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Incentivizing and Retaining Public Servants in Remote Areas

A discrete choice experiment with agricultural extension agents in Ethiopia

Mekdim D. Regassa, Gashaw T. Abate, and Zaneta Kubik

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ABSTRACT

Increased deployment of agricultural extension agents (EAs) in rural areas is grounded on their importance to spur agricultural productivity and mitigate spatial imbalances in welfare. However, the high turnover and the low motivation levels of EAs in remote areas pose challenges for equitable service provision and, in some cases, exacerbates geographic disparities. We assess the effectiveness of selected potential policy interventions to incentivize and retain EAs in remote areas of Ethiopia. To this end, we conducted a choice experiment to elicit preferences for job attributes of 761 EAs. We applied a random parameters logit model to estimate parameters of interest and to simulate the impact of possible policy interventions. The main results show that offering continuing education opportunities after two years of service increases uptake of an extension job in remote locations by 77 percentage points, which is significantly higher than the effect from doubling current salary levels (70 percentage points). EAs also expressed a strong preference for work environments with basic amenities, housing, transportation services, and well-equipped Farmer Training Centers (FTCs). Furthermore, the results from sub-sample analyses show that female EAs are less responsive to pecuniary incentives and are more concerned with the availability of infrastructure and services. Current salary levels, years of employment, and location of work are also important sources of heterogeneity in the response of EAs to potential policy changes.

JEL Classification: J22, J450, R280.

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1. INTRODUCTION

Transformation of the agricultural sector is deemed the fastest and the most effective means to achieve overall poverty reduction and to reduce the widely prevalent spatial economic disparity in low-income countries (de Janvry & Sadoulet 2009; Mellor 2018; Spielman, Mekonnen, & Alemu 2011). Agricultural extension holds an enormous potential to accelerate the transformation of the agricultural sector through transfer of knowledge and promotion of technologies, hence, spurring agricultural productivity (Davis 2008; Dercon et al. 2007). However, empirical evidence of agricultural extension impacts in low-income countries, including Ethiopia, is mixed. Extension systems are widely regarded as ineffective in meeting the needs of poor and remote households (Berhane et al. 2018; Birner et al. 2009; Davis, Swanson, & Amudavi 2009; Rivera, Qama, & Crowder 2018).

The main problem with public extension services in low-income countries is incentive failure. That is, the extension system is unresponsive to the demand of agricultural Extension Agents (EAs)[1] and farmers (World Bank and IFPRI 2010). A large literature has pointed to extrinsic factors – incentives related to the living and working conditions of EAs – as one of the main reasons for the poor performance of the extension system.[2] These studies have identified a range of factors, such as low salary, poor housing, job insecurity, lack of a transparent remuneration scheme, and inadequate resources to run Farmer Training Centers (FTC) as major constraining factors on the performance of EAs (Davis 2008; Davis et al. 2010; Kassa et al. 2012; Ragasa et al. 2016).

EAs are expected to play a key intermediary role between smallholder farmers, agricultural researchers, and policy makers. They promote the adoption of improved agricultural technologies and practices generated by the research system and facilitate the proper implementation of development policies designed by policy makers (Dercon et al. 2007; Feder et al. 2010; Ragasa et al. 2016). Effective delivery of these mandates requires adequate number of EAs that are qualified, motivated, and responsive to changes in farmers' demand and in the policy environment. However, observational studies conducted in low-income countries indicate that extension offices are often understaffed and that agents are often underqualified and unmotivated. Low morale, absenteeism, and high turnover are commonly reported among agricultural EAs (Davis et al. 2012; Feder et al. 2010; Kassa 2002; Kassa & Abebaw 2004; Kelemu, Sime, & Hailu 2014; Ragasa et al. 2016). This problem is particularly severe in remote areas, where quality extension services are much more needed (Davis et al. 2009; Ragasa et al. 2016).[3]

In the case of Ethiopia, rapid turnover of EAs and general underperformance, particularly in remote areas, poses a serious threat to the national agricultural extension system and the national goal of achieving food security (Kassa 2002; Kassa & Abebaw 2004). Cognizant of this, the government of Ethiopia has undertaken several policy measures to improve the attractiveness of jobs in rural extension. These include financial incentives, housing, improved working conditions (e.g. working tools, transportation), and various higher education and training opportunities, among

[1] Extension Agents (EAs) in Ethiopia are often named as Development Agent (DAs) to reflect the additional development activities they perform at grass-root level. We used the term extension agents since their primary responsibility is providing agricultural extension and advisory services.

