The nature and impact of repeated migration within households in rural Ghana

Eva-Maria Egger*
Julie Litchfield †

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Abstract

In this paper, we explore repeated migration within a household and consequent welfare outcomes. Specifically, we use a household panel survey collected in 2013 and again in 2015 in rural areas of Ghana. We exploit the rich information about migration experience as well as the panel nature of the data to overcome sources of selection, omitted variable and reverse causality bias. Wealth is measured with an index including indicators of housing quality. We apply Multiple Correspondence Analysis (MCA) to construct the welfare index and entropy-balancing weights (Hainmueller, 2012) to obtain a valid comparison group for our analysis. We provide evidence that households often have more than one migrant member and that they have different characteristics depending on who moved first. New migrants are more likely to be from a younger generation, they face lower migration costs, and only few of them remit. We find no effect of sending a new migrant on the change in the asset index. We conclude that the different nature of migration of new migrants implies neither an economic gain for the household nor a loss. The reason for the former is that the migrants remit less or not at all and the reason for the latter is that migration becomes less costly with prior experience.

*International Fund for Agricultural Development (IFAD), Rome, Italy. Email: E.Egger@ifad.org. This work was supported by the Economic and Social Research Council (Doctoral grant) and the research program consortium 'Migrating out of Poverty' (U.K. Department for International Development).

†Department of Economics, University fo Sussex

1 Introduction

Internal migration is a common and sizeable phenomenon in many developing countries. An estimated 740 million people live outside their region of birth (Bell and Muhidin, 2009). Differences in regional economic performance induce people to leave poorer areas and move to those where more and better opportunities are located. In Ghana, around 35 percent of people in the population Census of 2010 had moved from their place of birth to another location within the country (Ghana Statistical Service, 2013). Many people move from poorer to richer regions, some move with the whole household, others send a member of the household (Litchfield and Waddington, 2003; Molini et al., 2016).

Internal migration plays an important role in poverty reduction and economic development at the individual, household and macroeconomic level. On the one hand, it contributes to structural change in the country when rural workers move into non-agricultural work in urban areas (Harris and Todaro, 1970). On the other hand, migration of a household member can insure the sending household against income shocks in the origin. Such insurance can prevent households from falling into poverty. Moreover, the income earned by the migrant member can raise consumption levels at home or even pay for investments in profitable technologies (Stark and Bloom, 1985). Additionally, geographic mobility offers young people to advance their education and gain new skills if their origins do not provide these opportunities.

Because of its size and relevance for economic development, economists study internal migration, but data limitations and methodological issues remain a challenge. One focus of research is the question whether and how internal migration affects households at origin. This chapter contributes to this strand in the literature. We investigate the impact of having a new migrant on the welfare of origin households conditional on their prior migration experience.

The engagement in migration of some village or community members was shown to significantly reduce migration costs for later migrants from that same network. This local migration experience would also increase the probability to be successful at destination in terms of finding a job. Thus, households are more likely to send a migrant if they have access to such a network of migration experience (Munshi, 2003; McKenzie and Rapoport, 2007). Households themselves can gain migration experience through their engagement in migration. Bryan et al. (2014) provide experimental evidence that the idiosyncratic migration experience of a household in contrast to that of social networks significantly predicts the repetition of migration within this household. Migration experience at the household level is hence important for future migration decisions and their impacts on the household.

Furthermore, the focus on new migrants is adequate for a setting in which households have several migrant members who move at different points in time. This is revealed by the data available in this chapter. We use primary data from a new two-wave household panel survey conducted in Ghana in 2013 and 2015.[1] The surveys were designed with the goal to collect as much information as possible about migration.

The econometric challenge of the comparison between migrant and non-migrant households is unobserved heterogeneity. There are unobservable factors that determine both, the fact that a household has a migrant and the outcome of interest, for example household income. Any result from a simple comparison of these households with and without migrants would be biased. Instrumental variables and selection models have been used to address this issue, often however restricted by the cross-sectional structure of the data employed (Litchfield and Waddington, 2003; Adams et al., 2008).

Comparing households that all have prior migration experience reduces the selection bias to some extent in the analysis of this chapter. Gibson et al. (2011) demonstrate experimental evidence for different stages of selection, first that into migration, then into who moves. We apply entropy balancing weights (Hainmueller, 2012), similar to matching methods, and exploit the panel nature of our data to overcome remaining selection and omitted variable bias. The outcome variable of interest is an asset index.

Because there is little existing evidence on the consequences of idiosyncratic migration experience of households, we first describe migrants and their households in our new data to explore the dynamic patterns of migration. A comparison of the new migrants to those migrants who left the household before documents that new migrants are from a younger generation within households, such as children or grandchildren of the head. Their migration costs are lower and might be related to family networks and the households' prior engagement in migration. From these observations we derive hypotheses for the impact assessment. Then we estimate how the asset welfare of households with a new migrant changes compared to those without, conditional on the fact that all households have previously had

[1] As part of my PhD, I contributed to the completion of the data set by cleaning the data and ensuring that households and individuals can be matched between survey waves in close collaboration with the survey team in Ghana.

a migrant. We analyse whether there are heterogeneous effects by gender of the migrant, by type of migration (seasonal or permanent), reason for migration (family or work), and by destination.

We find no effect of sending a new migrant on the change in the asset index of origin households compared to those households who do not engage further in migration in the same period. This result is robust to a sensitivity analysis. Our interpretation is that the returns to migration might not show after the short period of our study. Households in our sample use their savings to finance migration. They hence do not experience a drop in their asset index. However, they also do not experience an increase in their asset index since the new migrant left. This could be, on the one hand, due to their use of savings to cover migration costs instead of investing into more assets and, on the other hand, because new migrants send only rarely and low remittances. We further suggest that due to prior engagement in migration our sample of households does not experience an initial decline in welfare. This could be caused by the migration costs or the loss in labour due to a member leaving (Taylor and López-Feldman, 2010). We however document that migration costs for new migrants are smaller than for prior migration, which indicates that migration experience at the household level reduces the costs of migration. In addition, prior to their move new migrants are either in school or doing unpaid work. It is thus less likely that their migration implies a loss in labour income for the household.

The chapter is structured as follows. In the next section, 2, we discuss the literature on impacts of migration on households left behind with respect to methodological challenges, knowledge gaps and evidence for our context. This is followed by the analytical framework for this study in section 3. Then we present the data used for the analysis (section 4) followed by a description of the migrants, migrant households and their prior migration experience (section 5). In section 6, we explain the methodology to estimate the impact of sending a new migrant on the welfare of origin households. In section 7, we provide results and robustness checks. Section 8 concludes.

2 Literature review

2.1 Evidence on the impact of migration on origin households

The research interest of this chapter is the short-term relationship between having a new migrant and the welfare of migrant sending households in rural Ghana. Many studies explored the more general question looking at the impact of having a migrant or not on some measure of well-being of the origin household. There exists also research that examines the effect of migration on the migrant's own welfare, e.g. Beegle et al. (2008), but this is not the focus of this chapter.

Theoretical models such as from the New Economics of Labor Migration (NELM, Stark and Bloom (1985)) cannot predict the direction of the impact of migration on origin households. The reason for this is that the impact depends on counteracting factors. For example, De Brauw and Harigaya (2007) model the impact of migration on consumption growth. It depends at the same time on the loss of farm production incurred by migration and the increase in consumption due to remittance receipt (De Brauw and Harigaya (2007), p.436) aside from the costs of moving.

Despite the use of similar outcomes in the literature, results differ. Antman (2012) reviews the research that examines the impact of migration on the left behind family members and Mendola (2012) reviews studies looking at rural out-migration and its impacts on sending households. Both summarise mixed results from the literature. The following examples illustrate the inconclusive findings.

Empirical evidence from China by De Brauw and Giles (2012) documents an increase in consumption growth as well as "increased accumulation of housing welfare and consumer durables" (p.3). Quisumbing and McNiven (2010) consider the impact of migration and remittances on assets, consumption and credit constraints in the rural Philippines. They find that a larger number of migrant children reduces the values of non-land assets and total expenditures per adult equivalent in the origin households. However, remittances have a positive impact on housing, consumer durables, non-land assets, total (per adult equivalent) and educational expenditures. They find no effect on status of credit constraint. Mendola (2008) finds an increase in investments in agricultural production among the left behind households with international migrants in Bangladesh, but she does not find an effect for internal migration. Taylor and López-Feldman (2010) provide evidence of a positive effect of migration to the US on land productivity of migrant-sending families in Mexico. They also document an increase in per-capita income via remittances. Damon (2010) finds only weak increases in asset accumulation in El Salvador, he finds no impact of migration and remittances on investments in agricultural production.

What gives rise to these mixed results? One explanation is that the counteracting factors of costs and rewards to migration materialize at different speeds (Taylor and López-Feldman, 2010). The loss in labour is felt immediately as are the costs of paying for the migration of a household member. The returns to migration in form of remittances contribute to higher consumption levels. They delay however until the migrant arrived at the destination, found a job and earned enough income to send some of it back home. It might take even longer for remittances to accumulate enough to invest in productive assets .

Other aspects that contribute to the mixed results are the different data, definitions for migration and methodologies used. Migrants, or migrant households, are not a random sample of the population, but observable and unobservable factors determine their participation in migration. These factors can affect the outcomes of interest at the same time. In addition, the outcome itself can affect the migration decision. This is especially an issue in cross-sectional data. Aside from very few randomized control trials (Bryan et al., 2014) or natural experiments (Gibson et al., 2013, 2011; Yang, 2008), the most common approach to overcome endogeneity of migration is to use an instrumental variable (e.g. Damon (2010)). For example, De Brauw and Harigaya (2007) use historical policies and migration patterns to predict the number of migrants in households in Vietnam. Additionally, they estimate the effect of migration on consumption growth with generalized method of moments (GMM) to control for reverse causality. Such an approach is only possible with longitudinal data or a large set of retrospective information on the relevant variables as in De Brauw and Rozelle (2008).

Only few studies consider migration experience at the household level in the form of seasonal migration. De Brauw and Harigaya (2007) and De Brauw (2010) provide evidence about the impact of seasonal migration on household welfare or agricultural production in Vietnam. While seasonal migration is most likely a repeated event, the authors do not specifically account for the repetition and potential learning process of the household. They measure the change in the number of migrants in the household without differentiating between households that have never had a migrant or those who have a migrant and send another one. Their choice to look at seasonal migration was purely motivated by pragmatic reasons due to the way migration information was reported in their data (De Brauw and

Harigaya (2007), p.434).

Bryan et al. (2014) conduct a randomized control trial in a region in Bangladesh that is seasonally affected by famine to understand underused seasonal migration. Their intervention was a cash transfer to vulnerable households conditioned to finance seasonal migration of one household member. The results show significant improvements of consumption levels for the treated households. According to the authors' model, migration results in success or failure in terms of finding a job at destination and sending remittances. Households learn from this experience and it predicts their future engagement in migration. Further evidence for the role of migration experience within the family is provided by Giulietti et al. (2014). The authors develop a model that differentiates between 'weak' and 'strong' network ties and their role for migration decisions. Their findings suggest that networks at community level (weak ties) and prior migration of a family member (strong ties) act complementary, but weak ties have a have a higher impact on the migration decision. No further analysis is conducted to investigate how such different networks might impact migration and household outcomes.

In this chapter, we assess the impact of having a new migrant on origin households. We condition the analysis on prior migration experience. Thus, we contribute to the literature aiming to understand whether households learn from migration and what the implications are for future migration at household level. This chapter uses the first panel data in Ghana that contain an extensive migration module and applies a new method from the evaluation literature.

2.2 Migration in Ghana

Ghana is a middle-income country according to the World Bank definition. It has been able to improve living standards remarkably in the past decade. The country's poverty headcount ratio decreased from 31.1 in 2005 to 24.2 in 2012 (World Bank, 2017). Despite these improvements, there remain challenges and small-scale agriculture is still the predominant income source in most regions. This gives rise to internal migration. Based on 2000 Census data, Castaldo et al. (2012) map poverty and migration rates at district level and find a clear correlation. Most people move out of the poor and into the richer regions.

Researchers document migration patterns in Ghana using various rounds of the Ghana Living Standards Survey (GLSS). Litchfield and Waddington (2003) show that in early rounds of the Ghana Living Standards Survey (GLSS) (those of 1991/92 and 1998/99) internal migration in Ghana was high and led mostly from rural to rural areas. This pattern is confirmed by Castaldo et al. (2012) for the GLSS5 in 2005. These movements were in most cases for economic reasons, to look for jobs, but around a third of migrants move also for family reasons. Molini et al. (2016) confirm with the latest GLSS6 (2012/13) that families in Ghana move to locations in hope of better prospects. Most migration in this recent survey leads again not only from rural to urban areas, but often from rural to rural areas.

The evidence on impacts of migration on household welfare is mixed also for Ghana. Adams (2006) find a poverty-reducing effect of internal and international remittances at household level after controlling for selection and the application of an instrumental variable. Adams et al. (2008) show that remittances are not used differently than income from other sources. At the margin, remittance-receiving households do not spend more on consumption or investment than households that do not receive remittances. These results stand in contrast to Adams and Cuecuecha (2013) who find a marginal decrease in food consumption and an increase in investments, particularly in education, housing, and health for remittance-receiving households. They conduct the same analysis, a multinomial two-stage selection model with an instrumental variable. Their instrument draws on historical railroad networks and employment opportunities in destination countries, whereas Adams et al. (2008) relied on social networks among ethnic and religious groups. The use of different instruments could explain the contrasting results.

Ackah and Medvedev (2010) also use the GLSS5 to define determinants of internal migration at the individual and community level as well as the impact of migration on household expenditure. They apply a Heckman two-stage selection model to control for the non-randomness of migration. Migration drivers are higher education and youth, as well as worse infrastructure in home communities. Households with internal migrants are relatively better off than those without. The effect is, however, only significant for rural to urban migrants and not for those who remain in rural areas. Also applying a Heckman selection model, Mahé and Naudé (2016) find that Ghanaian internal migrants send relatively little remittances and often even receive support from their origin households using the GLSS6 (2012/13) data in combination with the Africa Sector Database (ASD). Their hypothesis is that migration is in this case often a long-term strategy based on the observations that migrants are often young members of the household moving to obtain higher education. Molini et al. (2016), exploit the GLSS6 to compare households who migrated as a whole to those who stayed. They make use of historical migration networks as instrument in a two-stage selection model. The positive impact of migration on consumption that they find is attributed to specific directions of movement, from the inland to coastal areas, and to male headed and better educated households. The authors also emphasise the absence of sectoral change in the migration strategy of households.

