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E-mail address: mario.liebensteiner@wu.ac.at
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Estimating the Income Gain of Seasonal Labour Migration[+]

Mario Liebensteiner[*]

Vienna University of Economics and Business
Department of Economics

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[*] Contact: mario.liebensteiner@wu.ac.at

1 Introduction

Given free movement of labour, international migration occurs if, ceteris paribus, potential earnings abroad exceed potential earnings in the home country. The wage differential encourages individuals to migrate since they can thus obtain higher incomes and, hence, can realise a higher utility level. Henceforth, if a worker from a low-income country expects to maximise his or her present value of lifetime earnings in a high-income country (net of monetary and psychic costs), he or she will move. Nevertheless, the return to skills in the home and host country is a key factor of migration. If the destination offers a relatively low return to skills (i.e., people with low skills expect higher income gains relative to high skills), individuals will negatively select into migration. (Borjas, 2000)

Apart from permanent migration, it may be beneficial for an individual to migrate seasonally, i.e., for only a limited (short) period. Strong cultural and family boundaries, as well as limitations on permanent migration (e.g., visa or work-permit requirements, specific job characteristics, distance to destination, preference to consume in the home country, higher purchasing power of the host currency at home), can cause people to migrate seasonally to enhance earnings for a few months and then return to their families in their source country. (Hill, 1987; Joarder and Hasanuzzaman, 2008; Konseiga, 2007). Contrary to the Neoclassical approach that claims migrants return when they fail abroad (Borjas and Bratsberg, 1996), seasonal migration can be understood in the context of the New Economics of Labour Migration, which sees that migration is a household strategy and that migrants return after they successfully achieve their goals, in spite of persistently higher wages in the destination country (Borodak and Tichit, 2009; Dustman, 2003). Most striking is that, while permanent migration may have other objectives such as an escape from social or political pressure, the main target of seasonal migration is assumed to be income maximisation.

Armenia has experienced a massive labour exodus. According to Sahakyan (2006), 5 to 6 million Armenians permanently reside outside Armenia, mainly because of social, political and economic disadvantages. An estimated 3.2 million people have remained in the country. In 2008, the national labour force, which comprises approximately 1.3 million people (Gevorgyan et al., 2009). In recent years, a new trend of seasonal migration has developed. Males primarily migrate for a couple of

months to Russia to work where incomes are much higher than in Armenia. Russia's GDP per capita of US$9,370 in current US dollars (mean 2006–2010), exceeds Armenia's GDP of US$2,925 by 320 percent, suggesting a large income differential. The high demand for labour in the Russian construction sector attracts migrants from post-Soviet countries especially. A large share of the additional income earned abroad is remitted to the families remaining in Armenia and is used to finance small investment projects (such as housing or the setting up of small businesses) and education (Gevorkyan et al., 2006; Ambrosini et al., 2011).

Armenia's remittances stemming from *seasonal* migration account for 88 percent of all 2009 remittances (based on World Bank, 2011). When compared to other countries in the region (Azerbaijan, Georgia, Kazakhstan, Moldova, Tajikistan, Ukraine), which have average shares of 30 percent, Armenia stands out. Hence, research on seasonal migration from Armenia is of special importance. Nonetheless, seasonal migration bears great risks – for example, many seasonal migrants work illegally in the destination country or are unpaid (Gevorkyan et al., 2006). Estimates by the World Bank (Mitra et al., 2007) state that only one in eight seasonal migrants had a written agreement with their employer and in many cases, contract conditions were violated. In addition, there are substantial monetary costs (e.g., transfer costs) and emotional costs – such as being separated from their families or of ethnic intolerance in the host country (Derderian, 2007).

Thus, the question arises, how successful are seasonal migrants in terms of income maximization? This analysis aims to model seasonal migration's causal effect on average earnings. Based on matching techniques, the effect of seasonal migration is estimated at US$480 for a migrant relative to about US$50 that the migrant would have earned at home. The analysis addresses the problem of self-selection, which points toward negative selection of seasonal migrants in terms of income, skills and employment characteristics.

The remainder of the paper is structured as follows: Section 2 reviews the literature on migration regarding Armenia and seasonal migration in general; Section 3 describes the problems of self-selection, the methodology and econometric issues; Section 4 outlines the data based on a household survey and presents stylized facts; Section 5 reports the results; and summary and conclusions are provided in Section 6.

2 Literature review

This section reviews relevant studies in the context of short-term migration in general and seasonal and temporary migration as peculiar forms of it. This is of importance, as all forms of short-term migration may bear relevant issues for seasonal migration. In addition, papers on the income gains from permanent migration are discussed for comparison.

While extensive theoretical and empirical literature on the income gains of *permanent* migration (see Hanson, 2008, for a literature survey) exists, literature on *seasonal* migration is scarce. Little research on migration has been done, especially in the case of Armenia where mass emigration is still a big issue. To our knowledge, no empirical study has focused on the monetary impact of seasonal migration from Armenia.

The literature emphasises economic reasons as being the main motivation for *seasonal* migration (e.g., Budnik, 2009). To the contrary, political or social concerns would cause individuals to emigrate *permanently* (e.g., Gevorkyan et al., 2006; Joarder and Hasanuzzaman, 2008). According to Konseiga (2007), seasonal migration from Burkina Faso may serve as an escape from "income instability," with the advantage of keeping the immigrant's residence in the home country to avoid the risks involved with permanent migration. Consequently, seasonal migration serves as a strategy to escape poverty. Haberfeld et al. (1999) argue that seasonal migration within India provides a stable flow of income for households in less developed rural areas. Those households sending one or more migrants enhance their incomes significantly. Almost 60 percent of total household earnings stem from remittances. Thus, seasonal migration is found to enhance welfare. Budnik (2009) investigates short-term migration from Poland to the UK following Poland's accession to the EU in 2004. The results indicate that potential gains in earnings explain temporary emigration.

According to the New Economics of Labour Migration (Stark and Bloom, 1985), the migration decision is not reached as simply an individual decision but is reached on the household level. Thus, individuals migrate with the objective to enhance the well-being of the household. As a consequence, not only individual- but also household-characteristics play an important role in the propensity of migration. Stark and Fan (2007) develop a theoretical framework investigating the duration of

migration from Poland to Germany. Prior to 2011, migration to Germany was restricted to seasonal permits for a limited number of Polish emigrants. The authors conclude that seasonal migration, once those barriers to unlimited migration-duration were removed, would still be the best choice for those who previously migrated seasonally. Thus, seasonal migrants are not seen as latent permanent workers. In a descriptive analysis of a household survey in Armenia, Minasyan and Hancilova (2005) state that the overall perception of labour migrants (most of whom are seasonal migrants) towards permanent migration is low. Most labour migrants do not intend to migrate permanently. According to Stark and Fan (2007), seasonal migration can be the optimal strategy for maximizing lifetime utility. In an empirical study of emigrants from Romania, Ambrosini et al. (2011) reach the same conclusion, that individuals may choose short-term migration as a strategy to maximise lifetime earnings.

Görlich and Trebesch (2008) investigate the differences between seasonal and permanent migration from the Republic of Moldova – a country with similar patterns as Armenia regarding its substantial labour emigration and the large share of seasonal migrants working in the Russian construction sector. The authors' findings suggest that seasonal migration does not positively influence permanent migration, which corroborates the argument of an optimal strategy of seasonal migration.

Dustman (1993) stresses that, contrary to permanent migration, negative selection into temporary migration is possible because of economic circumstances (e.g., relative skill premium). Additionally, the findings point towards less investment in human capital in the case of temporary migration compared to permanent migration, because the shorter duration abroad puts less pressure on the native population through migrants' competing with them. Beine et al. (2008) provide evidence that the probability of emigrating permanently increases with higher education of individuals, especially those from low income countries. Yang (2008) explores the role of remittances from Filipino emigrants working overseas and finds that higher remittances help families in the home country (the Philippines) to support paying their children's school expenses and reduces the probability of child labour. Additionally, remittances promote the setting up of small businesses.

