0.0000
Log pseudolikelihood = -12068.832                 Pseudo R2       =    0.0535
```

entrepreneur	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
premitlogit	-.0941117	.1081327	-0.87	0.384	-.3060478	.1178244
provi1	-.4450649	.1773505	-2.51	0.012	-.7926655	-.0974642
provi2	-.2819941	.1405643	-2.01	0.045	-.5574951	-.006493
provi4	.6282993	.117229	5.36	0.000	.3985347	.8580639
provi5	.4906183	.086452	5.68	0.000	.3211755	.6600611
provi6	-.8192187	.0897933	-9.12	0.000	-.9952103	-.6432272
_cons	-1.847551	.0842278	-21.94	0.000	-2.012635	-1.682468

```
. mfx

Marginal effects after logit
      y  = Pr(entrepreneur) (predict)
         =  .11521202
```

variable	dy/dx	Std. Err.	z	P>|z|	[95%	C.I.]	X
premit~t	-.0095936	.01102	-0.87	0.384	-.031197	.01201	.066339
provi1*	-.0384063	.01276	-3.01	0.003	-.063406	-.013407	.015078
provi2*	-.0259251	.01158	-2.24	0.025	-.048631	-.00322	.025343
provi4*	.0800771	.01813	4.42	0.000	.044551	.115603	.0258
provi5*	.0517682	.00946	5.47	0.000	.033223	.070313	.41791
provi6*	-.0832918	.0091	-9.15	0.000	-.101137	-.065447	.478708

(*) dy/dx is for discrete change of dummy variable from 0 to 1

```
. logit entrepind premitlogit provi1 provi2 provi4 provi5 provi6, vce(robust)

Iteration 0:   log pseudolikelihood = -7610.5545
Iteration 1:   log pseudolikelihood =   -7510.61
Iteration 2:   log pseudolikelihood = -7507.5204
Iteration 3:   log pseudolikelihood = -7507.5171
Iteration 4:   log pseudolikelihood = -7507.5171

Logistic regression                               Number of obs   =      64451
                                                  Wald chi2(6)    =     193.83
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -7507.5171                 Pseudo R2       =     0.0135
```

entrepind	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
premitlogit	.1755345	.1140513	1.54	0.124	-.0480019	.399071
provi1	-.5415406	.2932019	-1.85	0.065	-1.116206	.0331246
provi2	-.4997776	.2425923	-2.06	0.039	-.9752497	-.0243055
provi4	-.5613036	.2192243	-2.56	0.010	-.9909753	-.131632
provi5	-.5647578	.1429778	-3.95	0.000	-.8449892	-.2845265
provi6	.1804155	.1380418	1.31	0.191	-.0901415	.4509724
_cons	-3.542077	.1355359	-26.13	0.000	-3.807722	-3.276431

```
. mfx

Marginal effects after logit
      y  = Pr(entrepind) (predict)
         =  .02378284
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
premit~t	.0040754	.00265	1.54	0.124	-.001113	.009264	.087581
provi1*	-.0098759	.0041	-2.41	0.016	-.017919	-.001833	.013685
provi2*	-.009317	.00356	-2.61	0.009	-.016301	-.002333	.022156
provi4*	-.0102514	.00308	-3.33	0.001	-.016286	-.004217	.03204
provi5*	-.012715	.00314	-4.05	0.000	-.018868	-.006562	.421592
provi6*	.0042083	.00324	1.30	0.194	-.002138	.010554	.479713

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Appendix E. Rosenbaum Sensitivity Analysis for Treatment Effects given OFW indication and wealth index

. psmatch2 remit, out(entrepind cropind poultind fishind forind salind manind servind trnind minind cnsind) p(ps_ofwWI) n
> oreplacement
There are observations with identical propensity score values.
The sort order of the data could affect your results.
Make sure that the sort order is random before calling psmatch2.

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
entrepind	Unmatched	.016431925	.019664163	-.003232238	.003493857	-0.93
	ATT	.016431925	.023474178	-.007042254	.00479069	-1.47
cropind	Unmatched	.011737089	.021376491	-.009639402	.003594264	-2.68
	ATT	.011737089	.017018779	-.00528169	.004078535	-1.29
poultind	Unmatched	.011150235	.020492709	-.009342474	.003519953	-2.65
	ATT	.011150235	.011150235	0	.003598445	0.00
fishind	Unmatched	.006455399	.009942554	-.003487155	.002476229	-1.41
	ATT	.006455399	.00528169	.001173709	.002617472	0.45
forind	Unmatched	.002934272	.002375166	.000559107	.001245924	0.45
	ATT	.002934272	0	.002934272	.001310704	2.24
salind	Unmatched	.093896714	.104120636	-.010223923	.00771019	-1.33
	ATT	.093896714	.064553991	.029342723	.009242187	3.17
manind	Unmatched	.007042254	.006352187	.000690066	.002022571	0.34
	ATT	.007042254	.006455399	.000586854	.002805747	0.21
servind	Unmatched	.00528169	.00800928	-.00272759	.002225609	-1.23
	ATT	.00528169	.007629108	-.002347418	.002744203	-0.86
trnind	Unmatched	.034037559	.042752983	-.008715424	.005082897	-1.71
	ATT	.034037559	.022300469	.011737089	.005666508	2.07
minind	Unmatched	0	.001159965	-.001159965	.000824627	-1.41
	ATT	0	.001760563	-.001760563	.001015865	-1.73
cnsind	Unmatched	.011737089	.021210782	-.009473693	.003581287	-2.65
	ATT	.011737089	.009976526	.001760563	.00355118	0.50