Due to weak instruments and bound to the use of cross-sectional data these studies lack means to control for unobservable factors that could contribute to reverse causality. It is therefore difficult to reconcile their results. This chapter contributes to the understanding of internal migration in Ghana and its consequences for origin households by using novel data. We utilize its rich questionnaire to document the diverse patterns of migration and we exploit the panel nature to reduce concerns of bias.

3 Analytical framework

This chapter investigates whether having a new migrant is related to a change in the welfare of the migrant's household at origin conditional on migration experience. The analysis is set in two periods, baseline and follow-up. All households have at least one member who is a migrant in the baseline period. Thus, they have previously engaged in migration, which we define as 'migration experience'. A migrant is defined in the surveys as a member of the household who is currently absent, left at least three months ago, but not more than five years.

A new migrant is defined as a household member who is present in the household in the baseline period and who then moves at least to another community and is still away in the follow-up period.[2] We look at new migrants, because it appears to be common for households to have more than one migrant and to see them move at different times. Thus, we are not interested in just the number of migrants, but in the dynamic aspect of another member migrating. Furthermore, it removes some of the selection bias of households into migration.

To give an example, imagine a household as depicted in the following table **??**:

[2]It is possible that the new migrant had migrated in the past. In such a case, not only the household as a whole would have migration experience but also the individual migrant. The response rate to the question asking how many times a migrant moved before is unfortunately very low so that we cannot control for this in the analysis.

Household member	Migrant in baseline	Migrant in follow-up
A	1	1
B	0	0
C	0	0
D	1	0
E	0	1
Total:	2	2

This household has five members. At baseline, member A and member D are away as migrants. In the follow-up period, member A is still away as a migrant, while member D has returned to the household. Now member E is away as a migrant. If we were to compare only the total number of migrants away, we would see no difference between these two periods for this household. However, member D might have returned with money for the household, and will now contribute again to the household production (farm or business), and he or she potentially returned with new skills that could improve the returns to her or his labour. At the same time, for member E to migrate, the household had to incur some costs, maybe by selling assets or using savings. These factors have different impacts on the household welfare, so that we focus on new migrants instead of the total number of migrants. Thus, this example household would be defined as a household with migration experience and a new migrant. Member E would be this new migrant.

Different aspects determine the impact of having a new migrant. First, migration is costly and can initially lead to a decline in welfare due to the costs incurred as well as the loss in labour. Secondly, migration is beneficial when migrants send money back to their origin household and thus create another source of income. Thirdly, migration can be beneficial for the migrant him or herself directly. There might be more and better opportunities to earn an income or pursue further education at destination than at origin. Moreover, the household has one member less to care for and it might derive utility from the fact that the migrant can find a better livelihood somewhere else.

However, it is not clear in which direction the effect should work and which factor dominates. The afore mentioned factors work in different directions. Additionally, in our specific case households have migration experience at baseline before they have a new migrant which can influence the effect. While sending a new migrant can incur costs, these might be lower conditional on prior migration experience of the household.

Following this discussion, we look at the impact of sending a new migrant conditional on migration experience. The sample is therefore first restricted only to households with migration experience at baseline. Then, households are assigned to a group called 'treated' and another one named 'control'. Households are in the treated group if they have at least one new migrant between the two periods. The remaining households without a new migrant between the two periods are in the control group.[3]

This definition implies that households can have more than one new migrant and they can have several baseline migrants. Our sample is restricted to those households whose new migrants were present members of the household in the baseline period.[4] Obviously, these definitions restrict the sample to a smaller set of observations than the original full survey.

4 Data

The data used for this analysis is a household survey collected in April/May 2013 and again at the same households in April/May 2015.[5] The data was collected by the Centre for Migration Studies (CMS), University of Ghana, Legon, through funding from the UK's Department for International Development (DFID) and made available by the Migrating out of Poverty Research Consortium, University of Sussex, UK.

In the first wave, around 1,400 households were surveyed, and in the second wave the team was able to follow up with around 1,100 of them.[6] The households are not nationally or regionally representative, but they were specifically chosen to oversample migrant sending households. While migration is a common phenomenon, it remains difficult to get a feasible sample in most nationally representative surveys.

[3]We could include households that had a return migrant at baseline, but no current migrant. They also have migration experience. However, there are no such households in our data.

[4]A special case are households that grew overall, which means that they had more members in the follow-up period than in the baseline due to new household formation. This can for example happen, when the son of the household head marries and his new wife and maybe a relative of hers join the household. If any of the newly joined household members then is a migrant in the follow-up period, we drop this household from the analysis. These households might represent a different form of household formation.

[5]In this way, the households are interviewed during the same season to avoid issues of seasonality between survey waves.

[6]While our analysis is based on a balanced sample, we still investigate the attrition of households. Specifically, we look at how many households that were not tracked in 2015 had a migrant at baseline. These households would have been included in our sample either in control or treatment group. We then compare their baseline characteristics to those of the treated and comparison households to assess to which group they might have belonged. Comparing also their asset index indicates how their attrition might bias our results due to their attrition. See appendix B on page 63 for a detailed discussion.

The survey was conducted in five regions, the Northern region, the Upper East, Upper West, Brong Ahafo, and Volta region. These regions were major source areas for internal migration based on the information in the 2010 Ghana Population and Housing Census (Ghana Statistical Service, 2013). The sampling procedure followed a two-stage stratified design. Using the Census, enumeration areas (EAs) were chosen that were "proportional to the total number of out-migrants from that region" (Sugiyarto and Litchfield (2016), p.2). In the second stage, a list of households without migrants, with seasonal, returned or currently absent migrants was obtained for each Primary Sampling Unit (PSU) in each EA. Then, 4 non-migrant households and 11 migrant households were chosen at random in each of these PSUs to be interviewed.

The questionnaire was directed at the household head and asked about the demographics of each household member, their education and employment status, as well as their migration history. The questions about migration are either about current migrants or in an extra section directed towards returned migrants. These sections cover, for example, information on destination, reason for migrating, financing of the move, remittance sending, and occupation at destination.

The construction of the panel data set required a rigorous checking of data consistency. We were able to correct the majority of errors of misreporting caused by wrong manual entries of some enumerators in the questionnaires, e.g. skipping rows in the household roster. We were able to rely on our local partners to identify name changes based on their local knowledge and we were able to correct other errors by manually checking each individual questionnaire when we had doubts.

In the questionnaire, migrants are members who are currently not living in the household and who have been away for at least three months, but less than ten (in 2013) or five years (in 2015). This definition follows Bilsborrow et al. (1984), page 146. 60 percent of households in the sample for this analysis have only one new migrant, 25 percent have two, and the remaining 15 percent have three or more new migrants in the study period.

The outcome variables of interest are measures of economic status. The questionnaire in 2013 did not contain a consumption module and questions about income are inconsistent between the survey waves and thus not comparable. We therefore use asset information to construct an index as measure for a household's economic status.

After cleaning the data and making sure that the main variables of interest are available for all households in both survey waves, we are left with a balanced panel of 960 household-year observations. 131 migrant households are in the treated group, and 349 in the control group. The majority of households with a new migrant is located in Brong Ahafo and in the Volta region and the majority of the comparison group live in the Volta and the Northern region (Table 1).

Table 1: Sample of treatment and control households across regions in 2013

	Control		Treatment		Total	
Region	N	%	N	%	N	%
Brong Ahafo	61	17.5	40	30.5	101	21
Northern	93	26.6	19	14.5	112	23.3
Upper East	54	15.5	25	19.1	79	16.5
Upper West	43	12.3	18	13.7	61	12.7
Volta	98	28.1	29	22.1	127	26.5
Total	349	100	131	100	480	100

5 Descriptive statistics

The rich information about migration in this survey allows us to draw a detailed picture of migration in these areas of Ghana. We explore the characteristics of migrants and their households and we compare those migrants who had moved at baseline to the new migrants who only moved between the baseline and the follow-up survey. This comparison reveals interesting patterns. From these descriptions we can then move on to the analysis of the welfare impact of having a new migrant in section 6.

5.1 Baseline and new migrants

First, we turn to the individuals who migrate. We compare those who were migrants in the baseline (2013) and those who moved as new migrants between baseline and follow-up survey (2015). This comparison helps to document how new migrants differ from previous migrants within households with migration experience.

In our sample, we have 951 migrants in 2013, and 215 new ones in the follow-up survey. The response rates to the questions about migrants vary. We hence always report the number of responses for each question. Due to such missing values we cannot utilise all information in the impact assessment. This motivates detailed descriptive statistics which later help us explain our results. Table 2 provides an overview of the basic demographic characteristics of the migrants by migrant status and gender. Of the 2013 migrants, 38 percent are female, in 2015 the share of women increased to 50 percent.

Table 2: Demographic information of migrants, by migrant status and gender

	Baseline (2013)		New (2015)	
	Male	Female	Male	Female
N all	*592*	*359*	*107*	*108*
Age (in years)	32.4	30.7	25.6	26.8
Marital status				
N	*543*	*330*	*95*	*92*
Single (%)	44.6	42.7	68.4	47.8
Married/living with partner (%)	54	50.6	30.5	48.9
Separated/Divorced/Widowed (%)	1.5	6.7	1.1	3.3
Relation to household head				
N	*592*	*359*	*107*	*108*
Head (%)	8.3	1.9	3.7	1.9
Spouse / partner (%)	3.4	11.4	2.8	3.7
Child/adopted child (%)	52.4	49	49.5	51.9
Grandchild (%)	4.7	6.7	13.1	12
Niece/nephew (%)	5.6	7	14	13.9
Parent (%)	5.4	2.2	0.9	2.8
Sibling (%)	17.2	12.5	10.3	5.6
Son/daughter-in-law (%)	0.2	2.2	1.9	0
Sibling-in-law (%)	1.2	3.1	0.9	1.9
Parent-in-law (%)	0	2.2	0	1.9
Grandparent (%)	0.2	0.6	0	0
Other relatives (%)	1.2	1.1	1.9	2.8
Not related (%)	0.3	0	0.9	1.9
Education				
N	*520*	*296*	*97*	*89*
None (%)	14	18.6	23.7	31.5
Primary (%)	16.7	18.6	22.7	15.7
Middle/Junior (%)	31	30.4	27.8	22.5
High/Senior (%)	21.5	19.3	15.5	16.9
College/Technical (%)	16.7	13.2	10.3	13.5
Occupation prior to migration				
N	*436*	*232*	*70*	*68*
In school / education (%)	16.7	20.3	32.9	36.8
Paid employee (%)	8.9	4.7	10	5.9
self-employed (%)	35.1	27.6	24.3	17.6
Unemployed, looking for job (%)	9.9	7.8	8.6	8.8
Doing unpaid work (%)	24.1	30.2	21.4	27.9
Retired (%)	0.5	0		
Apprenticeship (%)	2.3	5.6	1.4	1.5
Others (%)	2.5	3.9	1.4	1.5
Activity prior to migration				
N	*241*	*97*	*42*	*34*
Farming (%)	43.2	34	42.9	26.5
Trading (%)	7.5	35.1	7.1	14.7
Self-employment (%)	10	17.5	2.4	8.8
Teaching (%)	9.1	5.2	7.1	14.7
Others (%)	30.1	8.2	40.5	35.3

5.1.1 Age and marital status

The migrants in 2013 are on average 31 years old and around half of them are married.[7] In contrast, the new migrants in 2015 are only 26 years old and a third of the men are married, but 49 percent of women are married. Separated, divorced or widowed migrants are mostly found among women who are baseline migrants. Overall, it seems that new migrants are more likely to still be single, especially men.

5.1.2 Position in the household

Around half of migrants are children of the household head and there is not much difference between the sexes. There is however a difference between baseline and new migrants. The former are relatively more often the head himself or his wife as well as the brother or sister of the head. It is the first or second generation in the household, who moves first. New migrants are relatively more often from the third generation, 12 percent (13 percent for men) are grandchildren of the household head, or they are relatives of second degree such as nieces or nephews. It is possible that there exist priorities in who gets to move first, starting with the head or spouse, the children or the siblings of the head, and eventually other younger relatives.

5.1.3 Education

The new migrants are relatively less educated and a third of women in this group have no completed education. Only 14 percent of male and 19 percent of female migrants in 2013 state to have no education at all, while around a quarter of the new migrants is uneducated. Female migrants in both groups are relatively less educated with larger shares having no or only primary education than male migrants. The most common level of education is middle/junior high school; 30 percent of baseline migrants, 28 percent of new migrant men and 23 percent of new migrant women have completed this level. Higher levels are most likely among male baseline migrants (22 percent completed senior

[7] Age is measured in 2013 for baseline migrants, and in 2015 for new migrants. This is in order to avoid to make the baseline migrants artificially older by noting their age only two years after they had already been identified as migrants. However, we acknowledge that the baseline migrants might have been much younger when they moved, but the question about time since migration has a very low response rate, so that we cannot compute the age at migration.

high school, 17 percent technical/college or tertiary education) followed by their female counterparts. Among new migrants, a slightly larger share of women achieved these higher levels of education, 30 percent, compared to 26 percent of their male counterparts.

5.1.4 Occupation prior to migration

Almost a third of women migrants in 2013 were doing unpaid work. While 28 percent of women did unpaid work in 2015, 37 percent of them were in education before their move. Yet, relatively more women are in education than men are before their move. Relatively fewer of the new migrant men were self-employed before migrating compared to those at baseline, 24 percent compared to 35 percent respectively. Around 10 percent of migrant men in both groups were paid employees before their move compared to only around 5 percent of female migrants.

In terms of the type of work the employed or self-employed did prior to their move, farming is the most common among men in both years with a share of around 42 percent. While women were also active in farming prior to their move, they often worked as traders or in some other type of self-employment. 35 percent of baseline migrant women were traders, but only 15 percent of new migrant women. This group was primarily active as teachers or in service work, such as hairdressing, dressmaking, domestic work, specified in the category ‘others’. For men the category ‘others’ mostly included crafts, such as masonry and carpentry, or services like driving.