Much attention has been drawn to the income gains of migration from developing to developed countries. Aguayo-Téllez and Rivera-Mendoza (2011) analyse migration from Mexico to the US – a

country-pair with similar structures concerning migration as those from Armenia to Russia. The wage differential between the two countries is large (overall, US wages are 7.5 times higher). Mexico has experienced mass emigration to the US (to a great extent illegal) and, as a result, large social networks exist for Mexicans in the US – making emigration of Mexicans even more attractive. By moving from the interior of Mexico to the interior of the US, migrants gain 5.34 times the income of their counterparts in Mexico (i.e., individuals with similar characteristics), with larger gains for uneducated workers.

McKenzie et al. (2010) use experimental data from a random draw of a ballot of Tongans who applied to work permanently in New Zealand. Again, the authors look at permanent migration from a developing country to a mature economy. The experimental estimate for a migrant's income gain from migration is 263 percent per week ($NZ320). This is only about half of what the difference in GDP per capita suggests.

Yashiv (2008) concentrates on migration from Palestine to Israel. In this case, migration takes the form of commuting on a very frequent basis (daily in many cases, if border controls allow it). Consequently, this special form of migration may be regarded as a mixture of permanent migration (individuals work abroad permanently) and short-term migration (individuals cross the border frequently). Once again, the wage differential between the two countries serves as a migration premium that attracts migrants. However, "very low returns to skills in the foreign economy deter skilled workers, leading to negative self-selection" (Yashiv, 2008, p. 1). Hence, migrant workers are concentrated in low-skill tasks in Israel, while the distribution among occupations in Palestine is much more diverse.

From this section we conclude that seasonal migration is generally seen as an optimal strategy to enhance earnings. Many studies highlight the low probability of seasonal migration turning into permanent migration. Some studies find evidence for negative selection among seasonal migrants based on observable characteristics such as education. The literature on the income gains from permanent migration suggests high earnings potentials. A large share of the additional income of seasonal migration is remitted to support families in the home country.

3 Methodology and econometric approach

This study aims to measure the "average treatment effect on the treated" (ATT), defined as "the average income gain for a migrant when migrating seasonally." McKenzie et al. (2010, p. 914) highlight that "even estimates of the income gains from migration that go beyond simple cross-country comparisons of wage rates are likely to be misleading." Therefore, the methodology of causal inference provides a useful tool for analysing income gains. Following this literature, the decision about whether to migrate seasonally is declared as the treatment (D_i) an individual *i* receives, and the income gain is described as the potential outcome (ΔY_i). The suffixes *t'* and *t* represent the time before and after treatment. Thus, the two potential outcomes of an individual *i* can either be $\Delta Y_i^1 = inc_{i1t} - inc_{i0t'}$ for $D_i = 1$ in case of migration, or $\Delta Y_i^0 = inc_{i0t} - inc_{i0t'}$ for $D_i = 0$ in case of staying in Armenia. The causal income effect of migration for a seasonal migrant is defined as follows:

$$ATT_i = E\left(\Delta Y_i^1 - \Delta Y_i^0 \middle| D_i = 1\right) = E\left(\Delta Y_i^1 \middle| D_i = 1\right) - E(\Delta Y_i^0 | D_i = 1). \quad (1)$$

Only the first term on the right-hand side of equation (1) can be observed. The second term – the income growth of a migrant if he had stayed at home – is unobserved and has to be modelled by a counterfactual.

Borjas (1987) argues that non-random self-selection, based on observable and unobservable characteristics, is an important issue when investigating migration. Rearranging (1) yields

$$E\left(\Delta Y_i^1 \middle| D_i = 1\right) - E\left(\Delta Y_i^0 \middle| D_i = 0\right) = ATT_i + E\left(\Delta Y_i^0 \middle| D_i = 1\right) - E(\Delta Y_i^0 | D_i = 0) \quad (2)$$

which equates the ATT plus the self-selection bias. If self-selection into migration occurs, the groups of migrants and non-migrants would be heterogeneous in their characteristics. Therefore, *matching* chooses control individuals on a set of observable characteristics, *X*, similar to the treated individuals. The counterfactual outcome of a non-migrant can be used to model the ATT under the condition that

$$E\left(\Delta Y_i^0 \middle| X_i, D_i = 1\right) = E(\Delta Y_i^0 | X_i, D_i = 0). \quad (3)$$

In this case, conditional on X, a migrant's potential income growth in Armenia would have been the same as a non-migrant's potential income growth (which is observable). This is why simple comparisons of means of the outcomes between all migrants and all non-migrants may lead to biased results.

Equation (3) refers to the fundamental Conditional Independence Assumption (CIA) required for matching. Based on the set of included pre-treatment characteristics, migrants and non-migrants should be (ideally) homogeneous and differ only in their decision whether to migrate seasonally. A rich set of relevant covariates is assumed to fulfil the CIA.[1] (Huber et al., 2011; Zhao, 2008).

Only conditioning variables that affect both the migration decision and the potential income gain at home need to be included in X. Covariates affecting only D_i but not ΔY_i^0 (e.g., moving costs), or ΔY_i^0 but not D_i, do not need to be considered. However, excluding variables that affect both migration and wages will cause bias. Variables that affect only one, either migration or wages, should be omitted because they may increase the variance. In addition, including many variables can cause the common support assumption to be violated because the treatment decision may be fully explained.

Unobserved effects such as ability or motivation may also cause heterogeneity between the two groups of migrants and non-migrants in the sample. Given the definition of the differences in the potential outcomes (equation 1), we employ a difference-in-differences (DID) estimator (i.e., the income growth instead of the level). This eliminates unobserved time-invariant fixed effects and, hence, mitigates unobserved heterogeneity. (Caliendo and Kopeinig, 2008; Ham et al., 2011)

To obtain a perfectly balanced control group (i.e., migrants and non-migrants do not differ in their observable characteristics), *exact* covariate matching would be the ideal approach. However, because of the problem of high dimensionality in the covariates, in order to fulfil the CIA, exact matching is very restrictive. It is to be expected that few control individuals with exactly the same characteristics as migrants could be found. Thus, exact matching would result in a perfectly balanced but small sample of migrants and non-migrants.

[1] There is no way of testing the CIA statistically.

There is a trade-off between post-matching covariate-balance and the number of observations dropped from the sample (Rosenbaum and Rubin, 1985b). Thus, semi-parametric approaches for non-experimental studies, such as propensity score matching (PSM) or Mahalanobis distance matching (MAHAL; Rosenbaum and Rubin, 1984), can be used to find matches of treated and control individuals that are *similar* in their characteristics, keeping the number of observations in the sample high.

The literature highlights the performance accuracy of matching estimators. McKenzie et al. (2010) find that matching estimators obtained from a randomised experiment are accurate in replicating the income gain of migrants from Tonga to New Zealand. Smith and Todd (2005) also compare matching methods with the results from experimental data and conclude that matching estimators are indeed sensitive to the specifications. They conclude critically that there is no general optimal matching-operator for any data set. However, matching may be accurate when the data is of high quality with many variables related to the treatment participation and the outcome. Huber et al. (2010) run Monte Carlo simulations by applying real data rather than generated data, and they highlight that the choice of the matching method is less important if the tuning parameters are correctly specified. Not only McKenzie et al. (2010) and Smith and Todd (2005), but also Heckman et al. (1997) and Mueser et al. (2007) emphasise the application of DID with matching. The quality and large size of the data set used for this analysis, and the application of matching combined with DID, lead to the expectation of consistent estimates. For each matching method we set different tuning parameters to examine the sensitivity of the estimates. The rich set of covariates leads to the plausibility of the CIA.

Propensity score matching

If *p(X)* is the propensity of the decision to migrate, given a set of characteristics, *X*, then

$$Y_0 \perp D|X \Rightarrow Y_0 \perp D|p(X), \tag{4}$$

where ⊥ stands for statistical independence.

That means that if treatment and control group individuals have the same propensity score, *p(X)*, their distribution in *X* is also the same (Rosenbaum and Rubin, 1983). This has the advantage that individuals can be matched on a single scalar rather than on a set of characteristics and, thus, makes the common support problem of (exact) covariate matching less restrictive.