[2] The literature also puts forward intrinsic factors – incentives related to interest in the work, recognition, and assuming responsibility – as complementary reasons for the poor performance of agricultural extension. According to Herzberg (1987), while improvement in intrinsic factors encourage performance, poor extrinsic factors demotivate performance. Qualitative data collected from the EAs surveyed in this study in 2019 shows that extrinsic factors account for the largest share of the factors that hinder effective extension service in Ethiopia (see Table 8).

[3] This view is grounded in equity considerations and aims at reducing the existing spatial imbalances. Note, however, that massive deployment of EAs to remote areas might be questionable from a purely economic efficiency perspective if these areas have low agricultural potential.

others. The latest agricultural extension strategy of the country shows that additional interventions are being considered to further reinforce the role of EAs (ATA 2017).

However, the design of these interventions has not been grounded in systematic studies of the responsiveness of EAs to them. Moreover, the policy initiatives taken so far do not seem to have abated many of the problems EAs face, as rapid turnover of EAs persists, especially in remote rural areas (ATA 2017; Davis et al. 2010; Haile & Abebaw 2012; Kelemu et al. 2014). This suggests the need to study the nature and determinants of EAs' preference for job attributes and their labor supply choices to better design more effective policy interventions that can incentivize and retain EAs, in particular; and public workers in remote areas in general.

Our study fills this research gap by assessing the responsiveness of EAs to potential policy interventions employing a discrete choice experiment (DCE) design. Using a carefully designed DCE, we first test the responsiveness of EAs to alternative policy interventions in the realm of EA-specific job incentives, i.e. salary, educational opportunities, equipment, transportation facilities, and housing. We then simulate the impact of different policy changes on the perceived attractiveness of EA jobs. Furthermore, we compute EAs' willingness to pay (WTP) for job attributes related to different living and working conditions. Finally, we explore the heterogeneity in the results based on sociodemographic and current job characteristics of EAs to better tailor interventions. We expect that our findings will offer policy guidance on how to incentivize EAs and, more broadly, any public workers to work in remote rural areas of developing countries.

Our analysis offers several interesting insights. First, there is a general dissatisfaction among the EAs with the status quo and improvement in any of the proposed EA job aspects is seen as a better option. Second, contrary to popular perception, increasing salaries is not always the strongest incentive for EAs. Our findings suggest that offering educational opportunities is by far the most powerful instrument to attract and retain EAs in remote locations. Salary increases only comes in at a second position, followed by provision of housing and transportation facilities. EAs are also likely to respond to such incentives as availability of basic amenities, including improved access to electricity and mobile telephone network in the kebeles[4] to which they are posted, as well as adequately equipping FTCs with the necessary work materials. Additionally, the analysis of heterogeneity underlying our results demonstrates the importance of accounting for EA sociodemographic characteristics, such as age, gender, or job tenure, when designing policy intervention targeted to attract, retain, and motivate EAs. For instance, female EAs are more responsive than male EAs to nonpecuniary incentives, such as provision of transportation services.

The structure of the paper is as follows. Section 2 briefly describes the dataset used. Section 3 presents the research method, emphasizing the theoretical background and empirical estimation strategy of the DCE. Section 4 presents the main results, which are then discussed in Section 5. To conclude, the policy implications of the main results are presented in Section 6.

2. DATA AND DESCRIPTIVE STATISTICS

We use a dataset from a survey covering more than 700 EAs in the principal agricultural regions of Ethiopia. The data was collected by the International Food Policy Research Institute (IFPRI) in collaboration with Digital Green (DG) as part of a project that assessed the impacts of video-mediated agricultural extension service provision on farmers' knowledge and on the adoption of improved agricultural technologies and practices in Ethiopia (see Abate, et.al 2019 for a detailed description of the data). The data were collected in 2017, 2018, and 2019 and covered 896, 781,

[4] *Kebele* is the lowest administrative unit in Ethiopia. It is a sub-district administrative level that can be loosely equated with a village. The district-level administrative unit in Ethiopia is the *woreda*.

and 763 EAs, respectively, in the four main agricultural regions of the country – Tigray, Amhara, Oromia, and SNNP.[5] The dataset contains detailed information on the socio-demographic characteristics of EAs; the extension approaches they use; the incentives they have; their workload, motivation, and knowledge of cereal extension; and information about the kebeles where they work.