Table 3: Migration decision and facilitation

	Baseline (2013)		New (2015)	
	Male	Female	Male	Female
Who was mainly involved in the migration decision?				
N	*461*	*251*	*85*	*80*
Self (%)	73.3	62.5	67.1	41.3
Father (%)	11.9	15.9	14.1	25
Mother (%)	3.3	4.8	2.4	7.5
Siblings (%)	1.5	3.2	1.2	2.5
Relative (%)	5.2	6.4	8.2	12.5
Community members (%)	0.2	0	1.2	0
Recruitment agent (%)	2.2	2	1.2	1.3
Others (%)	2.4	5.2	4.7	10
What was the main reason to migrate?				
N	*467*	*254*	*88*	*81*
Job transfer/opportunity (%)	17.1	13.8	15.9	6.2
Seek work/better job (%)	61	50	47.7	22.2
Study training (%)	12.6	13	12.5	25.9
To get married (%)	0.4	6.3	0	12.3
To accompany family (%)	0.2	1.2	2.3	1.2
To join family (%)	2.8	12.2	11.4	13.6
Declining yields in agriculture (%)	3.4	1.6	2.3	1.2
Civil conflict/war (%)	0.6	0.4	0	0
Family dispute (%)	0.2	0.4	1.1	0
Flood (%)	0.2	0	0	0
To join friends (%)	0.2	0	0	0
For medical treatment (%)	0	0.4	1.1	0
Others (%)	1.1	0.8	5.7	17.3
Contact at destination				
N	*481*	*259*	*87*	*83*
Yes (%)	54.3	69.1	64.4	74.7
Type of contact				
N	-	-	*56*	*61*
Father (%)			10.7	6.6
Mother (%)			7.1	9.8
Siblings (%)			17.9	14.8
Relatives (%)			55.4	55.7
Recruitment agent (%)			5.4	3.3
Other specified (%)			3.6	9.8
Job fixed up prior to moving				
N	*479*	*256*	*85*	*71*
Yes (%)	20.3	19.9	29.4	8.5

5.1.5 Decision makers

Now, we are turning to the migration decision, facilitation of migration and its costs. We report the descriptive statistics for these categories in table 3. Gender differences exist when it comes to the migration decision itself. In both years, relatively more male migrants made the decision themselves according to the household head who is answering these questions. 73 percent in 2013 and 67 percent in 2015 of male migrants contrast 63 percent and only 41 percent of female migrants respectively. The father or other relatives make the decision for female migrants relatively more often, especially for the new migrant women. In line with their younger age and lower education, it is plausible that older relatives are main decision makers when it comes to the migration of these women.

5.1.6 Reason for migration

Among baseline migrants, 78 percent of men and 64 percent of women moved for better job opportunities (including the categories 'job transfer/opportunity' or 'seek work/better job'). 19 percent of female migrants moved to get married, accompany or join family in contrast to only 3 percent of male migrants moving for family reasons. Around 13 percent of baseline women moved for studying or training purposes. In 2015, work is still the dominating reason to move for male migrants (63 percent), but relatively more join family than baseline migrant men (11 percent compared to 3 percent). Female new migrants move relatively more for studying (26 percent compared to 13 percent of baseline migrants). Joining or accompanying family is more common among new migrants. 14 percent of male and 15 percent of female migrants do so. 12 percent of new migrant women moved to get married whereas that was the case for only 6 percent of baseline migrant women.

5.1.7 Contacts at destination

Contacts at the destination can provide an important support for migrants. In our sample, women rely on networks relatively more. Almost 70 percent of women who were migrants at baseline and 75 percent of the new migrant women had a contact at destination prior to their move. In 2013, the corresponding number for men is 54 percent and 64 percent for 2015. For new migrants, we also know which contacts the migrants had at destination. Around 55 percent of times, the migrant had a relative at destination, and 18 percent of men and 17 percent of women had their parent at destination. From table 2 we know, that most of these new migrants are second or third generation within the household and often not direct descendants of the household head. It is therefore possible to imagine that nieces and nephews or grandchildren follow their parent who moved in the past.

Finally, we also observe whether migrants already had a job agreed before their move. This is less common, especially among female new migrants. In contrast, almost 30 percent of new migrant men state to have a job waiting for them at destination. At baseline, around 20 percent of migrants had a job fixed up prior to their move irrespective of their gender.

5.1.8 Financing migration (Table 4)

In terms of costs, female migrants pay on average less than male migrants for their move, 212 Ghanaian Cedi (GHS) at baseline and 112 for new migrants compared to 220 and 137 respectively for men. It is worth noting that new migrants pay on average less than baseline migrants do. Previously, we learned that relatively more of the new migrants have a contact at their destination and their household has prior engagement in migration. These observations suggest that costs can be reduced through migration experience.

The most common way to finance migration in 2013 were savings (70 percent) indicating that migration is an investment under credit constraints. If loans are taken then only from family. In no or very few cases formal sources for credit are used and only in very few cases migrants rely on a moneylender or recruitment agent. Around 12 percent of migration was financed by selling assets. New migrants in 2015 also rely on savings (42 percent of male and 38 percent of female migrants), but less so. Selling of assets is less likely to be used to finance the migration of a new female migrant at only 5 percent. A third of new migrant men and 42 percent of new migrant women state ‘others’ as source of financing. The specified sources among this category are mainly money from a parent and in some cases from the migrant her or himself. We consider this type of money as individual savings. Another source of financing are private transfers to the household from other migrants, remittances. Around 9 percent of female migrants used remittances to cover their moving costs, male migrants less so at baseline and 6 percent of new migrant men.

Table 4: Migration costs and means of financing

	Baseline (2013)		New (2015)	
	Male	Female	Male	Female
Migration costs				
N	*220*	*111*	*65*	*58*
in GHS of 2015	222.5	212.3	137.1	111.6
Financing of migration				
N	*371*	*173*	*79*	*79*
Savings (%)	72	67.6	41.8	38
Formal loan (%)	1.1	1.7	0	0
Loan from family (%)	7	6.9	6.3	5.1
Borrowing from money lender (%)	0.8	0.6	2.5	0
Advance from recruitment agent (%)	1.6	2.3	0	1.3
Sale of assets (%)	12.7	11	10.1	5.1
Government schemes (%)	1.6	0	0	0
Scholarship (%)	0.3	0.6	0	0
Remittances from other migrants in the HH (%)	3	9.2	6.3	8.9
Others (%)	0	0	32.9	41.8

5.1.9 Repeated migration, seasonality and destination (Table 5)

The baseline migrants have relatively more migration experience, around half moved once before their current migration. In 2015, around 70 percent of the new migrants move for the first time. Again, this is in line with the younger age of the new migrants, their unmarried status and activity prior to migration (school or unpaid work). Correspondingly, relatively fewer of the new migrants are seasonal migrants, especially of the female migrants. At baseline, 16 percent of migrants were seasonal workers, the same share of new male migrants moved seasonally, but only 9 percent of female new migrants. The new migrants moved relatively more often to another region in Ghana than to remain in their own district or region. Female migrants on average stayed closer to their origin, with only 47 percent of them leaving their region in contrast to 61 percent of male migrants. This difference could be due to those women who migrate to get married which is often tied to ethnic and family networks that might be closer to the origin community.

Table 5: Migration experience: repetition, seasonality, destination and occupation

	Baseline (2013)		New (2015)	
	Male	Female	Male	Female
Repeated migration				
N	*389*	*203*	*84*	*80*
First time migrants (%)	49.4	59.6	70	65
Seasonal migration				
N	*474*	*259*	*86*	*84*
Seasonal (in contrast to permanent) (%)	15.2	16.6	16.3	9.5
Destination				
N	-	-	*86*	*83*
Same district (%)			10.5	18.1
Other district, same region (%)			29.1	34.9
Other region (%)			60.5	47
Occupation at destination				
N	*353*	*182*	*54*	*51*
Farming (%)	19.8	12.1	14.8	21.6
Trading (%)	15.9	39.6	18.5	21.6
Self-employment (%)	16.1	26.4	1.9	9.8
Teaching (%)	7.9	8.2	9.3	7.8
Others (%)	40.1	13.4	55.7	39.3

5.1.10 Occupation at destination

At destination, the patterns of occupation change compared to what migrants did prior to their move (see section 5.1.4). Self-employment is much less common among new migrants (2 percent for men and 10 percent for women), while 16 percent of male and 26 percent of female baseline migrants work self-employed. Between 12 and 22 percent of migrants in both years work in farming at destination. This suggests that geographical mobility implies also some occupational mobility. Trading is again a common occupation for baseline migrant women and also 22 percent of new migrant women work as traders.

5.1.11 Remittances

Remittance sending behaviour is different between baseline and new migrants (see table 6). In the baseline group, relatively more men remit money to their families, 64 percent compared to 54 percent of female migrants. Among new migrants, only 41 percent of men and 39 percent of women remit.

Baseline migrant men also remit larger amounts than their female counterparts (GHS 788 compared to GHS 655), but they all remit on average at least GHS 100 more than new migrants.

When asked how frequently they remit, new migrants remit relatively less frequent, half of them only on special occasions or in emergencies, whereas baseline migrants tend to remit mostly every couple of months or even monthly. New migrants are also less likely to remit goods to their origin household; only around 28 percent of them do so with no gender difference. Among baseline migrants, half of the women send goods back home and even 44 percent of men do so.

These observations that new migrants relatively more often get their migration financed from parents or paid themselves in contrast to baseline migrants, indicates that they might feel less obliged to remit money to their origin household.

Table 6: Remittances

	Baseline (2013)		New (2015)	
	Male	Female	Male	Female
Cash remittances				
N	*448*	*242*	*74*	*70*
Yes (%)	63.8	53.7	40.5	38.6
Amount				
N	*260*	*112*	*29*	*24*
in GHS of 2015	788.7	655.1	607.9	515.2
Frequency of remitting				
N	*267*	*120*	*29*	*26*
Weekly (%)	1.1	1.7	0	3.8
Fortnightly (%)	1.1	0	0	3.8
Monthly (%)	24.3	19.2	17.2	11.5
Every couple of month (%)	43.1	40.8	13.8	15.4
Every six months (%)	5.2	6.7	13.8	3.8
Every year (%)	6.4	9.2	3.4	11.5
Only on special occasions or emergencies (%)	18.7	22.5	51.7	50
Remittance of goods				
N	*427*	*228*	*74*	*71*
Yes (%)	44	49.6	28.4	26.8

5.1.12 Contact and support from origin households

We saw that family support is important for migration and its financing. Hence, migrants keep in frequent contact with their families (see table 7). Half of the baseline migrants contact their family at least once per week irrespective of their gender. New female migrants are even more likely to sustain frequent contact (57 percent being in contact at least weekly), as are new male migrants (53 percent). Despite the fact, that new migrants are less likely to send remittances to their origin household, they are in close contact with that household.

Finally, households sometimes also send money to the migrants to support them financially. This is relatively less common for baseline migrants, when 15 percent of male and 22 percent of female migrants received financial support from their families within the 12 months preceding the survey. Among the new migrants 26 percent of female migrants got money from home and 16 percent of male migrants.

Table 7: Contact and support from origin household

	Baseline (2013)		New (2015)	
	Male	Female	Male	Female
Frequency of contact				
N	*457*	*253*	*86*	*84*
More than once a week (%)	31.9	31.2	24.4	33.3
Weekly (%)	21.7	25.3	29.1	23.8
More than once a month (%)	19.9	22.9	24.4	22.6
Monthly (%)	8.3	10.3	9.3	8.3
More than once every three months (%)	5.7	3.6	3.5	3.6
More than once every six months (%)	3.9	2	1.2	1.2
More than once in a year (%)	5.9	2.8	3.5	2.4
I don't have contact with name (%)	2.6	2	4.7	4.8
Household sends money to migrant				
N	*400*	*214*	*67*	*70*
Yes (%)	15	22	16.4	25.7

These observations reveal that the new migrants in our sample are not moving for exactly the same reasons and do not share the same relationship with their origin households as the baseline migrants do.

5.2 Households

Before we investigate the impact of sending a new migrant on household welfare, we also look closer at the characteristics of the households that have a new migrant compared to those without. In table 8, we document the main characteristics of households with new migrants compared to those who do not send another migrant by 2015. All characteristics are measured at the baseline in 2013.

5.2.1 Household composition

Households who send a new migrant have on average between one and two more members than the comparison group. This indicates that they can afford to send members away as the remaining members are still enough to work on the family farm, in the family business or help with housework.

They have similar demographic structures measured with the dependency ratio (0.6) and female-to-male ratio (0.49). 29 percent of households that send a new migrant have a female head, 3 percentage points more than the control group. Heads of households in this group are on average 53 years old, those in treated households are on average one to two years older. Most heads are married, but 4 percentage points more among the control group. Relatively more heads in the treatment households are widowed, separated or divorced (22 compared to 18 percent). A negligible share is single (0.6 percent at baseline and 0.5 percent in 2015).

There are some differences between the groups of households with regards to their ethnicity. 29 percent of control households belong to the Mole Dagbani ethnic group and only 13 percent are of the Akan, 7 percentage points less than in the treated group. The share of Mole Dagbani is also smaller in the treatment group (24 percent) whereas the category 'others' is larger which indicates a more diverse distribution of treated households across ethnic groups.[8]

5.2.2 Education

Relatively more households sending a new migrant have heads with lower education, 84 percent completed no, primary school or middle school compared to 75 percent of heads in the comparison group.

[8] The category 'others' include Ga-Dangme, Guan, Gruni, Grussi and other unspecified groups.

In terms of the highest level of education in the household, this pattern seems to reverse. It is measured as the highest level of education of any adult member in the household to capture overall education in the household as we do not have a measure of the years in education. The highest level of education within households is on average higher than that of the household heads. In a third of households lives a member with higher education such as technical college or other tertiary education. In another 31 percent, someone has completed senior high school. In the control group, these shares are very similar.