The propensity to receiving the treatment can be estimated by any discrete choice model, such as probit or logit models (Caliendo and Kopeinig, 2009). Zhao (2008) shows that non-experimental methods still come to consistent estimates, even though the propensity score is incorrectly specified. Although Zhao tests for the specification of the error distribution, his argument of using the propensity score only to sort and match treated and control individuals also applies for the probit specification. Although the probit may suffer from misspecification, because only confounders relevant for the CIA are included, the probit is still consistent in ranking individuals among their propensity scores. As a consequence, the probit estimates are not relevant for interpretation, but only for ranking the observations among their propensity scores. Hence, the coefficient estimates are reported in the appendix (Table A2) but not commented on in the text.

In the simplest case of single pair matching, each treated individual is matched to a control individual with the nearest available propensity score. One-to-many matching (1:M) causes an effect where the bias may be reduced because of more information being included, but the variance may increase because of greater distances in propensity scores. (e.g., Caliendo and Kopeinig, 2009) The data quality, as well as the size of the control group, determines the result. To avoid large distances when applying 1:M matching, Huber et al. (2010) stress the usefulness of matching with callipers. This limits the distance in propensity scores to a particular radius.

Reweighting treatment and control individuals by their odds, $\hat{p}(X)/(1-\hat{p}(X))$ (Nichols, 2007), or by kernel weighting, puts weights on all control observations depending on their distances in propensity scores.[2] Different kernels (e.g., Gaussian, Epanechnikov, or tricube) can be implemented. Frölich (2004) notes that kernel estimates become more robust when the sample size gets large. Trimming is another option that drops an a-priori-set percentage of treated observations at which the propensity-score density of the control observations is the lowest.

[2] Kernel matching is described in more detail in Heckman et al. (1997) and Mueser et al. (2007).

This study includes a large group of control individuals and, thus, it is likely that 1:M matching and kernel-matching yield better results than matching on a single neighbour. Henceforth, we employ these methods, in combination with callipers and trimming.

Mahalanobis matching

With MAHAL, treated and control individuals are randomly ordered and, in a second step, the first treated individual is matched to its closest control according to the Mahalanobis distance, given in equation (5). Then this pair is eliminated from the set and the next pair gets matched. Hence, the process continues until all treated individuals have an assigned counterfactual individual.

$$D_{ij} = (X_i - X_j)' V^{-1} (X_i - X_j) \tag{5}$$

X is the set of observable characteristics, i and j refer to a treated and control individual respectively, and V represents the covariance matrix of X (Mueser et al., 2007). The major disadvantage of MAHAL is that it may not work well if X is of high dimension (which is the case in this study), because it treats all interactions of X as equally important (Stuart, 2010; Mueser et al., 2007). It is also possible to combine MAHL with propensity scores. This can be done by using the estimated propensity score, $\hat{p}(X)$, instead of X or by including $\hat{p}(X)$ as one additional variable in X. The first approach solves the problem of dimensionality (Guo and Fraser, 2010, p. 146; Rosenbaum and Rubin, 1985a).

To summarise, this study incorporates different matching estimators and specifications in order to test for robustness across alternative evaluation methods. Various choices – for example, the number of included neighbours, the kernel type, with or without replacement – bear potential trade-offs between bias and efficiency (Mueser et al., 2007). Kernel matching and 1:M matching may be effective in this analysis because the sample of control individuals is large. With calliper matching, the distance can be limited to a given range. This study benefits from the large sample of potential controls and the broad set of covariates, which lead to the expectation of consistent estimates among alternative estimators.

4 Data

Novel survey data from Armenian households, collected by the institute of Advanced Social Technologies,[3] are used. The survey's objective was to obtain a balanced sample, meaning that the same individuals of the same households were interviewed over the years 2006–2010 consecutively. The survey was conducted in three rounds: in the first round information on 2,750 households was collected for the years 2006–2008; the second and third rounds collected information for the years 2009 and 2010 respectively. Because of attrition,[4] 2,673 households remain in the year 2010. The data underwent an extensive cleansing process and were tested for consistency: doubtful information in the data was double-checked with the hard copies of the interviews or the respective households were recontacted by phone. Henceforth, the data set seems reliable for the Armenian population.

In our survey, almost 95 percent of all Armenian *seasonal* migrants move to Russia (followed by the Ukraine, Kazakhstan, and Greece), which is consistent with figures by ILO (2009) of 96.2 percent over the period 2002–2009. Russia is the primary destination for the following reasons: most Armenians speak Russian, there is a visa-free border regime with Armenia, historical ties exist between Russia and Armenia (as a former Soviet country), and – principally – Russia is home for the largest Armenian diaspora. Hence, limited cultural and linguistic barriers, as well as an Armenian community, deter monetary and psychic costs and predict seasonal migration from Armenia to Russia. (Derderian, 2007; ILO, 2009; Minasyan et al., 2007) As a consequence of the strong trend of seasonal migration to Russia, emigrants to source countries other than Russia were pruned from the sample.

Noticeably, seasonal labour migration from Armenia to Russia is almost exclusively a male phenomenon. Women follow other migration patterns.[5] Henceforth, we focus only on the male working-age (18–62 years) population in our data sample. To distinguish seasonal migration from other forms of migration (e.g., permanent migration), "seasonal migration" is defined as "leaving Armenia with the aim of finding work in Russia and returning home within 12 months." Moreover,

[3] www.ast.am
[4] Some of the households could no longer be reached in survey rounds two or three.
[5] Women tend to migrate to different countries and work in different occupational fields than men do.

distinct from *temporary* migration (or other forms of short-term migration), *seasonal* migration usually takes place repeatedly over time. As a consequence, migrants who leave Armenia for more than 12 months consecutively are disregarded. Thus, the final version of the data set consists of a total of 3,909 individuals, of which 598 are seasonal migrants and 3,311 are non-migrants.

The data set is structured in a monthly panel over the period 2006M01–2010M12. Each seasonal migration trip (i.e., the month before the decision to migrate) reflects a treated observation. In total, this makes 1,305 treated observations including all pre-migration characteristics, *X*, as well as the difference in pre-treatment and post-treatment incomes, ΔY_i . Hence, the sample of treated observations is structured in a cross section. The structure of the control sample is different. As there is no time point of leaving the country, for each individual we observe 59 observations (i.e., 5 years times 12 months; the last month drops because of the first difference in incomes). Because of attrition it can be less in some cases. This panel comprises 179,740 control observations in total.

The data include individual and household characteristics, determining the income effect according to relevant literature (e.g., Budnik, 2009; Ham et al., 2011; McKenzie et al., 2010). Among the individual characteristics are pre-migration earnings, age, marital status, educational attainment, field of occupation, employment status, sector of employment, industry of employment, work experience and migration experience. The household characteristics include the dependency ratio (i.e., the sum of children and pensioners divided by household size) and the region of origin. The unemployment rate in the region of origin is a regional characteristic obtained from OECD (2011). As there are hardly any benefits or social backups for the unemployed in Armenia (Mitra et al., 2007), this study does not distinguish between non-working and registered unemployed individuals. Hence, the term "unemployment" refers to both groups simultaneously.