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support On support	Total
Untreated	18,104	18,104
Treated	1,704	1,704
Total	19,808	19,808

. rbounds deltaentrep, gamma(1 1.1 1.2 1.3 1.4 1.5)

Rosenbaum bounds for deltaentrep (N = 1704 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	.069825	.069825	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.1	.031015	.137531	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.2	.013045	.229159	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.3	.005255	.336864	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.4	.002044	.450326	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.5	.000773	.559916	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07

. rbounds deltacrop, gamma(1 1.1 1.2 1.3 1.4 1.5)

Rosenbaum bounds for deltacrop (N = 1704 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	.099271	.099271	-3.2e-07	-3.2e-07	-3.2e-07	-3.2e-07
1.1	.052521	.170178	-3.2e-07	-3.2e-07	-3.2e-07	-3.2e-07
1.2	.026799	.257184	-3.2e-07	-3.2e-07	-3.2e-07	-3.2e-07
1.3	.013288	.353502	-3.2e-07	-3.2e-07	-3.2e-07	-3.2e-07
1.4	.006438	.45195	-3.2e-07	-3.2e-07	-3.2e-07	-3.2e-07
1.5	.003062	.546428	-3.2e-07	-3.2e-07	-3.2e-07	-3.2e-07

. rbounds deltafish , gamma(1 1.1 1.2 1.3 1.4 1.5)

Rosenbaum bounds for deltafish (N = 1704 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	.32736	.32736	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.1	.40729	.254331	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.2	.483718	.195634	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.3	.554596	.149306	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.4	.618816	.113238	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.5	.675962	.085452	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07

. rbounds deltafor , gamma(1 1.1 1.2 1.3 1.4 1.5)

Rosenbaum bounds for deltafor (N = 1704 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	.012674	.012674	-3.6e-07	-3.6e-07	-3.6e-07	-3.6e-07
1.1	.016503	.009508	-3.6e-07	-3.6e-07	-3.6e-07	-3.6e-07
1.2	.020613	.007153	-3.6e-07	-3.6e-07	-3.6e-07	-3.6e-07
1.3	.02493	.005394	-3.6e-07	-3.6e-07	-3.6e-07	-3.6e-07
1.4	.029391	.004075	-3.6e-07	-3.6e-07	-3.6e-07	-3.6e-07
1.5	.033945	.003085	-3.6e-07	-3.6e-07	-3.6e-07	-3.6e-07

. rbounds deltasal , gamma(1 1.1 1.2 1.3 1.4 1.5)

Rosenbaum bounds for deltasal (N = 1704 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	.000654	.000654	-4.5e-07	-4.5e-07	-4.5e-07	-4.5e-07
1.1	.00664	.000038	-4.5e-07	-4.5e-07	-4.5e-07	-4.5e-07
1.2	.035351	1.7e-06	-4.5e-07	-4.5e-07	-4.5e-07	-4.5e-07
1.3	.115996	6.2e-08	-4.5e-07	-4.5e-07	-4.5e-07	-4.5e-07
1.4	.264278	1.9e-09	-4.5e-07	-4.5e-07	-4.5e-07	-4.5e-07
1.5	.458199	5.4e-11	-4.5e-07	-4.5e-07	-4.5e-07	-4.5e-07

. rbounds deltasal , gamma(1 1.1 1.2 1.3 1.4 1.5) deltaman
option deltaman not allowed
r(198);

. rbounds deltaman , gamma(1 1.1 1.2 1.3 1.4 1.5)

Rosenbaum bounds for deltaman (N = 1704 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	.417414	.417414	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.1	.507931	.330917	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.2	.590339	.258758	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.3	.662984	.200105	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.4	.725471	.153363	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.5	.778201	.116678	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07

. rbounds deltaserv , gamma(1 1.1 1.2 1.3 1.4 1.5)

Rosenbaum bounds for deltaserv (N = 1704 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	.196884	.196884	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.1	.140656	.264293	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.2	.099479	.334262	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.3	.069809	.403969	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.4	.048687	.471271	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07
1.5	.033789	.53468	-2.9e-07	-2.9e-07	-2.9e-07	-2.9e-07

. rbounds deltatrn , gamma(1 1.1 1.2 1.3 1.4 1.5)

Rosenbaum bounds for deltatrn (N = 1704 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	.019564	.019564	-3.6e-07	-3.6e-07	-3.6e-07	-3.6e-07
1.1	.05447	.005746	-3.6e-07	-3.6e-07	-3.6e-07	-3.6e-07
1.2	.11774	.001556	-3.6e-07	-3.6e-07	-3.6e-07	-3.6e-07
1.3	.210378	.000395	-3.6e-07	-3.6e-07	-3.6e-07	-3.6e-07
1.4	.32517	.000095	-3.6e-07	-3.6e-07	-3.6e-07	-3.6e-07
1.5	.449738	.000022	-3.6e-07	-3.6e-07	-3.6e-07	-3.6e-07

. rbounds deltamin , gamma(1 1.1 1.2 1.3 1.4 1.5)

Rosenbaum bounds for deltamin (N = 1704 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	.041632	.041632	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.1	.03464	.049324	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.2	.02889	.056923	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.3	.024143	.064368	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.4	.020212	.071617	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.5	.016947	.07865	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07

. rbounds deltacns , gamma(1 1.1 1.2 1.3 1.4 1.5)

Rosenbaum bounds for deltacns (N = 1704 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	.310937	.310937	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.1	.419266	.216596	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.2	.523934	.146738	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.3	.618976	.097197	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.4	.701244	.063211	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07
1.5	.769825	.040492	-4.3e-07	-4.3e-07	-4.3e-07	-4.3e-07

* gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)