Table 8: Household characteristics at baseline, by group

	Households without new migrants (Control)	Households with new migrants (Treatment)
N	*349*	*131*
Household size (excluding currently absent migrants)	5.6	7.2
Dependency ratio	0.60	0.61
Female-to-male ratio	0.50	0.48
Female head (%)	0.26	0.29
Age of head in years	53.3	54.8
Marital status		
Single (%)	0.06	0.05
Married/ living with partner (%)	0.77	0.73
Separated/ Divorced/ Widowed (%)	0.17	0.22
Ethnicity of head		
Akan (%)	0.13	0.20
Ewe (%)	0.24	0.19
Mole Dagbani (%)	0.29	0.24
Others (%)	0.34	0.37
Education of head		
None (%)	0.41	0.41
Primary (%)	0.09	0.11
Middle/Junior (%)	0.25	0.32
High/Senior (%)	0.12	0.07
College/Technical (%)	0.12	0.08
Highest level of education in household		
None (%)	0.05	0.05
Primary (%)	0.11	0.08
Middle/Junior (%)	0.23	0.23
High/Senior (%)	0.30	0.31
College/Technical (%)	0.31	0.34
Employment status of head		
employee (%)	0.16	0.15
self-employed (%)	0.52	0.52
unpaid/unemployed (%)	0.23	0.25
inactive etc (%)	0.09	0.08
Main income source		
Public sector (%)	0.12	0.08
Private sector (%)	0.04	0.05
Own business (%)	0.28	0.26
Own farm (%)	0.42	0.51
Private transfers (%)	0.11	0.07
Others (%)	0.03	0.03
Migration experience		
Household has returnee (%)	0.17	0.24
Number of current migrants	1.9	2.1
Number of prior migration spells of current migrants	1.3	0.9
Share of seasonal migrants (%)	0.16	0.09
Share of female migrants (%)	0.35	0.41
Share of migrants with job (%)	0.60	0.66

5.2.3 Employment status and income source

Most household heads are self-employed, more than 50 percent in both groups. Around 24 percent of all heads are unemployed or doing unpaid work. 15 percent of them are working as paid employees. The majority of households earns the largest share of their income from their own farm. Farming is more common among the households with a new migrant than among those without, 51 percent and 42 percent respectively. Around 28 percent of households without a new migrant run their own business compared to 26 percent of households with a new migrant. 12 percent of control households rely on either public sector employment income or private transfers, which comprise remittances from migrants or other relatives. The respective share of households with new migrants is around 7 percent.

5.2.4 Migration experience

Around 24 percent of households with a new migrant had a member who returned to the household. In the comparison group, 17 percent of households have a returnee. Households have on average two migrants currently away in 2013 independent of the group. This is another indication for how common migration of more than one member is in our setting.

There are relatively more treated households whose baseline migrant moved for the first time. In contrast, baseline migrants in control households had migrated on average 1.3 times before. These households also have a relatively larger share of seasonal migrants in 2013, 16 percent compared to 9 percent in households that have a new migrant. It seems more common for control households to send the same member away repeatedly than to have a new migrant. This is also consistent with the difference in household size reported above.

Only a third of baseline migrants are women in households without a new migrant contrasting 41 percent in households with new migrants. The share of migrants who have a job at destination is relatively higher among households that later send a new migrant. On average, 66 percent of baseline migrants from these households have a job at destination. That is 6 percentage points more than for the comparison group.

5.3 Summary

In summary, there are some differences between households with a new migrant and the control group when we compare their characteristics at baseline. They differ in household size, ethnicity and livelihood. Households with new migrants are relatively larger and most live from family farm income. Additionally, their prior experience with migration appears to be successful in terms of the share of baseline migrants that have a job at destination and they are more likely to have a return migrant who potentially transmits important information for future migration.

Our sample reflects households in a setting where family farms or businesses are common, as is migration. Migration is mostly long-term and not seasonal, even though repeated migration is not unusual. The migration decision is made in a credit constraint environment. It strongly depends on the availability of savings to cover moving costs.

We observed that new migrants are different from baseline migrants. They are from a younger generation, often going to further their education or for work reasons. Fewer of them send remittances to their origin households than previous migrants. Family networks as well as frequent contact to the origin household, however, suggest strong ties between migrant-sending households and new migrants.

From these findings we cannot clearly predict the relationship of migration and household welfare, nor can we hypothesise its direction. In some cases, new migrants might be sent to diversify income sources and it is seen as an investment expecting returns to the household in form of remittances. In this case, we would expect to see a negative impact of the initial investment costs due to our short panel period as remittances usually delay to arrive and materialise in origin households (Taylor and López-Feldman, 2010). In other cases, it could be possible that migrants are already successful at their destination and are sending remittances that improve the household welfare.

Other migrants moved financially supported from their families to pursue more education or find new opportunities in other locations. This could be in line with human capital models of migration (Sjaastad, 1962). In these cases, it would be possible to find a negative effect on welfare of origin households due to the incurred migration costs and the loss in labour, but it is also possible that due to prior migration experience there is no impact on the origin households. This could even imply a positive impact as fewer members in the household leave more financial resources available for those who stay.

6 Methodology

Theoretically, there are no clear answers to the question whether migration has a positive or negative effect on the welfare of left-behind households. The New Economics of Labour literature (Stark and Bloom, 1985; Taylor, 1999) suggests that the migration decision is part of the overall household strategy in a context of market imperfections, but it cannot provide clear predictions for the impact of this decision (Mendola, 2012). As documented in the descriptive part migrants move for different reasons, which might imply different costs and different remittance sending behaviour. Additionally, prior experience with migration at the household level is also expected to affect the costs and migrants' remittance behaviour.

It remains an empirical question to study how having a new migrant relates to the welfare of origin households conditional on prior migration experience.

6.1 Empirical Strategy

We estimate the impact of having a new migrant on household welfare in the following specification:

$$\Delta Y_{i,t} = \beta_1 \text{NewMig}_i + \beta_2 \Delta Year_t + \beta_3 \Delta X_{i,t} + \beta_4 \Delta LM_{c,t} + \Delta\epsilon_{i,t} \tag{1}$$

Our interest is to see how the welfare of households changes when they have a new migrant. With two time periods, we regress the change in the outcome variable Y for household i on the treatment status of household i, NewMig_i and other variables. NewMig_i is a dummy indicating whether the household has a new migrant or not. We also control for the general change of welfare over time by including a variable indicating the survey year, $Year_t$. Further controls are household characteristics, $X_{i,t}$, and labour market properties that vary over time, $LM_{c,t}$. The specification in changes automatically discards any unobservable characteristics of the households that do not vary between the survey waves.

The parameter of interest is β_1, the coefficient of the indicator whether a household has a new migrant or not. It measures the effect of having a new migrant between the two survey waves on the change in welfare of the origin household compared to those households that did not see another member migrate. It should be interpreted as an average treatment effect on the treated (ATT).

The time-varying household characteristics, $X_{i,t}$, are the dependency ratio, whether the household has a returned migrant and the employment status of the household head (unemployed/unpaid work, self-employed, employed or inactive). These can all affect household welfare and they can change within the time period under investigation. If a household has another child or if one of the older members becomes too old to work, the welfare might decline, as per capita income declines. Similarly, if a household head becomes unemployed this affects household welfare negatively. Finally, a migrant who returns to the origin household can, on the one hand, bring home money and invest it in assets to increase welfare or, on the other hand, the returnee might have failed at destination and now presents an additional burden to the household.

The local labour market variable, $LM_{c,t}$, is the employment rate in a community c. It is measured as the share of individuals who work as wage employees relative to the local labour force. This is included because a household seeking to diversify its income sources will consider local opportunities, where household members could earn a wage.[9]

6.2 Dependent variable: Asset index

As outcome variable we construct an asset index. Starting from Sahn and Stifel (2000) researchers used the rich information on assets available in many developing country household data sets to construct an index as welfare measure. The main argument for the use of the asset information instead of conventional measures such as consumption or income is that the latter are much more volatile

[9]This measure is obtained using all individuals in our data in each community. Based on their main activity we define those who are employed and we sum all who are either employed, unemployed, doing unpaid work or self-employed. This captures how common paid employment is in a community and thus reflects the local opportunities for wage work outside the family farm or business. It is important to note that this measure is not correctly measuring the true employment rate, because our data is not representative of the local population. We looked into the possibility to obtain local labour market information from other locally representative datasets. However, we cannot use Census data because it is only available for one year before our survey was conducted so that we cannot control for variation over time. Alternatively, we could use the Ghana Living Standard Survey or the Ghana Socioeconomic Panel Survey (Institute of Statistical, Social, and Economic Research (ISSER),University of Ghana and Economic Growth Center (EGC), Yale University, 2015), but only half of the districts in our survey are covered in these surveys and neither of these datasets is available for the years of our survey.

and more difficult to measure. For a long-term assessment of the economic status of households, assets have been proven to be more stable and more reliable measures. Filmer and Pritchett (2001), McKenzie (2005), and Booysen et al. (2008) all used asset indices to compare poverty reductions in various countries and the use of such welfare indices has been increasing since the concept of multi-dimensional poverty was introduced (for a discussion see Ravallion (2011)).

It is important to note that a welfare index is a relative, not an absolute measure. It is very useful for comparisons of welfare between groups and/or over time. A detailed explanation of the method applied to construct the index (Multiple Correspondence Analysis) can be found in the appendix A on page 58.

An asset index is a composite measure using information about asset ownership and/or other welfare indicators in survey data. The researcher is interested in one continuous measure that captures the welfare of a household. In its simplest format, we can think of an asset index as the sum of its weighted components:

$$A_i = p_1 a_{1,i} + p_2 a_{2,i} + \ldots + p_k a_{k,i} \tag{2}$$

The asset index of household i is the sum of each of the individual asset indicator dummies, a_k weighted by an asset specific weight, p_k. Each indicator is equal to 1 if the household owns this specific asset, 0 otherwise. There are different possibilities to assign weights. The simplest, but most arbitrary, is to assign equal weights for each indicator. Ideally, one would use the price of each asset as weight. That is most times impossible due to lack of data. Alternatively, there are three statistical methods used in the literature to retrieve the indicator weights, Principal Component Analysis (henceforth PCA), Factor Analysis (FA), and Multiple Correspondence Analysis (MCA). These methods follow the same idea, but differ in their assumptions and restrictions imposed on the data. We apply the non-parametric and least restrictive method of MCA.

We use assets which are comparable to those found in the most commonly used household surveys in developing countries, the Demographic and Health Surveys (DHS). These are indicators of housing quality. They comprise the number of rooms, dwelling ownership, the presence of a bathroom and a toilet, main source of drinking water, and the floor and wall material.[10]

In table 9, we tabulate the ownership of each of these indicators by year and treatment status and describe the major changes observed.

Table 9: Asset ownership by group and year

	Control		Treatment	
	2013	2015	2013	2015
N	*349*		*131*	
Number of rooms				
1	0.10	0.08	0.04	0.07
2	0.17	0.15	0.15	0.15
3	0.22	0.20	0.21	0.24
4	0.15	0.19	0.18	0.15
5 or more	0.35	0.37	0.42	0.37
Dwelling ownership				
Owned	0.83	0.85	0.89	0.90
Rented	0.17	0.09	0.11	0.05
Other	0.00	0.05	0.00	0.05
Bathroom	0.96	0.93	0.95	0.98
Toilet	0.37	0.36	0.41	0.42
Main source of drinking water				
Pipe borne water inside	0.12	0.18	0.11	0.16
Pipe borne water outside	0.29	0.30	0.21	0.18
Borehole	0.32	0.30	0.34	0.35
Dug well	0.13	0.09	0.13	0.14
Tanker service	0.00	0.01	0.00	0.00
Stream/river/lake	0.09	0.09	0.15	0.12
Rain water	0.01	0.00	0.01	0.01
Bottled or sachet water	0.05	0.01	0.05	0.04
Other	0.00	0.01	0.00	0.00
Floor material				
Mud	0.20	0.19	0.28	0.16
Raw wood, boards	0.00	0.01	0.00	0.00
Cement/concrete	0.77	0.77	0.69	0.80
Burnt brick	0.01	0.00	0.02	0.01
Terrazo	0.00	0.01	0.00	0.02
Floor tile	0.00	0.01	0.01	0.02
Polished wood	0.01	0.00	0.01	0.00
Wall material				
Bamboo or other organic materials	0.04	0.04	0.05	0.05
Cloth, cardboard, cans	0.01	0.00	0.00	0.00
Zinc	0.05	0.11	0.02	0.16
Raw wood	0.00	0.00	0.00	0.00
Mud, adobe, cane wall	0.36	0.35	0.40	0.32
Block, bricks, stone, prefabricated material, polished wood	0.50	0.49	0.50	0.46
Other	0.03	0.01	0.03	0.01

The ownership status and presence of a bathroom or toilet are relatively stable. There are some larger

[10]We were not able to include landownership, neither as a simple dummy variable whether a household owns land or not, nor in terms of land size. The reason for this is that this question is only available in the 2015 survey.

changes between years for floor and wall material and smaller changes for the number of rooms and the source of drinking water. These changes also differ between treatment and control group which is important for our identification strategy. If all changes would go in the same direction we would not be able to identify an effect of having a new migrant on the change in the index.

Figure 1 presents the asset index in 2013 of households with a new migrant and of those without, figure 2 depicts the same for 2015.

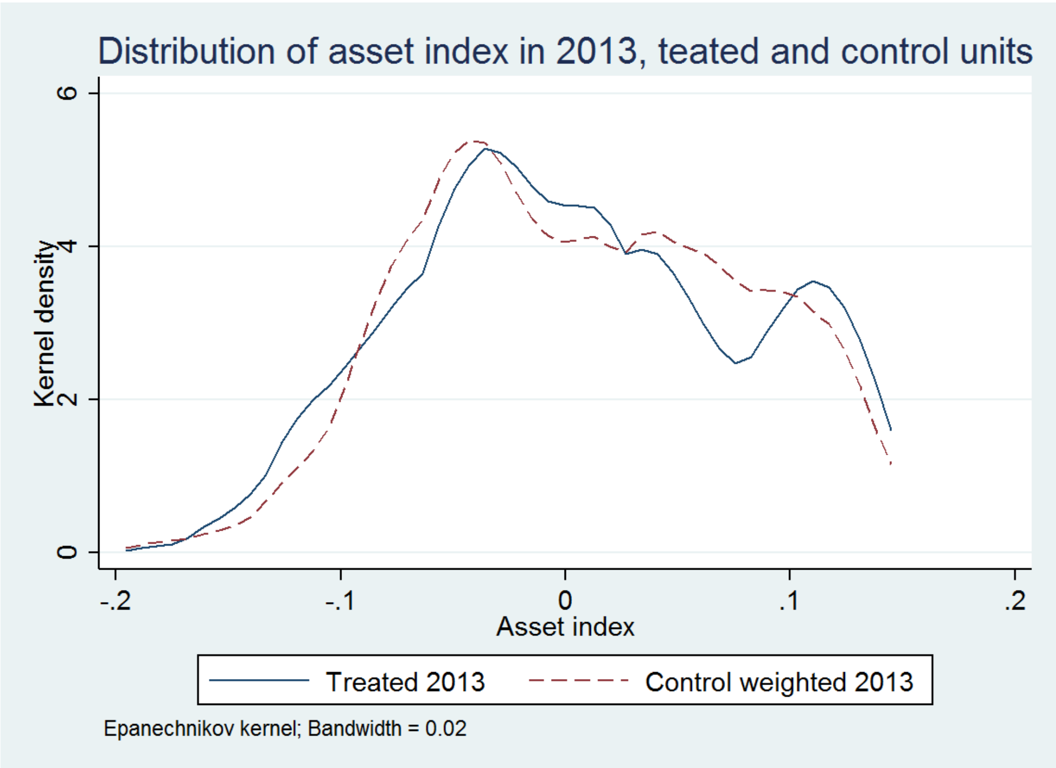

Figure 1: Asset index of treated and control households in 2013

These figures illustrate that the distribution of the asset index overlap in 2013, but they shift apart in 2015. It seems that households without a new migrant have a higher distribution of the index. Note that the distribution for control households are weighted to make households comparable applying a method which is described in section 6.3.1. This explains the overlap in the baseline year (figure 1).