Table 1: Descriptive statistics

Variable		Migrants	Non-migrants	Standardised difference	
	Nt	mean	mean	in %	p>|t|
Income *(in US$)*[1]	1305	21.19	113.43	-78.8	***
Age /10 *(in years)*[2]	1305	3.84	3.81	2.5	
Age squared / 1000 *(in years)*[2]	1305	1.59	1.62	-2.7	
Married[2]	1305	0.78	0.73	13.6	***
Education[2]					
Primary	1305	0.06	0.08	-7	**
Secondary	1305	0.81	0.69	27.2	***
Tertiary	1305	0.13	0.23	-26	***
Occupation[1]					
No occupation	1305	0.9	0.44	112.4	***
Managers	1305	0	0.06	-32.5	***
Professionals	1305	0.01	0.06	-27	***
Technicians and associate professionals	1305	0	0.03	-22.1	***
Clerical support workers	1305	0	0.01	-12.6	***
Service and sales workers	1305	0.01	0.07	-30	***
Skilled agricultural, forestry and fishery workers	1305	0.01	0.09	-33.3	***
Craft and related trades workers	1305	0.03	0.08	-24.1	***
Plant and machine operators, and assemblers	1305	0.01	0.07	-31.8	***
Elementary occupations	1305	0.02	0.06	-22.8	***
Armed forces occupations	1305	0	0.03	-23.5	***
Employment status[1]					
Unemployed	1305	0.9	0.44	112.4	***
Employed	1305	0.06	0.4	-87.5	***
Self-employed	1305	0.04	0.16	-42.3	***
Sector of employment[1]					
None	1305	0.9	0.44	112.4	***
Private	1305	0.02	0.17	-53.1	***
State	1305	0.08	0.39	-78.8	***

Variable		Migrants	Non-migrants	Standardised difference	
	Nt	mean	mean	in %	p>|t|
Industry of employment[1]					
None	1305	0.9	0.44	112.4	***
Agriculture, fishing, and mining	1305	0.02	0.11	-38.2	***
Manufacturing	1305	0.01	0.07	-27.8	***
Construction	1305	0.02	0.05	-12	***
Services	1305	0.04	0.33	-80.7	***
Work experience / 10 *(in years)*[2]	1289	1.22	1.24	-1.6	
Work experience squared / 1000 (in years)[2]	1289	0.26	0.29	-10.4	***
Migration experience[2]	1244	0.65	0.11	136.6	***
Household size[2]	1203	5.24	5.17	4.1	
Dependency ratio[2]	1203	0.27	0.27	1.9	
Regional unemployment rate in Armenia (in %)[2]	1305	7.56	7.02	12.7	***
Urban[2]	1305	0.52	0.65	-26.1	***
Region of origin[2]					
Yerevan (capital city)	1305	0.13	0.36	-55.6	***
Aragatsotn	1305	0.06	0.05	7	**
Ararat	1305	0.11	0.08	9.8	***
Armavir	1305	0.08	0.09	-2.2	
Gegharkunik	1305	0.18	0.07	35.5	***
Lori	1305	0.08	0.08	0.1	
Kotayk	1305	0.05	0.09	-13.7	***
Shirak	1305	0.24	0.07	45.9	***
Syunik	1305	0.01	0.05	-26.1	***
Vayots	1305	0.02	0.02	5.2	**
Tavush	1305	0.02	0.04	-9.3	***

Notes: ***, **, * indicate significance of the difference at the 1%, 5%, and 10% level. [1] monthly time variant; [2] yearly time variant

Notably, because of missing values, some of the variables do not contain information on the full sub-sample of 1,305 treated observations. The dependency ratio includes 100 missing observations in the sample of treated individuals. To a lesser extent, work experience and migration experience suffer from missing values. Thus, all matching estimations are re-estimated in a reduced form, omitting dependency ratio. It is likely that the exclusion of dependency ratio will not bias the estimates as this variable may influence only the migration decision but not the potential outcome. Nevertheless, the same is not true for work experience and migration experience, as both probably have an impact on the migration decision and the potential income; therefore, they are kept in the estimation.

The common support assumption of matching requires a control group that is large enough relative to the treatment group to find control individuals who are similar to treated individuals in their propensity scores (Blundell and Dias, 2000). The large sample of non-migrants as potential control individuals relative to the sample of seasonal migrants in this analysis guarantees enough potential overlap in the propensity to receiving the treatment. The data at hand ensure that there are plenty of control individuals to be matched on many covariates. Table 1 provides a summary of the relevant covariates used in this study. It is important to highlight that some variables vary over months while others show annual variance only. The variables represent pre-migration characteristics for migrants to ensure exogeneity of confounders (i.e., confounding variables are not influenced by the treatment in a way that is related to the outcome variables).

In Table 1 we observe considerable heterogeneity in standardised differences[6] within the two groups of migrants and non-migrants. On average, migrants tend be to negatively selected into migration. Compared to non-migrants, migrants tend to be poorer, have less work experience, work in regions with greater unemployment rates, and many report being unemployed. Migrants and non-migrants are equally distributed in primary schooling, though more migrants reach a secondary schooling level, but fewer have a tertiary degree. The dependency ratio is the same for migrants and non-migrants. The average seasonal migrant is 38.4 years old, has received secondary education, is unemployed, has 12.2 years of work

[6] Formula according to Rosenbaum and Rubin (1985a).

experience, has already gained migration experience, lives in a household with 5.2 members, and comes from a region with a high unemployment rate (7.6 percent). These findings provide a first look at the relative distribution of characteristics of migrants and non-migrants, indicating that *negative self-selection* into seasonal migration is an issue.

Notably, the literature suggests relevant requirements for the data used to produce accurate non-experimental estimates: (i) treatment and control groups should overlap considerably in their probabilities of receiving the treatment (i.e., the common support assumption; McKenzie et al., 2010); (ii) treatment and control groups should be located in the same labour market prior to treatment (Heckman and Smith, 1999); (iii) data for both groups should be collected in an analogous way (e.g., collected in the same questionnaire) (Heckman, Ichimura, Todd, 1997); and (iv) the pre-treatment outcome (i.e., the pre-migration income) should be included, to capture potential unobserved effects. This variable may absorb unobserved willingness or ability (McKenzie, 2010; Mueser et al., 2007). The used data set fulfills those requirements and, thus, is considered suitable for matching.

Descriptive evidence

Table 2 reveals that the incomes of male Armenian income-recipients (employees and self-employed) increased by 22 percent in 2007 and by 14 percent in 2008. In 2009 the income growth rate dropped to -9 percent and in 2010 remained low at 4 percent, resulting in an income of US$187 for 2006–2010. The average income of the total working-age population, including the many unemployed, is considerably less at US$104 for 2006–2010. Obviously, a great share of the migrants are unemployed or have substantially low income. Armenian migrants earn significantly more in Russia, compared to their incomes in Armenia. Over the period 2006–2010, they received incomes of US$523. Notably, this includes a small share of migrants who remain unemployed in Russia. Some individuals probably migrated seasonally to Russia without finding a job there. It is also possible that some of these migrants were not paid by their employer because of their illegal status.

Table 2: Incomes of Armenians at home and in Russia in US$

	Urban			Rural			Total			
	Non-migrants	Migrants	Total	Non-migrants	Migrants	Total	Non-migrants	Migrants	Total	Total
	Incomes of sample population in Armenia (incl. unemployed)									Incomes of Armenian migrants in Russia
2006	101	52	96	53	35	50	84	44	79	477
2007	127	75	122	69	41	65	107	59	101	509
2008	152	78	145	82	49	77	128	65	121	566
2009	139	76	132	74	50	70	115	64	109	519
2010	144	70	136	83	44	77	122	58	114	529
mean	132	70	126	72	44	67	111	58	104	523
	Incomes of employees and self-employed in Armenia (excl. unemployed)									
2006	187	149	185	114	117	114	164	135	150	
2007	227	197	225	141	129	139	200	169	184	
2008	257	231	256	162	156	162	228	197	213	
2009	238	214	236	146	139	145	207	179	190	
2010	241	202	239	162	146	160	216	177	196	
mean	230	199	228	145	137	144	203	171	187	

From Table 2 we also observe a great disparity in incomes between the urban and the rural population. During the period 2006–2010, the majority (52 percent) of seasonal migrants came from urban areas rather than from rural areas,[7] with the tendency to a more equal distribution over the years. Incomes in urban areas are on average 40 percent higher than in rural areas. This reflects the fact that Armenia has a vast agricultural sector and that in rural areas agriculture is the primary source of income. Nevertheless, people's living is mainly based on subsistence farming without prospects of high profitability. According to OECD (2011, p. 31), "it is still preferable for farmers to engage in other economic activities or to look for better job opportunities as migrant workers (mostly Russia), as their absolute amount of income is very low." This is also reflected in our sample, where a considerable amount of individuals from rural areas emigrates seasonally.

In our sample the number of seasonal migration trips from Armenia to Russia increases from 2006 to 2008 and then declines, as shown in Table 3. Seasonal migration happens to a great extent in the first

[7] We do not observe rural-to-urban migration within Armenia.

quarter of the year. Seasonal migration is identified as a process of repeated migration. Once an individual has migrated, there is a high probability of re-migration. On average, a migrant emigrates 2.3 times during the years 2006–2010. Of a total of 598 migrants, 336 emigrate more than once. The average length of the stay abroad is 7.9 months. Those findings are backed by Minasyan and Hancilova (2005, p. 40): "(...) the majority of migrants left the country either in the beginning or in the end of spring and returned to Armenia by the end of autumn / beginning of winter. As for the duration of the trip, the majority of seasonal migrants have stayed abroad for 5–11 months (67.5%)." The Moscow district is the primary destination (53 percent of all seasonal migration trips), which is in line with ILO (2009).