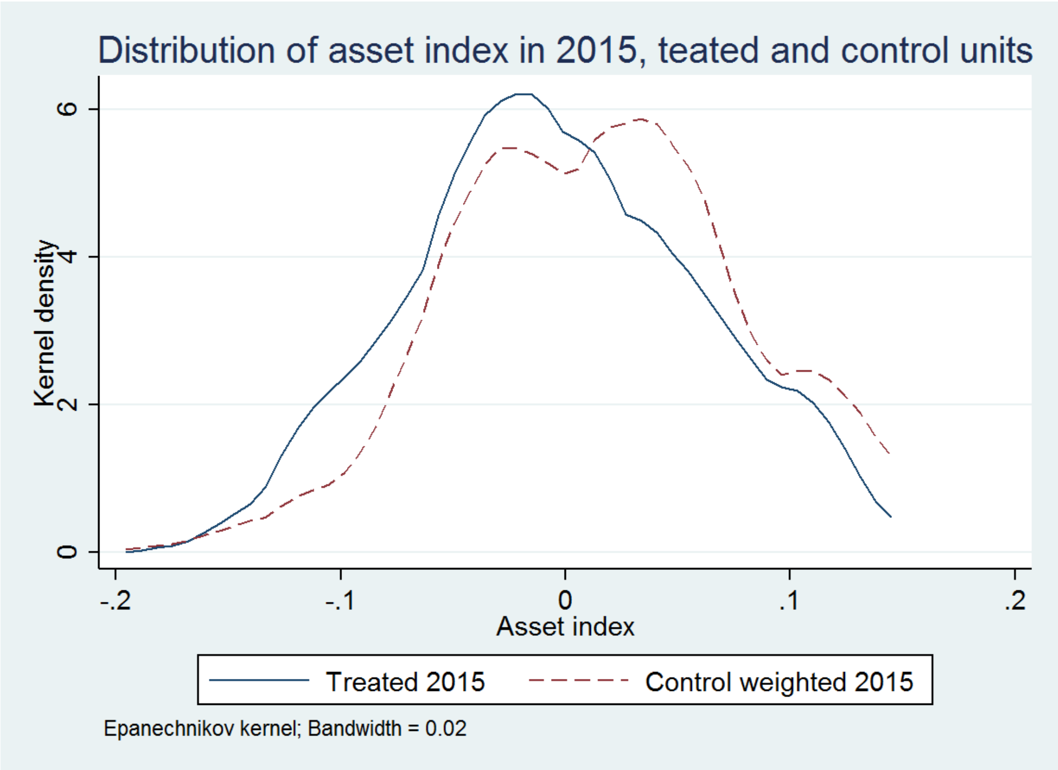

Figure 2: Asset index of treated and control households in 2015

6.3 Identification strategy

Several issues challenge the empirical identification of the impact of migration on households left behind.

First, we can think of factors that simultaneously affect both the migration decision and the outcome. For example, risk aversion of a household might prevent it from engaging in migration or in more profitable but riskier technologies in their farm or business. Hence, such households would be less likely to have a new migrant and would remain at a lower welfare level. Such omitted variables would bias the coefficient of interest. In the given example, we would overestimate a negative effect of having a new migrant. We cannot foresee the direction of the effect, but it would be biased upwards.

By modelling a first difference specification, we capture any unobservable factors at the household level. Like fixed effects, this controls for time-invariant characteristics and the vector of household characteristics accounts for observable characteristics that vary over time. We assume that unobservable factors such as risk aversion are not varying over two years.

Secondly, the migration decision could be influenced by the outcome variable. This is especially a problem with cross-sectional data (Antman, 2012). The change in asset ownership in the period preceding our baseline could affect the treatment status of households. We cannot exploit previous data to control for this, but by balancing households on baseline characteristics we only compare those that look similar and thus capture any effect the prior welfare change had on households (see detailed discussion of the weighting method in section 6.3.2).

The specification in equation 1 assumes that new migrants are randomly allocated across treated and comparison households. Migration is however not a random process, but instead a strategic decision determined by observable (e.g. education, income) and unobservable (e.g. risk attitude, motivation) characteristics of the household. We will have to address the selection bias arising from this non-random treatment assignment.

Depending on the main drivers of selection of a new migrant, the bias could lead both ways, upwards or downwards. For example, the literature on self-selection finds that highly educated migrants tend to be positively selected and thus lead to overestimations of the outcomes of these migrants; the opposite applies to unskilled migrants (Borjas, 1987). In our context, not only migrant characteristics, but also household structure and prior migration experience are important determinants of the selection into having new migrants.

For unbiased identification, natural experiments (among others Gibson et al. (2011)) or randomized control trials (Bryan et al., 2014) are the ideal approach. Without such settings at hand, many researchers rely on either instrumental variables or matching approaches to reduce the issue of selection bias. Common instrumental variables for migration are historical road or rail networks that led to location-specific migrant networks (for example Woodruff and Zenteno (2007)). For Ghana, Adams and Cuecuecha (2013) rely on ethnic groups and their social networks that make it more or less likely for households to send migrants.

The common instruments could be used to predict whether households engage in migration or not, but less so to predict whether conditional on prior migration experience households have new migrants. We expect that this decision depends primarily on household-level characteristics. We therefore rely on a weighting method based on the assumptions of matching approaches.

The weighting method makes the comparison group look like the treated group in terms of observable characteristics at baseline. This approach assumes selection on observables. It means that conditional on observable characteristics, having a new migrant is as good as random (Wooldridge, 2010). This balance is achieved for observable characteristics that are expected to influence the likelihood to be a treated household and the outcome variable (Imbens, 2015). Once these observables are balanced, the selection bias is reduced (Heckman et al., 1998).

6.3.1 Entropy balancing weights

Conventional matching methods, such as Propensity Score Matching (PSM), require the researcher to define a specification for the propensity score, which then leads to balanced treatment and comparison groups after matching (Imbens, 2015). This process involves several stages and adjustments of the specification and sometimes the improvement of balance in one covariate goes hand in hand with worsening the balance of another covariate (Iacus et al., 2012). Due to this laborious process the matching method is prone to model dependence and researcher discretion (King and Nielsen, 2016). For example, in many cases only the means of matching variables between treated and control group are compared, not accounting for potential differences in the distribution of variables (Lee, 2013).

To simplify this process, some researchers have developed matching methods that achieve balance before the matching itself. One is the entropy balancing developed by Hainmueller (2012). This approach defines weights for each observation that ensure a predefined balance of covariates. The balance can be defined in terms of the first, second and even higher order moments of the covariates. The main advantages of this method are that balance checks become redundant, the majority of observations are retained, the computation of the weights is fast, and the method can be combined with many other matching and regression methods, similarly to inverse probability weighting methods and regression adjustment procedures (Imbens, 2015).

Entropy weights, w, minimise the entropy distance metric which is defined as:

$$\min_{w_i} H(w) = \sum_{i|D=0} w_i log(\frac{w_i}{q_i}) \tag{3}$$

and which is subject to balance (Equation 4), and normalizing constraints (Equations 5 and 6 respectively):

$$\sum_{i|D=0} w_i c_r i(X_i) = m_r \qquad \text{with} \qquad r \in 1, ..., R \qquad \text{and} \tag{4}$$

$$\sum_{i|D=0} w_i = 1 \qquad \text{and} \tag{5}$$

$$w_i \geq 0 \qquad \text{for all} \qquad i \qquad \text{such that} \qquad D = 0 \tag{6}$$

q_i is a base weight defined as 1 over the number of control units. $c_{ri}(X_i)$ "are a set of R balance constraints that are imposed on the covariate moments of the reweighted control group" (Hainmueller and Xu, 2013). Finally, it computes a set of weights that minimize the first equation (3) subject to the balance constraint, the normalisation constraint, and the non-negativity constraint.

The procedure is easily implemented in the software Stata using the command *ebalance*. The command first defines the first moment of the covariates using only the treated units. Then the control units are re-weighted so that their mean is equal to that of the treated units for the chosen covariates complying with the normalizing constraints (5 and 6). The same procedure applies to higher moments. It is important to note that one has to consider the sample at hand when using this method. Entropy balancing is a useful method only if the treated and control units do not look radically different and there can only be as many balance conditions as control observations. Like in other matching methods this implies the assumption of common support. Observations that make it impossible to achieve the balance defined by the researcher are dropped and weights are only computed for the remaining observations.[11]

Once the weights are computed, they are applied to estimate equation 1 with weighted least squares (WLS). This approach works like any Regression Adjustment method (Wooldridge, 2010).

[11] In our case, we drop 91 observations, 22 treated and 69 control households. Around a third of these are dropped due to missing values for some of the covariates that we required to be balanced. Others had extreme values for some covariates, e.g. a dependency ratio of 5.

6.3.2 Variables to balance

The decision which variables to include in the entropy balancing weight computation follows the suggestions about PSM by Imbens (2015). We include all variables that we consider substantive for having a new migrant or for the outcome. We also include squared terms of continuous variables. A. Smith and E. Todd (2005) stress the importance to include a rich set of such covariates, preferably past measures of the outcome variable and to ensure that one compares units within the same labour market or, more generally speaking, from the same geographical context.

Region dummies should capture any such factors that relate to migrant networks, regional development and economic opportunities. Most importantly, we control for the household size and dependency ratio of elderly and children to adult members to capture the household structure. These variables are important for the household decision about migration as well as the household's welfare. Another important characteristic is the main household income source, that is whether the household earns its living from agriculture, employment, its own business, public or private transfers. We also control for the employment status of the household head (employed, self-employed, unemployed or inactive) to capture economic activity. As a measure for human capital in the household, we include the highest level of education of adult members in the household. Many studies show that education is an important predictor for households' welfare. It is also related to migration decisions as higher educated people have higher expected incomes at home as well as at possible destinations (Sjaastad (1962)). We include a dummy for female household heads, shown to be a strong predictor for household welfare in the rural context as well as reflecting a households' options for migration decisions (Adams and Cuecuecha, 2013). In addition, age and marital status of the household head are added to control for the life-cycle of a household (Lipton, 1980). Ethnicity was found to be an important factor in creating and maintaining migrant networks in Ghana (Awumbila et al., 2016). Such networks are important determinants for migration decisions as they reduce the risk and costs associated with migration (Carrington et al., 1996), which is why we include the ethnicity of the household head. We also include our measure of community employment rate. We choose this measure, because if a household seeks to diversify its income sources, it will also consider other opportunities in the community where household members could earn a wage (Bazzi, 2017).

Economic welfare is an important predictor for migration decisions and it is our outcome variable. In a credit constraint context, only households at a certain level of wealth are able to afford migration McKenzie and Rapoport (2007). Thus, only households with a similar level and distribution of welfare should be compared. While we do not have information on economic welfare pre-dating our baseline as suggested by A. Smith and E. Todd (2005), we include a rich set of asset indicators and information on asset purchases. Asset indicators are those that are used to construct the asset index. Asset purchase is a dummy that is equal to 1 if a household has purchased a specific asset within the past five years before the baseline survey, 0 otherwise.[12] In this way, we can capture a certain level of wealth and investment behaviour of the household that pre-dates the baseline survey.

6.3.3 Balance statistics for treatment and control group

Here we present an overview of the balanced characteristics of treated and control households. The summary statistics provide evidence that the balance is achieved using the entropy weights. Figure 3 plots the kernel density of household size in 2013 for treatment and control group. The latter is represented once without applying the entropy balancing weights, and then with weighting.

[12] These assets are electric household goods, white household goods, livestock, generator, car, computer, electronic appliances, other investments, agricultural land, agricultural machinery, non-agricultural land, new house.

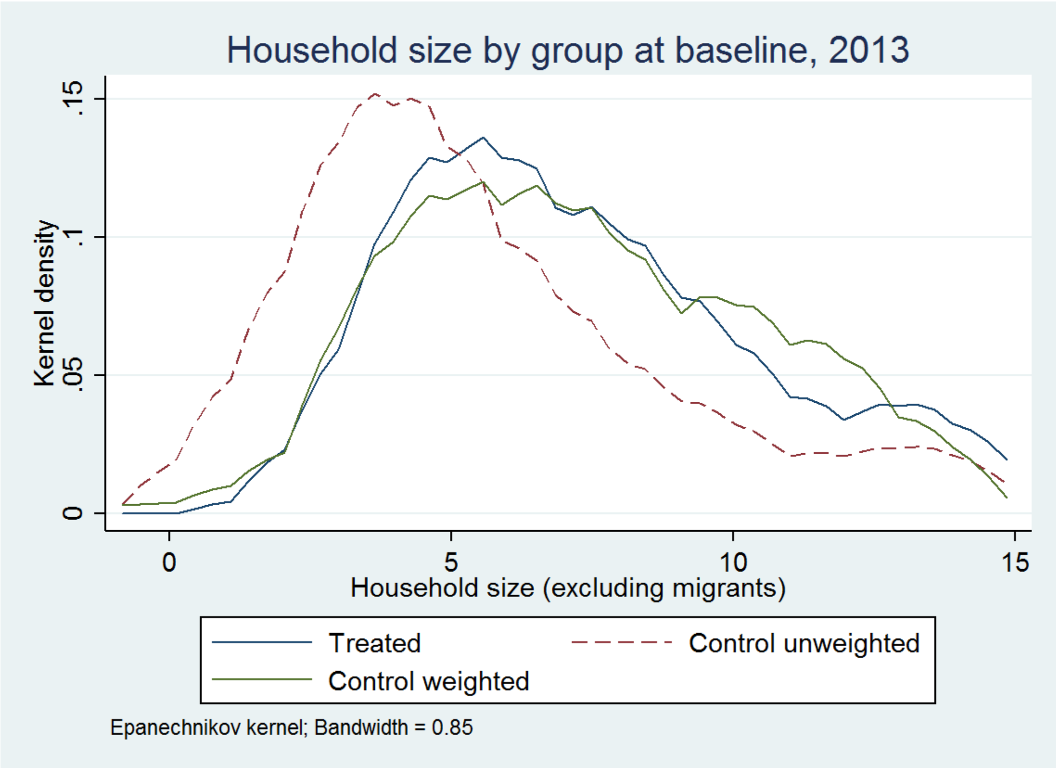

Figure 3: Kernel density of household size in 2013, by treatment groups

Without the weights, the dashed line shows a very different distribution. Control households are on average smaller than treatment households so that sending a new migrant is much more likely if there are more members that could make this choice. Thus, it is important to make households more comparable concerning this variable. The overlap between the treated distribution and the weighted control distribution confirm that the balance is achieved using the entropy weights.

In table 10, we show the mean and variance of the variables that were included in the construction of the entropy balancing weights with the weights applied to the control group. Using the weights leads to identical means of all variables and the variance is in some cases only slightly different. The last column lists the standardised differences between treated and control observations. They are all smaller than (+/-) 0.01. The entropy balancing weights construct a comparable sample of households to reduce the selection bias.

Even though we are not able to include the change in the outcome variable for the years before our analysis, we included information on the asset purchases within the two years prior to the baseline survey. Households purchased larger assets within a two year period preceding our survey. It is therefore plausible to expect also further changes in assets.

Table 10: First and second moments of covariates after applying entropy balancing weights, by group in 2013

	Mean		Variance		Standardised
	Treated	Control	Treated	Control	difference
Dependency ratio	0.660	0.658	0.846	0.844	0.002
Female household head	0.299	0.298	0.211	0.210	0.001
Highest level of education in household					
Primary	0.075	0.075	0.070	0.069	0.000
Middle/Junior	0.224	0.224	0.175	0.174	0.001
High/Senior	0.313	0.313	0.217	0.216	0.001
College/Technical	0.343	0.343	0.227	0.226	0.001
Ethnicity of head					
Akan	0.194	0.194	0.158	0.157	0.001
Ewe	0.194	0.194	0.158	0.157	0.000
Mole Dagbani	0.231	0.231	0.179	0.178	0.001
Main income source					
Private sector	0.052	0.052	0.050	0.050	0.000
Own business	0.269	0.268	0.198	0.197	0.001
Own farm	0.500	0.499	0.252	0.251	0.003
Private transfers	0.075	0.075	0.070	0.069	0.000
Others	0.030	0.030	0.029	0.029	0.000
Asset purchases in preceding 2 years					
Electronic goods	0.403	0.402	0.242	0.241	0.002
White goods	0.187	0.186	0.153	0.152	0.000
Livestock	0.284	0.283	0.205	0.204	0.001
Generator	0.022	0.022	0.022	0.022	0.000
Car	0.067	0.067	0.063	0.063	0.000
Computer	0.052	0.052	0.050	0.050	0.000
Electric Appliances	0.082	0.082	0.076	0.076	0.000
Other Investments	0.104	0.105	0.094	0.094	-0.001
Agricultural land	0.224	0.224	0.175	0.174	0.001
Agricultural machinery	0.022	0.022	0.022	0.022	0.000
Non-agricultural land	0.127	0.127	0.112	0.111	0.000
New house	0.313	0.313	0.217	0.216	0.001
Household size (excl. migrants)	7.299	7.280	9.640	9.615	0.006
Age of household head	55.276	55.136	218.021	217.450	0.009
Marital status					
Married/ living with partner	0.739	0.737	0.194	0.194	0.004
Separated/ Divorced/ Widowed	0.216	0.216	0.171	0.170	0.001
Employment status of head					
self employed	0.522	0.521	0.251	0.250	0.003
unpaid/unemployed	0.246	0.246	0.187	0.186	0.001
inactive etc.	0.090	0.090	0.082	0.082	0.000
Community employment rate	0.090	0.090	0.005	0.005	0.003
Household has returnee	0.246	0.246	0.187	0.186	0.001

Continued on next page

Table 10 – continued

	Mean		Variance		Standardised
	Treated	Control	Treated	Control	difference
Household receives remittances	0.545	0.543	0.250	0.249	0.003
Number of current migrants	2.090	2.084	1.842	1.837	0.004
Number of rooms (Base = 1)					
2	0.149	0.149	0.128	0.127	0.000
3	0.201	0.201	0.162	0.161	0.001
4	0.179	0.179	0.148	0.147	0.000
5 or more	0.425	0.424	0.246	0.245	0.002
Dwelling ownership(Base = Owned)					
Rented	0.119	0.119	0.106	0.105	0.000
Bathroom	0.403	0.402	0.242	0.241	0.002
Main source of drinking water (Base = pipe borne water inside)					
Pipe borne water outside	0.209	0.209	0.167	0.166	0.001
Borehole	0.343	0.343	0.227	0.226	0.001
Dug well	0.127	0.127	0.112	0.111	0.000
Tanker service	0.000	0.000	0.000	0.000	
Stream/river/lake	0.149	0.149	0.128	0.127	0.000
Rain water	0.007	0.007	0.007	0.007	0.000
Bottled or sachet water	0.052	0.052	0.050	0.050	0.000
Floor material(base = Polished wood)					
Mud	0.291	0.291	0.208	0.207	0.001
Raw wood, boards	0.000	0.000	0.000	0.000	
Cement/concrete	0.679	0.677	0.220	0.219	0.004
Burnt brick	0.015	0.015	0.015	0.015	0.000
Floor tile	0.007	0.007	0.007	0.007	0.000
Wall material (base = others)					
Bamboo or other organic materials	0.060	0.060	0.057	0.056	0.000
Cloth, cardboard, cans	0.022	0.022	0.022	0.022	0.000
Zinc	0.396	0.395	0.241	0.240	0.002
Mud, adobe, cane wall	0.493	0.491	0.252	0.251	0.002
Block, bricks, stone, prefabricated material, polished wood	0.030	0.030	0.029	0.029	0.000
Access to public services					
Electricity	0.634	0.633	0.234	0.233	0.003
Natural gas	0.142	0.142	0.123	0.122	0.000
Safe drinking water	0.694	0.692	0.214	0.214	0.004
Sewerage system	0.067	0.067	0.063	0.063	0.000
Garbage collection	0.112	0.112	0.100	0.100	0.000
Telephone	0.291	0.291	0.208	0.207	0.001
Region(Base = Brong Ahafo)					
Northern	0.142	0.142	0.123	0.122	0.000
Upper East	0.201	0.201	0.162	0.161	0.001
Upper West	0.134	0.134	0.117	0.117	0.000
Volta	0.224	0.224	0.175	0.174	0.001

7 Results

7.1 Main results

How does having a new migrant affect the asset welfare of households left behind conditional on prior migration experience? To answer this question we estimate weighted least squares regressions applying the entropy balancing weights. Table 11 presents the results. The coefficient of interest is the dummy variable of having a new migrant. This estimates the average effect on the change in the asset index for households with a new migrant between baseline and the follow-up survey compared to households without a new migrant.

Table 11: Effect of having a new migrant on asset index, weighted least squares

	Asset index		
	(1)	(2)	(3)
New Migrant	-0.011	-0.017	-0.016
	(0.007)	(0.011)	(0.011)
Household has return migrant (=1)			-0.015*
			(0.008)
Dependency ratio			0.002
			(0.004)
Employment status of household head (base = inactive/others)			
Employee			0.014
			(0.015)
Self-employed			-0.001
			(0.016)
Unpaid work / unemployed			-0.003
			(0.018)
Local employment rate			0.138
			(0.104)
Entropy balancing weights	No	Yes	Yes
Observations	*960*	*960*	*960*
Adjusted R-squared	0.584	0.522	0.528
Number of clusters	93	93	93

Significance levels * 10% ** 5% *** 1%. First difference estimator. S.E. clustered at community level.

In column 1, we show results without applying entropy balancing weights suggesting that they might be biased due to selection. The effect of migration on household welfare could be driven by the fact that only households who are less likely to improve their welfare due to household characteristics sent a new migrant because of these same characteristics. We then apply balancing weights to the regression in column 2. The coefficient becomes larger but remains insignificant.

In column 3, time-varying household and local labour market characteristics are included that we consider relevant for the welfare of households. Of all control variables, only that indicating whether a household had a return migrant or not is significant.[13] Households are on average slightly worse off if they had a migrant return to their home.

The inclusion of time-varying covariates improves the precision of the estimates minimally, as indicated by a higher adjusted R-squared statistic. The coefficient of interest becomes minimally smaller. On average and everything else constant, sending a new migrant does not change the asset index of households significantly compared to those who do not send another migrant.

Next, we interact the number of new migrants and its squared term with the treatment dummy (see table 12). With this interaction we want to estimate the effect of the intensity of the treatment on the outcome. Around 40 percent of treated households have two or more new migrants. Thus, the effect might differ depending on the number of new migrants. Yet, there is again no significant effect when we allow for variation in the number of new migrants.

We now look further into the role of migrant characteristics. Table 13 lists the coefficients of the main estimation, each time interacting the treatment dummy with a migrant feature. These characteristics are whether the new migrant is female or whether they are seasonal migrants. Finally, we also differentiate between the effect of new migrants who move within the same region and those moving to another region.

None of these interactions shows a significant effect on the asset index. There are three possible explanations for the fact that we do not find an impact of having a new migrant on households' asset index. One refers to the outcome variable used, one to the role of migration experience and the other to the sample investigated.

First, considering that asset indices are less volatile than for example consumption measures, it might

[13]There might arise the concern that the measure of local employment is not well defined. When we drop this variable from the estimation, results remain unchanged (see appendix table 20 on page 68).

Table 12: Number of new migrants, weighted least squares

	Asset index
Number of new migrants	-0.008
	(0.009)
(Number of new migrants)^2	0.001
	(0.002)
Entropy balancing weights	Yes
Other controls	Yes
Observations	*960*
Adjusted R-squared	0.525
Number of clusters	93

Significance levels * 10% ** 5% *** 1%. First difference estimator. S.E. clustered at community level.
Other controls include whether the household has a returned migrant, employment status of the household head, dependency ratio and community employment rate.

Table 13: Interaction of treatment with the characteristics of new migrants

	Dependent variable: Asset index		
Migrant characteristics (X):	Female migrant	Seasonal migrant	Remained in region
New Migrant * X	-0.009	0.010	-0.013
	(0.011)	(0.014)	(0.021)
New Migrant	-0.010	-0.017	-0.005
	(0.014)	(0.012)	(0.022)
Entropy balancing weights	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Observations	*960*	*960*	*960*
Adjusted R-squared	0.528	0.528	0.528
Number of clusters	93	93	93

Significance levels * 10% ** 5% *** 1%. First difference estimator. S.E. clustered at community level. Other controls include whether the household has a returned migrant, employment status of the household head, dependency ratio and community employment rate.

be due to their stable nature that we do not find a significant effect in the short period of two years. We emphasise that the estimated effect is that of households sending a new migrant compared to those who do not. Hence, even a zero effect does not imply that there was no change in the asset index, but it means that the index of treated households changed in the same direction and magnitude as that of the control group. The distributional graphs of the welfare index (figure 1 and 2 in section 6.2) indicated some changes in the welfare of households. It appears, however, not to be significantly different between the groups once we control for observable and unobservable household characteristics. Booysen et al. (2008) also point out that because assets are more durable than other consumption goods, they tend to show an increase in asset wealth more than a reduction of the same. As our coefficients are negative, it is possible that we cannot find a significant effect due to this issue.

Secondly, we suggest that migration of a new migrant might be less costly than first-time migration. If we consider migration as an investment, then we would expect an initial decline in welfare and in the longer run an increase as suggested by Taylor and López-Feldman (2010). We do not observe that households with a new migrant experience a decline in welfare that could have been caused by the cost of migration and the loss of a working household member. In the descriptive statistics we saw that the average costs of migration for baseline migrants in 2013 was above 200 Ghanaian Cedis (in 2015 prices) compared to on average 120 Ghanaian Cedis for new migrants by 2015 (see table 4). This documents that costs for new migrants are relatively lower than for previous migrants.[14] Similar to the reduction of migration costs with the growth of social migrant networks, the migration experience at the household level itself can reduce costs of migration (McKenzie and Rapoport, 2007). This could be happening through similar channels, such as information transfer and family connections at the destination to find a job.

Another reason for not finding an effect might be that we are looking at the wrong sample. Some of the new migrants move for family reasons, such as marriage or joining other family members, while the majority moves for work. These reasons can have quite different implications for household welfare. We therefore estimate the effect of a new migrant including the interaction of the treatment with an indicator for those households whose new migrant moves for family reasons. Table 14 shows the results. They do not change neither for the main estimate, nor when we look at specific characteristics

[14] Using the information on previous migration we find that migrants who move the first time - independent of whether they are new or baseline migrants - pay on average more than those who moved the second time or more often (see appendix table 18 on page 68).

of the migrant, for example gender. All we observe is that the coefficient of the interaction that indicates households with a new migrant moving for family reasons is positive, while the overall treatment effect is negative. Both are however always insignificant.

Table 14: Having a new migrant by reason for migration, weighted least squares

	Dependent variable: Asset index			
Migrant characteristics:	All	Female migrant	Seasonal migrant	Remained in region
New Migrant * X		-0.011	0.011	-0.014
		(0.012)	(0.013)	(0.021)
New Migrant	-0.019	-0.012	-0.020	-0.006
	(0.012)	(0.014)	(0.012)	(0.023)
New Migrant moves	0.011	0.015	0.013	0.014
for family reason	(0.017)	(0.019)	(0.018)	(0.018)
Entropy balancing weights	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	*960*	*960*	*960*	*960*
Adjusted R-squared	0.521	0.528	0.528	0.528
Number of clusters	93	93	93	93

Significance levels * 10% ** 5% *** 1%. First difference estimator. S.E. clustered at community level. Other controls include whether the household has a returned migrant, employment status of the household head, dependency ratio and community employment rate.

We also conduct a Chow test of stable coefficients across the sub-samples of family reason and work reason. We cannot reject the hypothesis that the sample should remain pooled and we should not separately estimate the effect (see test statistics in appendix table 19 on page 68).[15] The results presented here can be challenged concerning methodological concerns, which we address in the next section.

7.2 Sensitivity analysis

One concern is measurement error in the asset index. The measurement error could be even larger as it is a linear variable constructed from individual factor variables. In consequence, the estimates are still unbiased and consistent, but less precise which could explain the insignificant results (Wooldridge

[15]This tests whether all coefficients of the sub-sample with family migrants are equal to zero and should thus not be treated separately from the pooled sample.

(2010), pp.287). We would be concerned if there was a reason to think that measurement error in the index was systematically related to the independent variables in our model.