Table 3: Number of migration trips to Russia over time

	2006	**2007**	**2008**	**2009**	**2010**	**total**
Q1	136	148	175	90	91	640
Q2	72	81	106	84	76	419
Q3	17	19	37	24	17	114
Q4	33	44	31	20	4	132
Total	258	292	349	218	188	1305
Q1 in total	52.7%	50.7%	50.1%	41.3%	48.4%	49.0%

There is a considerable difference in educational attainment between migrants and non-migrants. Among the highly educated, 23 percent of the non-migrants hold a tertiary degree compared to 13 percent of seasonal migrants, indicating negative selection. Consistently, the share of medium-educated individuals, i.e., finished secondary school, is 81 percent among migrants and only 69 percent among non-migrants. The share of primary-educated individuals is almost equal to that with 6 percent of migrants and 8 percent of non-migrants. Hence, seasonal migration attracts low- and medium-educated individuals who may face low job opportunities in Armenia. The Russian construction industry demands a low- and medium-educated labour force, however, not only domestically but also from abroad.

Table 4: Skill distribution of migrants among industries and occupations

	Total migrants prior to migration	Total migrants in Russia	Low educated migrants in Russia	Medium educated migrants in Russia	High educated migrants in Russia
	Shares in industry (%)				
Unemployed	90.7	5.5	8.8	5.5	4.3
Agriculture & mining	2.2	0.9	0.0	0.9	1.2
Manufacturing	1.2	3.5	0.0	4.1	1.8
Construction	2.4	78.6	78.8	79.7	71.8
Services	3.5	11.4	12.5	9.9	20.9
Obs.	*1,305*	*1,305*	*80*	*1,062*	*163*
	Shares in occupation (%)				
Unemployed	90.7	5.5	8.8	5.5	4.3
Low-skilled occupations	5.0	82.5	87.5	86.8	51.5
Medium-skilled occupations	2.5	4.1	2.5	4.0	5.5
High-skilled occupations	1.8	7.8	1.3	3.8	38.7
Obs.	*1,305*	*1,305*	*80*	*1,062*	*163*

Table 4 decomposes the group of migrants by educational attainment and industries, as well as by occupational fields. Although the majority of highly educated seasonal migrants work in the construction industry in Russia, which is also true for the low- and medium-educated, the shares are distributed disproportionately. Of the highly educated migrants 72 percent work in the construction sector and 21 percent work in industries with higher skill requirements (services). Among the groups of low- and medium-educated, the shares in the construction sector are slightly higher at 79 and 80 percent respectively, while the shares in service industries are lower at 13 and 10 percent.

One can find similar patterns among the occupational fields of seasonal migrants with dissimilar educational attainment. Because of the small number of observations in some categories, the ten occupational fields were grouped into three skill categories: (i) the highly skilled occupations comprise managers; professionals; and technicians and associates; (ii) the medium-skilled occupations comprise clerical support; service and sales; skilled agriculture, forestry, and fishery workers; and (iii) the low-skilled occupations comprise the remaining occupational fields. The lion's share (around 87 percent) of the low- and medium-educated migrants work in low-skilled occupations (mainly construction sector), while only 52 percent of the highly educated migrants work in low-skill occupations. In comparison, 1 and 4 percent of the low- and medium-educated migrants work in high-skill jobs, while 39 percent of the

highly educated migrants are employed in high-skill jobs. This result may be surprising for *seasonal* migration. One might assume that there were no short-term, high-skill positions available for seasonal migrants, who work abroad for only a couple of months. However, there may be high demand for tasks requiring higher education, for example, technicians or specialists, so that seasonal migrants are hired.

5 Results

The estimates of the ATT by different matching specifications are reported in Table 5. All estimates are based on the full set of covariates: pre-treatment income, age, age squared, marital status, education, industry, work experience, work experience squared, migration experience, dependency ratio, regional and time dummies. The estimates are highly significant and economically large in magnitude ranging from US$463 to US$488. This implies that a seasonal migrant increases his income in Russia by roughly US$480 compared to what he would have earned in Armenia – around US$50.[8] However, one should keep in mind that working conditions are worse for Armenian seasonal migrants in Russia compared to working conditions in Armenia. Seasonal migrants work, on average, longer hours and in many cases seven days a week (e.g., Minasyan and Hancilova, 2005).

The results are insensitive to various specifications of the matching operators and include many treated individuals. All matching operators and specifications are re-estimated with exact matching on region and time and with additional specifications, but are not reported because of space limitations. The results are similar to those reported and maintain the argument of robust results.

One possible problem that would lead to overestimated income gains of seasonal migration may be the phenomenon of a drop in incomes before the migration, because of expected income gains in the subsequent periods – known as "Ashenfelter's dip" (Ashenfelter, 1978). Nevertheless, our sample of seasonal migrants consists mainly of unemployed individuals, who clearly cannot have a dip in incomes.

[8] The counterfactual income varies slightly depending on the matching method employed.

Even for those who are employed or self-employed, there is no evidence for a decline in incomes in the months before migrating.

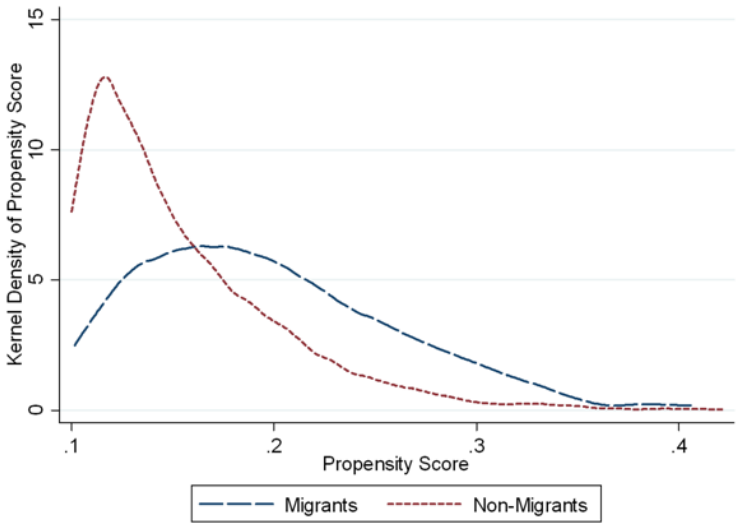
Table 5: Average treatment effects on the treated (baseline model)

Method	Nt	ATT	P>|t|	Method	Nt	ATT	P>|t|
Propensity score matching				Kernel weighting			
1:1 with replacement				Gaussian kernel			
No calliper	1134	475	***	No calliper	1134	475	***
Calliper 0.001	1084	481	***	Calliper 0.001	1084	481	***
Trimming 5%	1060	485	***	Trimming 5%	1060	485	***
1:5 with replacement				Epanechnikov kernel			
No calliper	1134	474	***	No calliper	1134	475	***
Calliper 0.001	1084	481	***	Calliper 0.001	1084	481	***
Trimming 5%	1060	484	***	Trimming 5%	1060	485	***
Reweighting				Mahalanobis matching			
By odds	1134	475	***	Incl. propensity score and *X*	1134	476	***
				Incl. only propensity score, no *X*	1134	472	***

Notes: ***, **, * denote significance at the 1%, 5%, and 10% level based on 1,000 bootstrap replications

Prior to matching, there was considerable heterogeneity in the covariates among the groups of migrants and non-migrants (reported in Table 1). Appendix Table A1 demonstrates the accuracy of balancing the covariates with selected matching operators. A comprehensive table of all employed estimators and specifications is not possible because of space limitations. Most variables do not show significance in standardised biases, pointing towards good covariate-balance after matching. This corroborates the consistency of the various matching operators. Graph 1 shows the shows the right tail (propensity scores greater than 0.1) of the distribution of the propensity scores for treated and control individuals estimated from the baseline of the probit regression. The overlap among migrants and non-migrants conforms to the common support assumption.