We therefore estimate the main regression and exclude each time one component of the index to see how sensitive the results are to this.[16] We find stable results across index compositions presented in table 15.

[16] We also change the variables we determine to be balanced with the entropy balancing weights. Instead of the individual asset components, we include the asset index and its squared term at baseline. When we run our main regression using these weights, the results become weakly significant, but coefficient size only changes by 0.001 and is only significant at 10-percent level (see in appendix table 21 on page 69).

Table 15: Sensitivity of results of asset index using different ways to construct the asset index, weighted least squares

	Dependent variable: Asset index						
	Exclude specific item from asset index construction						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of rooms	Dwelling ownership	Bathroom	Toilet	Drinking water	Floor material	Wall material
New Migrant	0.019	-0.017	-0.017	-0.015	-0.020	-0.013	-0.009
	(0.014)	(0.012)	(0.012)	(0.011)	(0.015)	(0.009)	(0.008)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Entropy balancing weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	*960*	*960*	*960*	*960*	*960*	*960*	*960*
Adjusted R-squared	0.515	0.473	0.524	0.47	0.462	0.544	0.485
Number of clusters	93	93	93	93	93	93	93

Significance levels * 10% ** 5% *** 1%. First difference estimator. S.E. clustered at community level. Other controls include whether the household has a returned migrant, employment status of the household head, dependency ratio and community employment rate.

7.3 Community shocks

One major concern challenging our identification strategy is that of unobserved shocks experienced by the households between the two survey waves. A shock could reduce household welfare and at the same time motivate people to leave their home or deter migration, as savings would be used to cover the damages of the shock instead of financing migration. This could affect whether we observe an impact of having a new migrant on welfare of households left behind.

In 2015, the enumerators interviewed village elders to collect information about the communities. These surveys included questions about shocks experienced by the village, and how many people were affected by it. The questions were asked open ended, so that the respondent could name any type of shock that s/he considered relevant. The most commonly named shocks are droughts, flooding or crop infestation by insects. We identified the communities where at least 50 percent of inhabitants were affected by such a shock.

In table 16, we present the results of the main specification, only that we include a dummy variable indicating a major shock at the community level and interact this with the treatment indicator. This interaction captures the impact of households that experienced a shock and have a new migrant in 2015.

The impact of having a new migrant on the asset index remains insignificant. Neither the coefficient of the shock variable nor its interaction with the treatment are significant. We note that there are fewer observations in these regressions due to missing values for the shock variables in six communities. We ran the main regression including a dummy for these communities. The dummy is positive and significant. On average, households in those communities for which we do not have any information about shocks, experience an increase in their asset index (see appendix table 23 on page 70). We suggest that their missing information concerning shocks actually means that they did not experience any shock which could explain their higher asset index. If we include them in the estimation replacing their missing value of the shock with a zero, the main results are still insignificant (see appendix table 23 on page 70).

After this test, one could still argue that an unobserved idiosyncratic shock at the household level interferes with our results. For example, a household would normally have experienced an increase

Table 16: Effect of new migrant on household welfare controlling for major shocks in community, weighted least squares

	Asset index
New Migrant	-0.021
	(0.018)
New Migrant * Shock	0.015
	(0.023)
Shock	-0.018
	(0.017)
Entropy balancing weights	Yes
Other controls	Yes
Observations	*902*
Adjusted R-squared	0.521
Number of clusters	87

Significance levels * 10% ** 5% *** 1%. First difference estimator. S.E. clustered at community level.
Other controls include whether the household has a returned migrant, employment status of the household head, dependency ratio and community employment rate.

in its asset index, but due to a negative shock interfered with this trajectory, for example a household member falling sick and not being able to earn income. Instead of investing in better walls or expanding the rooms of the house, the money is used to send another member as new migrant to find an income somewhere else or to pay for the medical bills. We document, however, in table 3 (page 18) that only in very few cases a new migrant had moved due to negative events, such as declining yields in agriculture, a family dispute, a flood or for medical treatment. Besides from lack of evidence that the reason of migration is an idiosyncratic shock, new migrants barely send remittances. If they had been sent to support the household through a crisis, one would expect regular remittances and maybe also higher amounts.

8 Conclusion

This paper documents the dynamic nature within households of internal migration in rural Ghana. Using a new dataset from 2013 and 2015, we show that many households with migrants at the baseline send a new migrant by 2015. Looking more closely at these migrants and their households, we provide an insight into the nature of such repeated migration. Within the same household, migrants move for different reasons, at different times and their connection with the origin household differs as well.

This motivates the question how households with prior migration experience are affected if they have a new migrant. There are hypotheses for positive, negative or no effect due to the variety of factors involved and their counteracting impacts.

We find that having a new migrant does not have an impact on the welfare measured with the asset index of origin households compared to those without a new migrant. We suggest that this is partially due to the stable nature of such an index over the short period of our analysis. In order to identify an impact, the households in our sample would have needed to invest in their housing to different amounts between treated and control group. However, their investment priorities might lie somewhere else, for example in their farm or business. Unfortunately, the questions about other forms of investment were not consistent between the two survey waves and those that were, had very low response rates so that we cannot provide an answer to this hypothesis.

Another insight we gain is that new migrants pay relatively less for their migration than baseline migrants. This indicates that migration becomes cheaper with the migration experience of the household so that a negative effect of migration incurred by moving costs might not materialize in this case. Furthermore, we observed that new migrants are in many aspects different from baseline migrants. Among the differences are for example the fact that new migrants are from a younger generation, coming straight from school and often not sending any remittances or only for special occasions. This also supports the zero effect we find for the asset index. Households with prior migration experience might not send a new migrant in expectation of future remittances and income diversification. Instead, the new migrants might move primarily to improve their own situation.

These unanswered hypotheses point at the limitations of this study. The effect we estimate is that of only two years or less since a new migrant left the household. The comparison of studies using longitudinal data from longer periods with those of short periods indicates that the positive returns to migration might only present itself after a certain period (Davis et al., 2010; Taylor and López-Feldman, 2010). More data collection is required to confirm our results over the longer run.

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Appendix

A Multiple Correspondence Analysis to construct asset index

An asset index is a composite measure using information about asset ownership and/or other welfare indicators in survey data. The researcher is interested in one continuous measure that captures the welfare of a household. In its simplest format, we can think of an asset index as the sum of its weighted components as specified in equation 7:

$$A_i = p_1 a_{1,i} + p_2 a_{2,i} + \ldots + p_k a_{k,i} \tag{7}$$

The asset index of household i is the sum of each of the individual asset indicator dummies, a_k weighted by an asset specific weight, p_k. Each indicator is equal to 1 if the household owns this specific asset, 0 otherwise. There are different possibilities to assign weights. Filmer and Pritchett (2001) apply Principle Component Analysis (PCA) to retrieve weights for each asset to construct an asset index that reflects household wealth. PCA uses the cross-sectional covariance of all individual assets to define the linear combination of these assets with the largest variance. This would be the first principal component. The linear combination orthogonal to this first one would be the second principal component and so on. This method thus assumes that the variation in assets explained by all components is complete and accurate. The PCA also imposes the linear constraint of equal distance between categories and ordered categories (Booysen et al., 2008). It is however arbitrary to judge whether a cement wall is of better or lower quality than a burnt brick wall, and even if that was established it is not clear that the difference in quality would be the same between a burnt brick and a cement wall as between a cement and a mud wall.

In response to the strong assumptions of PCA, Sahn and Stifel (2000) applied the less restrictive method of Factor Analysis (FA). This method also assumes that the cross-sectional variance-covariance matrix of individual asset indicators can reveal a common factor. It can therefore be used to extract the linear combinations of those individual assets that reflect this factor the best. In contrast to PCA, it allows individual assets to explain variances and not all indicators have to explain the full covariance matrix. This approach however requires imposing a linear relationship and assumes normality for model estimation (Asselin, 2009). This assumption and the arbitrary choice of rotation methods in the second step of FA seem restrictive and arbitrary (Booysen et al., 2008).

The third approach, used in chapter **??**, is the non-parametric approach to let the data reveal the individual asset weights without the imposition of any functional form, that is Multiple Correspondence Analysis (MCA). MCA is also more suitable to a setting with categorical variables than PCA. Our asset measures are always expressed in categorical variables. Asselin (2009) explains in detail the advantage of MCA over FA or PCA to construct multidimensional poverty measures. Booysen et al. (2008) for example use MCA to construct an asset index to compare poverty dynamics across time and countries.

The construction of an asset index using MCA can be described in three steps. First, we construct an indicator matrix I as form of normalization of the data. This means that we generate a dummy for each of the variable categories that is equal to one if the household, for example, has wooden walls and zero for all other types of walls and so on. It is important to note that for each asset variable the categories are mutually exclusive and exhaustive. A household cannot have a one for both, wooden walls and brick walls; neither can the household have only zeros for the categories of wall quality. The result of this data manipulation is the indicator matrix I in which the rows represent a household observation for the year 2013, and the columns represent an asset category.

In the second step, we apply MCA to this indicator matrix. The columns are vectors for each subcategory of each asset item, e.g. brick wall, cement wall, mud wall all comprise one column vector each for the asset item 'wall material'. The MCA computes the principal coordinates of each of these categories. These coordinates capture the contribution of each category in the first one-dimensional axis of best fit, which explains most of the variation in the indicator matrix I and can therefore be understood as the unobserved underlying factor. In other words, these coordinates are the average of the normalized scores of each population unit in this category. These coordinates will serve as the weights for each indicator category in the construction of the asset index.

Thirdly, we apply these weights to each asset category to compute the asset index to each household-year observation as in equation 7. We present the results from the MCA displaying the principal coordinates and their contribution to the overall category variance in the appendix figures 4 and 5 (page 60 and 61).

```
Multiple/Joint correspondence analysis          Number of obs     =        593
                                                Total inertia     =  .01661842
    Method: Burt/adjusted inertias              Number of axes    =          2
```

Dimension	principal inertia	percent	cumul percent
dim 1	.0051666	31.09	31.09
dim 2	.0021568	12.98	44.07
dim 3	.0009358	5.63	49.70
dim 4	.0005249	3.16	52.86
dim 5	.000335	2.02	54.87
dim 6	.0002993	1.80	56.67
dim 7	.000156	0.94	57.61
dim 8	.0001396	0.84	58.45
dim 9	.0000911	0.55	59.00
dim 10	.0000541	0.33	59.33
dim 11	.0000215	0.13	59.46
dim 12	4.02e-06	0.02	59.48
dim 13	1.95e-06	0.01	59.49
dim 14	5.68e-07	0.00	59.50
Total	.0166184	100.00	

Figure 4: Explanatory power of each dimension of MCA

Categories		mass	overall quality	%inert	dimension_1 coord	sqcorr	contrib
roomn1							
	0	0.032	0.562	0.002	0.016	0.280	0.002
	1	0.003	0.562	0.020	-0.183	0.280	0.018
roomn2							
	0	0.029	0.018	0.003	0.000	0.000	0.000
	1	0.005	0.018	0.016	-0.002	0.000	0.000
roomn3							
	0	0.027	0.022	0.006	-0.008	0.016	0.000
	1	0.007	0.022	0.021	0.028	0.016	0.001
roomn4							
	0	0.029	0.023	0.003	0.004	0.007	0.000
	1	0.006	0.023	0.017	-0.019	0.007	0.000
roomn5							
	0	0.022	0.128	0.015	-0.021	0.036	0.002
	1	0.013	0.128	0.025	0.034	0.036	0.003
q95_1							
	0	0.005	0.611	0.079	-0.235	0.222	0.056
	1	0.029	0.611	0.014	0.043	0.222	0.010
q95_2							
	0	0.029	0.611	0.014	0.043	0.222	0.010
	1	0.005	0.611	0.079	-0.235	0.222	0.056
q97a_1							
	0	0.001	0.011	0.004	0.004	0.000	0.000
	1	0.033	0.011	0.000	-0.000	0.000	0.000
q97b_1							
	0	0.022	0.742	0.014	0.088	0.736	0.033
	1	0.013	0.742	0.024	-0.153	0.736	0.057
q98_1							
	0	0.031	0.623	0.004	0.038	0.608	0.008
	1	0.004	0.623	0.033	-0.292	0.608	0.065
q98_2							
	0	0.025	0.037	0.009	0.006	0.007	0.000
	1	0.009	0.037	0.025	-0.018	0.007	0.001
q98_3							
	0	0.023	0.143	0.013	-0.035	0.128	0.005
	1	0.012	0.143	0.024	0.066	0.128	0.010
q98_4							
	0	0.031	0.121	0.002	-0.011	0.115	0.001
	1	0.004	0.121	0.017	0.091	0.115	0.006
q98_5							
	0	0.034	0.308	0.000	0.001	0.300	0.000
	1	0.000	0.308	0.002	-0.289	0.300	0.002
q98_6							
	0	0.031	0.108	0.002	-0.011	0.108	0.001
	1	0.004	0.108	0.017	0.090	0.108	0.006
q98_7							
	0	0.034	0.143	0.000	0.001	0.122	0.000
	1	0.000	0.143	0.003	-0.135	0.122	0.001
q98_8							
	0	0.033	0.088	0.001	0.002	0.018	0.000
	1	0.002	0.088	0.011	-0.048	0.018	0.001

Figure 5: Summary of first dimension of MCA

q99_1							
	0	0.027	0.630	0.021	-0.082	0.515	0.035
	1	0.008	0.630	0.071	0.277	0.515	0.117
q99_2							
	0	0.034	0.192	0.000	-0.000	0.035	0.000
	1	0.000	0.192	0.004	0.138	0.035	0.000
q99_3							
	0	0.009	0.632	0.072	0.252	0.492	0.113
	1	0.025	0.632	0.026	-0.092	0.492	0.041
q99_4							
	0	0.034	0.319	0.000	0.001	0.005	0.000
	1	0.000	0.319	0.012	-0.052	0.005	0.000
q99_6							
	0	0.034	0.064	0.000	0.000	0.045	0.000
	1	0.000	0.064	0.003	-0.137	0.045	0.000
q99_7							
	0	0.034	0.069	0.001	-0.004	0.068	0.000
	1	0.001	0.069	0.032	0.238	0.068	0.007
q101_1							
	0	0.033	0.232	0.001	-0.008	0.166	0.000
	1	0.002	0.232	0.016	0.162	0.166	0.009
q101_2							
	0	0.034	0.286	0.000	-0.001	0.038	0.000
	1	0.000	0.286	0.004	0.090	0.038	0.000
q101_3							
	0	0.033	0.423	0.001	-0.001	0.003	0.000
	1	0.002	0.423	0.019	0.025	0.003	0.000
q101_5							
	0	0.021	0.551	0.029	-0.112	0.551	0.052
	1	0.013	0.551	0.048	0.184	0.551	0.085
q101_6							
	0	0.018	0.661	0.043	0.157	0.618	0.086
	1	0.016	0.661	0.048	-0.173	0.618	0.095
q101_7							
	0	0.033	0.013	0.001	-0.003	0.013	0.000
	1	0.002	0.013	0.030	0.064	0.013	0.001

Figure 6: Summary of first dimension of MCA, continued

The comparison of asset indices for the same household over time yields two potential problems. The first is that the coordinates used as weights should be consistent over time to make the index comparable between periods. The coordinates are retrieved from the data and result from the cross-sectional variation of assets across households. If we now pooled the two survey waves to compute the coordinates, this variation would be different than that of one cross-section and some of the variation would only reflect variation over time. Therefore, we will rely only on the data of the base year 2013 to retrieve the coordinates as in Booysen et al. (2008). Then we use these to compute the index in both years. In the appendix table 22 (page 70), we also present the main results using the pooled sample to compute the asset index. The results barely change.