Graph 1: Propensity score distributions of treated and control observations



To summarise, different matching techniques with various specifications in their tuning parameters yield robust estimates of the ATT. The high quality data, a large sample of control individuals, and a high-dimensional set of control variables help to support the matching identification. An average migrant in the sample is estimated to gain about US$480 in income by seasonally migrating to Russia, compared to the counterfactual scenario of staying in Armenia. The counterfactual earnings are estimated at around US$50. Thus, migrants earn roughly ten times more in Russia than at home. One has to be aware that this interpretation holds true only for the group of migrants, because of the self-selection issues. Non-migrants have higher pre-migration incomes and, thus, would probably face lower relative income gains. We address this issue further in more detail below.

Average treatment effects for sub-samples

The results presented above are applied in more detail among different sub-samples of migrants and presented in Table 6. 1:1 PSM without exact matching on region and time is applied.[9] The time development of the income effect of seasonal migration on the migrants (panel i) shows an increase from US$432 in 2006 to US$502 in 2008, and a decline to US$463 in 2010, most likely as a result of the financial crisis. The number of seasonal migrations to Russia increased from an initial 203 in 2006 to 335 in 2008 and decreased to 172 in 2010 when income gains were less attractive for migrants.

Table 6: Average treatment effect on the treated

1:1 PSM (basic model)			
	Nt	ATT	p>|t|
(i) 2006–2010	1134	475	***
2006	203	432	***
2007	236	476	***
2008	335	502	***
2009	188	494	***
2010	172	463	***
(iii) By employment status			
Employees and self-employed	109	243	***
Unemployed	1025	500	***
(iv) By area of origin			
Origin: urban area	589	466	***
Origin: rural area	545	489	***
(v) By destination			
Destination Moscow	624	496	***
Destination non-Moscow	500	451	***
(vi) By education			
Primary education	72	308	***
Secondary education	914	469	***
Tertiary education	148	588	***

Notes: ***, **, * denote significance at the 1%, 5%, and 10% level based on bootstrapping.

[9] All results are checked for robustness by applying 1:1 PSM with exact matching on region and time and region, time, and income, given in appendix Table A4.

The income gain for the migrant is largely driven by the great share of unemployed with zero incomes prior to migration (85 percent) that tends to boost this effect. Unfortunately, the data set does not allow estimating the Average Treatment Effect on the Untreated (ATU) – the income effect of seasonal migration for a non-migrant – as the relatively small sample of seasonal migrants would serve as the control group for non-migrants. Consequently, the estimates of the ATU would be biased because the common support assumption is likely to fail. Henceforth, we estimate the ATT for the migrants who received income (i.e., employees and self-employed) before the migration. Disregarding the great share of unemployed migrants prior to migration creates a sub-sample similar to the sample of non-migrants who have jobs in Armenia. This effect is likely to come close to the ATU. Panel iii of Table 6 separates the sample of migrants into two samples for employment status prior to migration: employees and self-employed; and migrants unemployed prior to migration. The results differ considerably. For the sample of 1,025 unemployed migrants the effect is US$500, of which the counterfactual earnings are zero. Within the sample of 109 employed and self-employed migrants the income effect is US$243, the estimated counterfactual income is US$176. This relative difference in the ATTs implies that seasonal migration is most beneficial for those who are unemployed prior to migration, which supports the argument of a strategy to escape poverty.

One can also draw conclusions from the regional disparities of migration. Despite the divergence of average incomes between urban and rural areas (Table 2), there is only minor divergence in the income effects for seasonal migrants (panel iv of Table 6). The average income increase for migrants coming from urban areas is about US$466, while for migrants coming from rural areas it is US$489. The explanation for this small gap is the high share of unemployed prior to migration for migrants coming from urban and rural areas (91 percent and 92 percent respectively). Hence, the gap is primarily driven by the difference in the zero-income prior to migration and the income earned abroad. Also, the number of observations of seasonal migration trips to Russia is somewhat homogenous, with 589 observations from urban areas and 545 observations from rural areas.

In addition, the average income effect on the migrant is estimated for those whose destination is the Moscow region and for those who migrate to other districts in Russia (panel v of Table 6). Migrants who seasonally migrate to Moscow increase their incomes by about US$496, while the rest increase their incomes by US$451. This regional gap in ATTs is not large. It may be that other regions than Moscow are also characterised by high demand for construction workers (seasonal migrants).[10] Nevertheless, it is possible that the gap of about US$50 may explain why the majority of 624 seasonal migrations choose Moscow as their destination.

Panel vi of Table 6 reveals that higher educational attainment is associated with a larger income gain in seasonal migration. Migrants with primary education increase their monthly incomes abroad by US$308–$357.[11] Secondary education increases the ATT to US$469, and tertiary educational attainment increases it to US$588. Despite the higher expected earnings associated with education, the highly educated may have higher costs in migrating seasonally. Seasonal migrants with tertiary education may have high reservation wages, and there may be incompatibilities of skills in other countries (De Coulon and Piracha, 2005).[12] Hence, the relative returns to skills may favour the low- and medium-educated. Those individuals with tertiary education who migrate seasonally tend to work in high-skill industries (i.e., services), which pay higher wages in Russia, or they work, although overqualified, in the construction industry – but for relatively higher wages compared to the less educated.

[10] One such region may be Sochi, the venue for the 2014 Olympic Winter Games, where the construction of sports facilities and infrastructure has been in progress.
[11] Because of the small number of observations, this coefficient is sensitive to the specifications of the matching operator, as the differences reported in Tables 6 and A2 suggest.
[12] Highly skilled workers (e.g., a lawyer) may not be able to shift their skills to another country because of incompatibilities of the language, cultural differences, or differences in the rules of law.

Table 7: PSM: average treatment effects on the treated

1:1 PSM						
	Single-shot migrants			*Multiple-shot migrants*		
	Nt	ATT	p>|t|	Nt	ATT	p>|t|
2007–2010	230	399	***	904	491	***
2007	25	444	***	211	475	***
2008	89	437	***	246	527	***
2009	37	397	***	151	506	***
2010	53	312	***	119	522	***

Notes: ***, **, * denote significance at the 1%, 5%, and 10% level based on bootstrapping.

Table 7 compares the estimated ATTs of migrants who leave Armenia only once (single-shot migrant) to those who leave multiple times (multiple-shot migrant). The year 2006 is excluded because it may be possible that an individual in this sample migrated only once, in fact in 2006, but may have also migrated before 2006–2010 and, thus, would not comply with the definition of a single-shot migrant. Interestingly, those migrants who migrate only once in the sample period 2006–2010 seem to be less successful in terms of increased income. The difference of US$92 (US$491–US$399) in 2007–2010 suggests that those Armenian seasonal migrants, who face higher increases in incomes relative to their migrant fellow Armenians, tend to repeat their seasonal migration attempts. Even the decomposition by years leads to the inference that this holds true, although the point estimates have to be viewed with caution because of the small number of observations within the group of one-time migrants. Nonetheless, the gap in incomes between single- and multiple-shot migrants is consistently large over time and robust to the specification (see Table A5 for a robustness check).

6 Summary and conclusions

This article highlights the importance of seasonal migration as a strategy to escape poverty and unemployment, especially for the unskilled labour force. This process is seen to happen repeatedly over the sample horizon 2006–2010. On average a seasonal migrant chooses to work abroad 2.3 times for 7.9

months. Previous descriptive research on migration from Armenia based on household surveys (e.g., Minasyan and Hancilova, 2005; Minasyan et al., 2007) back the accuracy of our data set.

In line with the reviewed literature, the wage differential between Russia and Armenia lures Armenian migrants to Russia. Based on non-experimental methods, results of the income gain of a seasonal migrant compared to the counterfactual scenario of staying in Armenia are estimated at around US$480. Hence, seasonal labour migrants successfully increase their incomes abroad. Nevertheless, this is less than what the difference in GDP per capita of US$537 (2006–2010) would suggest. The paper's findings show cross validation for the results being insensitive to the specifications. Various matching techniques and tuning parameters estimate robust income effects of seasonal migration.

Seasonal migrants tend to negatively self-select into migration according to pre-migration characteristics – in terms of education, employment and income – and tend to work in low-skill positions (primarily in the construction sector) in Russia. We conclude that the relatively low skill premium for migrants attracts, to a great extent, unemployed and low- to medium-educated Armenian seasonal migrants and deters high-skill migration. These findings help us to better understand the dynamics of seasonal migration and to draw conclusions relevant for individuals' development.

In accordance with Stark et al. (2006), we conclude that seasonal labour migration may become an increasingly important source of income for individuals from low income countries in general and Armenia in particular. Global integration – resulting in faster and cheaper transportation, cheap money transfers, better connectivity because of migration networks, cheap communication, and the reduction of visa restrictions for seasonal migrants[13] – decreases the monetary and emotional costs of migration and enhances the frequency of seasonal migration. These developments are paralleled by slow changes in Armenia itself in areas, which would improve the income position of Armenians at home (e.g., social security system, job growth, integration into other markets).

[13] Russia has removed entry barriers for migrants from former Soviet countries and promotes seasonal migration from these countries.

Seasonal migrants may not necessarily act as latent permanent migrants but may choose seasonal migration as an optimal strategy when job opportunities in the home country are low. In Armenia, seasonal migration is a phenomenon primarily for those who are unemployed. Highly educated individuals who are employed can afford to stay in Armenia, out of preference for the home country over a foreign country. We observe repeated seasonal migratory behaviour for those who are relatively more successful in increasing their incomes. After being employed abroad for a few months, individuals return to their families.

Because of large remittances flows, seasonal migration increases the purchasing power of the Armenian population, resulting in increased spending in education, private consumption and investment. The results in this analysis indicate that seasonal labour migration is indeed successful in income maximisation and, as a consequence, may have stimulating effects on the home economy (through remittances). Henceforth, the Armenian government could enhance this effect by developing a regulated seasonal migration process. This may be done by providing information for migrants, by working with Russian representatives to lower the risks of migration, and by providing opportunities for those who return from seasonal migration.

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Appendix

Table A1: Post-Matching covariate-balance of one-to-one PSM

	1:1 PSM			1:5 PSM			Kernel (Epanechnikov)			MAHAL with *p(X)* only		
	% standar-dised bias	t	p>|t|	% standar-dised bias	t	p>|t|	% standar-dised bias	t	p>|t|	% standar-dised bias	t	p>|t|
income	0.3	0.09		-4.2	-1.37		0.3	0.09		-4.4	-1.39	
age / 10	6.9	1.84	*	2.6	0.69		6.9	1.84	*	0.5	0.13	
age squared / 1000	7.8	2.13	**	3.5	0.94		7.8	2.13	**	1.2	0.31	
married	2.9	0.71		2.4	0.59		2.9	0.71		3.0	0.76	
primary education	6.8	1.85	*	2.7	0.71		6.8	1.85	*	6.1	1.65	*
secondary education	-4.1	-1.08		-2.0	-0.51		-4.1	-1.08		-1.9	-0.48	
tertiary education	0.0	0.00		0.4	0.10		0.0	0.00		-2.1	-0.55	
no industry (unemployed)	1.5	0.49		5.2	1.65		1.5	0.49		3.5	1.10	
agriculture, fishing, and mining	0.0	0.00		-1.1	-0.43		0.0	0.00		-0.7	-0.29	
manufacturing	0.4	0.18		-0.9	-0.35		0.4	0.18		-1.8	-0.67	
construction	-1.9	-0.52		-1.1	-0.32		-1.9	-0.52		1.0	0.28	
services	-1.0	-0.43		-4.1	-1.71	*	-1.0	-0.43		-3.0	-1.25	
work experience / 10	1.9	0.48		1.8	0.45		1.9	0.48		2.4	0.61	
work experience squared / 1000	2.4	0.65		2.1	0.56		2.4	0.65		2.0	0.54	
migration experience	-0.4	-0.09		-3.2	-0.64		-0.4	-0.09		-1.3	-0.27	
dependency ratio	-9.7	-2.32	**	-7.1	-1.68	*	-9.7	-2.32	**	1.4	0.32	
Yerevan	-5.5	-1.56		-2.8	-0.79		-5.5	-1.56		0.0	0.00	
Aragatsotn	-10.9	-2.23	**	-6.1	-1.30		-10.9	-2.23	**	-2.0	-0.43	
Ararat	9.5	2.26	**	5.4	1.25		9.5	2.26	**	-3.2	-0.72	
Armavir	-6.4	-1.47		-4.1	-0.97		-6.4	-1.47		2.3	0.55	
Gegharkunik	9.4	1.96	*	4.6	0.94		9.4	1.96	*	1.6	0.33	
Lori	5.7	1.42		2.5	0.60		5.7	1.42		3.5	0.85	
Kotayk	1.4	0.38		2.1	0.58		1.4	0.38		1.0	0.29	
Shirak	-2.2	-0.44		-1.2	-0.25		-2.2	-0.44		-0.3	-0.05	
Syunik	-1.6	-0.69		-0.9	-0.38		-1.6	-0.69		-2.1	-0.90	
Vayots	2.5	0.56		-0.6	-0.13		2.5	0.56		-0.6	-0.13	
Tavush	-3.6	-0.92		0.2	0.06		-3.6	-0.92		-2.4	-0.67	
month_2006_01	3.6	1.01		2.8	0.75		3.6	1.01		2.0	0.58	
month_2006_02	7.3	1.64		2.6	0.55		7.3	1.64		1.1	0.23	
month_2006_03	0.5	0.10		1.7	0.35		0.5	0.10		0.5	0.10	
month_2006_04	-3.3	-0.64		1.4	0.29		-3.3	-0.64		5.1	1.17	
month_2006_05	0.7	0.20		1.3	0.37		0.7	0.20		2.2	0.63	
month_2006_06	-0.9	-0.30		0.0	0.00		-0.9	-0.30		-1.7	-0.58	
month_2006_07	-2.7	-1.00		-1.4	-0.58		-2.7	-1.00		-1.7	-0.71	
month_2006_08	-2.7	-1.00		-1.4	-0.58		-2.7	-1.00		-0.9	-0.38	
month_2006_09	0.0	0.00		0.0	0.00		0.0	0.00		0.9	0.58	
month_2006_10	0.0	0.00		-0.2	-0.06		0.0	0.00		-0.8	-0.28	
month_2006_11	-2.7	-1.00		-0.2	-0.08		-2.7	-1.00		1.8	1.00	
month_2006_12	-0.7	-0.16		1.5	0.37		-0.7	-0.16		6.0	1.68	*
month_2007_01	-0.6	-0.13		0.6	0.13		-0.6	-0.13		-4.2	-0.88	
month_2007_02	-3.2	-0.64		-1.6	-0.32		-3.2	-0.64		-3.2	-0.64	
month_2007_03	2.6	0.53		0.6	0.12		2.6	0.53		-4.5	-0.89	
month_2007_04	4.3	0.91		1.2	0.24		4.3	0.91		1.5	0.33	
month_2007_05	-1.5	-0.39		0.0	0.00		-1.5	-0.39		3.0	0.90	
month_2007_06	0.8	0.24		0.3	0.10		0.8	0.24		2.4	0.78	
month_2007_07	0.8	0.30		0.5	0.18		0.8	0.30		-1.6	-0.54	

To be continued on next page...