The second issue is that prices for assets might change over time and in response to this the demand for assets and the distribution of assets across households might change.[17] There is, though, no reason to think that households with a new migrant would react differently than control households to price changes in their asset purchase behaviour.

B Attrition

Some households of the baseline survey were not successfully tracked in the follow-up two years later. These were around 300 households. For the analysis in chapter **??** it is important to understand, whether some of these households would have been part of the sample of interest and what implications their attrition has for the analysis. Of the 300 households that attrited, 167 had a migrant in 2013. They would have been part of the analysis either as treated or control units. In order to understand whether these households would have been more or less likely to be in the treatment group and whether they are substantially different from our sample we compare the baseline characteristics of households. The comparison is between the 167 attrited households with migration experience, the control and the treatment households.

Table 17 shows results of a Logit and of a Multinomial Logit (MNL) estimation of the status of a household on baseline characteristics. The most important difference between sample and attrited households is their size as we see in the first row of the regressions. Attrited families are significantly smaller than those that were successfully re-interviewed. Furthermore, treated households are significantly larger than both control and attrited observations. There are a few other weakly significant coefficients. The regional differences are notable. Attrition is highest in the Volta region, 46 percent of attrited units were located here, 25 percent in Brong Ahafo, and only 5 percent in the Upper West. In the Logit estimation the base category of regions is Brong Ahafo, so that only the coefficient for Upper West appears significantly. In contrast, treated households are much more likely to be located

[17] While there has been high inflation in Ghana between 2013 and 2015 there is no data on the price changes for each individual asset (Ghana Statistical Service, 2015b,a). Moreover, it is difficult to measure the market price of a mud wall or a brick wall, as we would need to decide whether to measure only the material or also the service to build the wall.

in Brong Ahafo than in Volta or Northern region as we observe in the MNL results.

Table 17: Likelihood for household to attrite, Logit and Multinomial Logit results

	Logit	MNL (Base = Control)	
		Attrited	Treated
		(N = 167)	(N = 170)
Household size	-0.129***	-0.084**	0.202***
	(0.040)	(0.042)	(0.038)
Dependency ratio	0.136	0.112	-0.119
	(0.165)	(0.164)	(0.194)
Age of head in years	-0.009	-0.011	-0.007
	(0.008)	(0.009)	(0.007)
Number of current migrants in 2013	-0.115	-0.098	0.048
	(0.094)	(0.095)	(0.075)
Female head	-0.204	-0.121	0.420
	(0.289)	(0.294)	(0.279)
Highest level of education in household (Base = None)			
Primary	0.920	0.833	-0.382
	(0.866)	(0.874)	(0.671)
Middle/Junior	1.254	1.194	-0.280
	(0.799)	(0.803)	(0.603)
Senior Secondary	1.152	1.107	-0.232
	(0.807)	(0.812)	(0.605)
Higher	1.220	1.259	0.078
	(0.827)	(0.832)	(0.605)
Main occupation of head (Base = Inactive/Other)			
Employee	-0.685	-0.603	0.540
	(0.442)	(0.451)	(0.559)
Self-employed	-0.748*	-0.685*	0.435
	(0.383)	(0.390)	(0.465)
Unpaid work / unemployed	-1.314**	-1.247**	0.478
	(0.512)	(0.523)	(0.470)
Marital status of head (Base = Single)			
Married/living with partner	0.974*	0.998*	0.137
	(0.567)	(0.577)	(0.511)
Separated/Divorced/Widowed	0.864	0.904	0.194
	(0.613)	(0.625)	(0.557)
Region (Base = Brong Ahafo)			
Northern	-0.310	-0.710*	-1.984***
	(0.369)	(0.389)	(0.399)
Upper East	-0.698	-0.704	-0.014
	(0.459)	(0.477)	(0.370)
Upper West	-1.216**	-1.347**	-0.499

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Table 17 – continued

	Logit	MNL (Base = Control)	
		Attrited (N = 167)	Treated (N = 170)
	(0.572)	(0.579)	(0.391)
Volta	0.119	-0.075	-0.847***
	(0.275)	(0.285)	(0.326)
Household has seasonal migrant	-0.464*	-0.424	0.222
	(0.275)	(0.278)	(0.240)
Household has returnee	-0.327	-0.236	0.445
	(0.357)	(0.365)	(0.297)
Main income source(Base = Public sector)			
Private sector	0.713	0.866*	0.688
	(0.509)	(0.525)	(0.588)
Own business	0.378	0.421	0.192
	(0.436)	(0.441)	(0.485)
Own farm	-0.022	0.161	0.786
	(0.480)	(0.488)	(0.503)
Private transfers	0.478	0.523	0.173
	(0.480)	(0.487)	(0.534)
Others	-0.015	0.048	0.317
	(0.755)	(0.779)	(0.738)
Asset purchases in preceding 2 years			
Electronic goods	0.239	0.226	0.050
	(0.252)	(0.257)	(0.243)
White goods	-0.129	-0.094	0.043
	(0.305)	(0.314)	(0.319)
Livestock	-0.180	-0.170	0.048
	(0.323)	(0.327)	(0.274)
Generator	-0.750	-0.620	0.514
	(1.137)	(1.160)	(0.694)
Car	1.213**	1.633***	1.384**
	(0.507)	(0.567)	(0.557)
Computer	-0.700	-0.784	-0.190
	(0.500)	(0.522)	(0.608)
Electric Appliances	0.094	-0.007	-0.551
	(0.293)	(0.301)	(0.365)
Other Investments	0.263	0.293	0.199
	(0.367)	(0.376)	(0.383)
Agricultural land	-0.412	-0.342	0.203
	(0.356)	(0.364)	(0.275)
Agricultural machinery	0.915	0.911	0.107
	(0.856)	(0.877)	(0.733)

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Table 17 – continued

	Logit	MNL (Base = Control)	
		Attrited (N = 167)	Treated (N = 170)
Non-agricultural land	-0.080	-0.171	-0.442
	(0.343)	(0.355)	(0.351)
New house	-0.456	-0.306	0.607**
	(0.286)	(0.292)	(0.255)
Constant	-1.227	-1.177	-2.665**
	(1.170)	(1.177)	(1.133)
Observations	*699*	*699*	*699*
log likelihood	-296	-573	-573
Likelihood Ratio Chi2	81.64	178.8	178.8

These observations suggest that attrited households were less likely to be among the treated group. They appear however still different from the control group in the sample, so that we cannot assume that they are missing at random. To have a better sense of how their exclusion from the analysis might affect the results of the impact assessment, we look at the distribution of the asset index. It is important to note that the index is constructed based on the cross-sectional distribution of assets in the baseline sample. Thus, the distribution changes once we include the attrited household in the construction of the index. Figure 7 plots the kernel density of the asset index at baseline. We differentiate between the attrited households, the control and the treated. The latter two groups show two different graphs. One is the asset index when we construct it including the attrited households, the other one (indicated with 'sample') when we construct it only for the households included in the analysis. This is the index used in the analysis of chapter **??**.

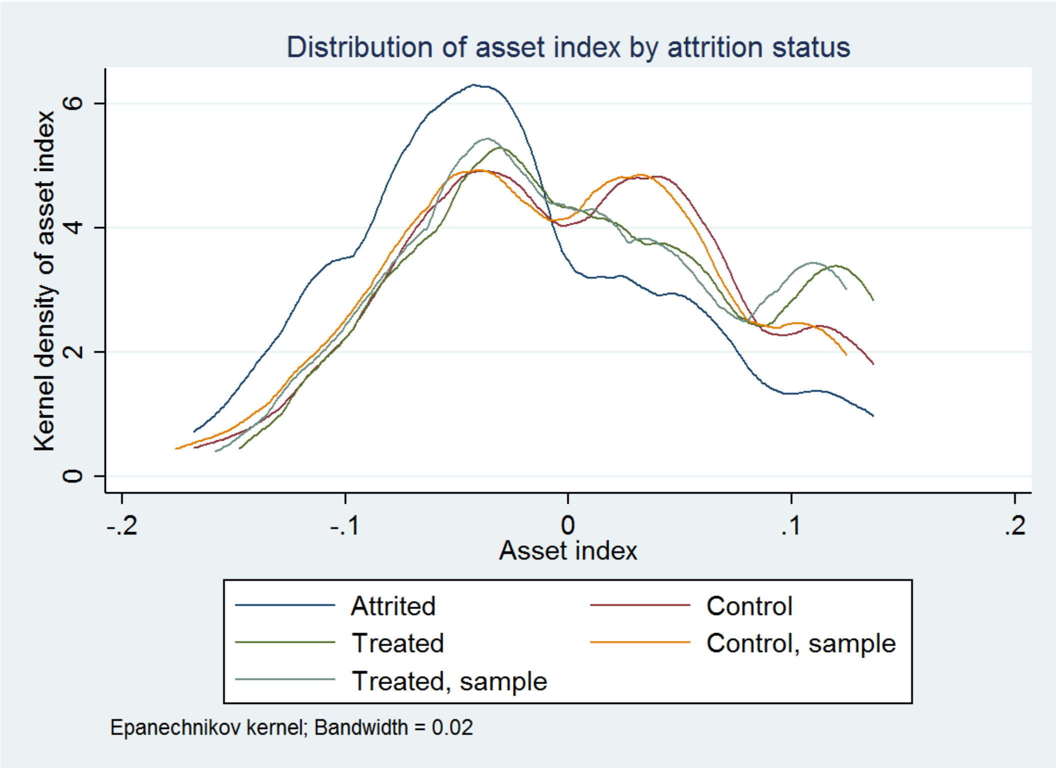

Figure 7: Distribution of asset index for attrited, treated and control households in 2013

The exclusion of the attrited observations from the index construction implies a change in the distribution of the index. However, the distribution of treatment and control units are very similar. The attrited households have a lower asset index distribution. This could result from their smaller size which is associated with assets of housing quality. For the results of the analysis, we can only conclude, that the initial asset index distribution would look different for the control group, it would be lower. However, the application of balancing weights would ensure that the analysis would be based on a comparable sample. The analysis looks at the impact of having a new migrant on the change in the asset index between survey years. The data does not allow to see whether attrited households are on a positive or negative growth trajectory regarding their asset index. If we assume that they are in the control group (based on their observables) a positive change in their asset index would bias our results upwards, we would possible find a significant negative effect, and vice versa.

C Additional tables

Table 18: Migration costs by number of times migrant moved before

	New migrant in GHS of 2015	*N*	Baseline migrant in GHS of 2015	*N*
First time	160.3	*74*	331.0	*137*
Moved at least once before	78.2	*41*	142.3	*132*

Table 19: Results of Chow test; H_0 = Coefficients are stable across sub-samples

F(8, 464) =	1.13
Prob > *F* =	0.3389

Table 20: Effect of having a new migrant on asset index dropping local employment rate from control variables, weighted least squares

	Asset index
New Migrant	-0.016
	(0.011)
Household has return migrant (=1)	-0.015*
	(0.009)
Dependency ratio	0.001
	(0.004)
Occupation of household head (base = inactive/others)	
Employee	0.015
	(0.015)
Self-employed	0.001
	(0.015)
Unpaid work / unemployed	-0.002
	(0.018)
Entropy balancing weights	Yes
Observations	*960*
Adjusted R-squared	0.524
Number of clusters	93

Significance levels * 10% ** 5% *** 1%. First difference estimator. S.E. clustered at community level.

Table 21: Effect of having a new migrant on asset index, weighted least squares. Entropy balancing weights constructed including the asset index and its squared term at baseline instead of individual asset indicators.

	Asset index		
	(1)	(2)	(3)
New Migrant	-0.011	-0.018*	-0.017*
	(0.007)	(0.010)	(0.010)
Household has return migrant (=1)			0.002
			(0.005)
Dependency ratio			0.008
			(0.014)
Occupation of household head (base = inactive/others)			
Employee			-0.006
			(0.016)
Self-employed			-0.004
			(0.017)
Unpaid work / unemployed			-0.018**
			(0.008)
Local employment rate			0.125
			(0.094)
Entropy balancing weights	No	Yes	Yes
Observations	*960*	*960*	*960*
Adjusted R-squared	0.584	0.546	0.552
Number of clusters	93	93	93

Significance levels * 10% ** 5% *** 1%. First difference estimator. S.E. clustered at community level.

Table 22: Effect of having a new migrant on asset index, weighted least squares. Asset index constructed from data pooling both survey waves.

	Asset index
New Migrant	-0.016
	(0.010)
Entropy balancing weights	Yes
Other controls	Yes
Observations	*960*
Adjusted R-squared	0.539
Number of clusters	93

Significance levels * 10% ** 5% *** 1%. First difference estimator. S.E. clustered at community level.
Other controls include whether the household has a returned migrant, occupation of the household head, dependency ratio and community employment rate.

Table 23: Effect of new migrant on household welfare controlling for sample that did not respond to shock question, weighted least squares

	Asset index	
New Migrant	-0.016	-0.024
	(0.011)	(0.017)
Community not in sample	0.023**	
	(0.011)	
Entropy balancing weights	Yes	Yes
Other controls	Yes	Yes
Observations	*960*	*960*
Adjusted R-squared	0.529	0.532
Number of clusters	93	93

Significance levels * 10% ** 5% *** 1%. First difference estimator. S.E. clustered at community level.
Other controls include whether the household has a returned migrant, occupation of the household head, dependency ratio and community employment rate.