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level

Table A1 continued: Post-Matching covariate-balance of one-to-one PSM

	1:1 PSM			1:5 PSM			Kernel (Epanechnikov)			MAHAL with *p(X)* only		
	% standar-dised bias	t	p>|t|	% standar-dised bias	t	p>|t|	% standar-dised bias	t	p>|t|	% standar-dised bias	t	p>|t|
month_2007_08	2.5	0.91		0.8	0.28		2.5	0.91		-0.8	-0.26	
month_2007_09	0.9	0.45		0.4	0.17		0.9	0.45		-1.7	-0.71	
month_2007_10	0.9	0.45		-0.2	-0.08		0.9	0.45		0.0	0.00	
month_2007_11	0.0	0.00		-0.7	-0.27		0.0	0.00		-2.6	-0.91	
month_2007_12	0.0	0.00		2.0	0.45		0.0	0.00		0.6	0.14	
month_2008_01	4.9	1.09		2.9	0.64		4.9	1.09		4.0	0.83	
month_2008_02	-2.8	-0.55		-4.9	-0.93		-2.8	-0.55		-1.5	-0.28	
month_2008_03	-11.3	-2.03	**	-4.6	-0.87		-11.3	-2.03	**	-9.4	-1.65	*
month_2008_04	-0.5	-0.09		-1.2	-0.25		-0.5	-0.09		-4.5	-0.83	
month_2008_05	-11.4	-2.28	**	-1.9	-0.43		-11.4	-2.28	**	3.3	0.79	
month_2008_06	4.6	1.27		-0.4	-0.10		4.6	1.27		-3.5	-0.77	
month_2008_07	0.0	0.00		1.8	0.57		0.0	0.00		4.0	1.30	
month_2008_08	0.7	0.18		2.0	0.54		0.7	0.18		1.4	0.36	
month_2008_09	-3.0	-0.82		-2.2	-0.63		-3.0	-0.82		-5.5	-1.36	
month_2008_10	0.0	0.00		-0.9	-0.31		0.0	0.00		1.7	0.58	
month_2008_11	-0.8	-0.33		-0.8	-0.33		-0.8	-0.33		-2.6	-0.91	
month_2008_12	1.4	0.36		3.3	0.89		1.4	0.36		5.0	1.36	
month_2009_01	-0.7	-0.18		-0.1	-0.04		-0.7	-0.18		0.0	0.00	
month_2009_02	3.8	0.88		0.6	0.14		3.8	0.88		-2.5	-0.53	
month_2009_03	-5.9	-1.17		-3.1	-0.63		-5.9	-1.17		0.0	0.00	
month_2009_04	14.1	3.41	***	2.6	0.54		14.1	3.41	***	5.3	1.17	
month_2009_05	2.7	0.65		1.7	0.42		2.7	0.65		6.8	1.78	*
month_2009_06	2.4	0.78		0.8	0.24		2.4	0.78		0.8	0.24	
month_2009_07	1.7	0.71		-1.2	-0.42		1.7	0.71		-0.9	-0.30	
month_2009_08	0.9	0.33		0.0	0.00		0.9	0.33		-0.9	-0.30	
month_2009_09	0.0	0.00		0.8	0.21		0.0	0.00		1.6	0.43	
month_2009_10	3.5	1.64		0.2	0.06		3.5	1.64		0.9	0.33	
month_2009_11	-0.9	-0.45		-0.4	-0.19		-0.9	-0.45		1.9	1.41	
month_2009_12	-1.6	-0.43		-1.6	-0.43		-1.6	-0.43		3.2	1.00	
month_2010_01	0.0	0.00		1.1	0.28		0.0	0.00		-3.0	-0.65	
month_2010_02	6.3	1.52		1.9	0.42		6.3	1.52		5.2	1.19	
month_2010_03	-10.7	-1.99	**	-3.5	-0.70		-10.7	-1.99	**	2.9	0.60	
month_2010_04	3.5	0.75		1.2	0.24		3.5	0.75		-2.4	-0.47	
month_2010_05	0.6	0.15		-0.1	-0.03		0.6	0.15		-8.8	-1.69	*
month_2010_06	0.8	0.21		0.8	0.21		0.8	0.21		-0.8	-0.20	
month_2010_07	-3.7	-1.42		-1.7	-0.75		-3.7	-1.42		-1.9	-0.82	
month_2010_08	-2.5	-0.73		-3.0	-0.86		-2.5	-0.73		-0.9	-0.26	
month_2010_09	1.7	0.71		-0.5	-0.18		1.7	0.71		-1.8	-0.58	
month_2010_10	-3.5	-1.16		-0.9	-0.33		-3.5	-1.16		2.8	1.34	

Notes: ***, **, * indicate significance at the 1%, 5%, and 10% level

Table A2: Probit regression estimates of the baseline model

	Coef.	Std. Err.	p>|z|
Income *(in US$)*	0.00	0.00	
Age/10 *(in years)*	1.10	0.13	***
Age squared / 1000 *(in years)*	-1.67	0.16	***
Married	0.02	0.05	
Primary education	*baseline*		
Secondary education	0.10	0.05	***
Tertiary education	0.04	0.06	
No industry (unemployed)	*baseline*		
Agriculture, fishing, and mining	-1.19	0.08	***
Manufacturing	-1.07	0.11	***
Construction	-0.74	0.09	***
Services	-1.23	0.08	***
Work experience / 10 *(in years)*	0.31	0.06	***
Work experience squared / 1000 (in years)	-0.50	0.16	***
Migration experience	1.22	0.03	***
Dependency ratio	-0.61	0.08	***
Yerevan	*baseline*		
Aragatsotn	0.51	0.06	***
Ararat	0.41	0.05	***
Armavir	0.54	0.06	***
Gegharkunik	0.69	0.05	***
Lori	0.51	0.06	***
Kotayk	0.10	0.06	
Shirak	0.87	0.05	***
Syunik	-0.06	0.13	
Vayots	0.45	0.10	***
Tavush	0.04	0.09	

Notes: ***, ***, * indicate significance of the difference at the 1%, 5%, and 10% level. The probit regression includes time dummies and a constant, which are not reported.

Table A3: ATT by changing the set of included covariates

1:1 PSM				
		Nt	ATT	p>|t|
(i)	Basic model	1134	475	***
(ii)	Cumulative exclusion of			
	Dependency ratio	1233	472	***
	Marital status	1233	470	***
(iii)	Cumulative inclusion of			
	Occupation	1134	477	***
	Sector	1134	476	***
	Employment status	1134	472	***

Notes: ***, **, * denote significance at the 1%, 5%, and 10% level based on bootstrapping.

Table A4: Average treatment effects on the treated

Part A: PSM with *exact matching* on region and time					Part B: PSM with *exact matching* on region, time, and pre-treatment income			
		Nt	ATT	p>|t|		Nt	ATT	p>|t|
(i)	2006-2010	1134	482	***	(i) 2006-2010	1134	484	***
	2006	203	432	***	2006	203	436	***
	2007	236	482	***	2007	236	478	***
	2008	335	511	***	2008	335	514	***
	2009	188	496	***	2009	188	497	***
	2010	172	476	***	2010	172	475	***
(iii)	By employment status				(iii) By employment status			
	Employees and self-employed	109	231	***	Employees and self-employed	109	246	***
	Unemployed	1025	503	***	Unemployed	1025	505	***
(iv)	By area of origin				(iv) By area of origin			
	Urban area	589	478	***	Urban area	589	469	***
	Rural area	545	496	***	Rural area	545	489	***
(v)	By destination				(v) By destination			
	Destination Moscow	624	505	***	Destination Moscow	624	505	***
	Destination Non-Moscow	500	454	***	Destination Non-Moscow	500	445	***
(vi)	By education				(vi) By education			
	Primary education	72	357	***	Primary education	72	367	***
	Secondary education	914	476	***	Secondary education	914	475	***
	Tertiary education	148	591	***	Tertiary education	148	589	***

Notes: ***, **, * denote significance at the 1%, 5%, and 10% level based on bootstrapping.

Table A5: PSM: average treatment effects on the treated

1:1 PSM with exact matching on region and time							**1:1 PSM with exact matching on region, time, and pre-treatment income**						
	Single-shot migrants			*Multiple-shot migrants*				*Single-shot migrants*			*Multiple-shot migrants*		
	Nt	ATT	p>|t|	Nt	ATT	p>|t|		Nt	ATT	p>|t|	Nt	ATT	p>|t|
2007-2010	230	406	***	904	506	***	2007-2010	230	403	***	904	502	***
2007	25	450	***	211	485	***	2007	25	446	***	211	479	***
2008	89	448	***	246	533	***	2008	89	456	***	246	534	***
2009	37	390	***	151	520	***	2009	37	397	***	151	522	***
2010	53	323	***	119	542	***	2010	53	322	***	119	543	***

Notes: ***, **, * denote significance at the 1%, 5%, and 10% level based on bootstrapping.