The main part of our analysis is based on a choice experiment module we added to the last round of the IFPRI-DG survey, which was conducted between February and April 2019. Based on a novel discrete choice experiment design, each EA in the survey sample was presented with eight pairwise choices. Each choice set contained two job profiles with varying levels of selected job attributes, as well as an opt out option. This resulted in 18,264 rows of data that allowed us to elicit information on the preferences and the trade-off EAs made among job attributes.

Table 1 presents summary statistics of the socio-demographic characteristics of the EAs in the sample. They are predominantly male (76 percent), young (less than 30 years of age), and have a college diploma. Average work experience in agricultural extension service provision is six years on average, and most of them come from the same locality in which they are working, i.e., they lived in the same district as a child. About half of the EAs in the sample are computer illiterate.

Table 1. Sociodemographic characteristics of agricultural Extension Agents in study sample, by remoteness tercile

Characteristics		All	Nearest tercile	Middle tercile	Farthest tercile
Male		0.76	0.75	0.75	0.76
Age, years		28.6	**30.7**	28.4	**26.5**
Years working as an EA		6.47	**8.67**	6.23	**4.44**
Years working in current kebele		2.31	**2.59**	2.45	**1.89**
Education:	Certificate, yes=1	0.16	**0.13**	0.15	**0.19**
	Diploma, yes=1	0.60	**0.64**	0.61	**0.54**
	Degree, yes=1	0.25	**0.23**	0.24	**0.27**
Computer literate, yes=1		0.46	0.45	0.48	0.45
Mobile with internet access, yes=1		0.48	0.47	0.50	0.48
Spent childhood:	In working kebele, yes=1	0.09	**0.12**	0.11	**0.05**
	In working woreda, yes=1	0.62	**0.68**	0.61	**0.56**
	In working zone, yes=1	0.85	**0.87**	0.85	**0.83**
EAs in kebele, number		3.42	**3.60**	3.38	**3.28**
Farmers' field days organized, number		1.91	**1.89**	1.76	**2.08**
Working hours per week:	Planting season	49.0	**52.4**	47.7	**46.9**
	Harvesting season	36.7	**40.2**	35.3	**34.4**
	Slack season	23.9	**26.9**	22.8	**22.1**
	Average	36.5	**39.8**	35.3	**34.4**
Knowledge score:	Teff	70.3	71.1	70.0	69.9
	Maize	67.4	68.5	67.2	66.4
	Wheat	65.5	65.3	65.4	65.8
	Average	67.7	68.3	67.5	67.4
Observations		2,438	826	806	806

Source: Authors' calculation based on Digital Green's EA survey, 2017, 2018 & 2019.
Note: Knowledge refers to EAs' work-related knowledge score (out of 100) obtained through quizzes. The knowledge questions focused on growing practices of teff, maize and wheat. Differences that are statistically significant are shown in bold.

We also check if spatial inequality in extension services is reflected in our data.[6] The analysis of the profile of EAs disaggregated by remoteness of their location in columns 2, 3, and 4 of

[5] SNNP refers to Southern Nations, Nationalities, and Peoples' region.

[6] See (Abate et al. 2019) for more detailed discussion of the spatial inequality in extension service in Ethiopia.

Table 1 indicate considerable differences between EAs in more or less remote locations.[7] EAs working in relatively remote locations are younger, less experienced, less educated, and exert less effort as measured by weekly working hours. These observations are corroborated by the results of locally weighted polynomial regressions of respective outcome variables on the distance from the center of kebele in which an EA works to the local woreda center, as shown in Figure A1 and Table A2 in the Appendix.

Table 2. Work environment of agricultural Extension Agents in study sample, by remoteness tercile

	All	Nearest tercile	Middle tercile	Farthest tercile
Perception of EA about their job				
EA satisfied with the existing incentive structure, yes=1	0.15	**0.19**	0.15	**0.12**
EA job as compared to other public jobs, worse=1	0.62	0.63	0.60	0.62
EA job as compared to private sector jobs, worse=1	0.84	0.82	0.87	0.83
Location characteristics of the surveyed EAs, 2019				
Access to mobile network, yes=1	0.99	1.00	0.99	0.98
Access to electricity, yes=1	0.31	**0.37**	0.31	**0.24**
Distance to the nearest market, km	6.2	**5.4**	6.2	**7.0**
Distance to the district capital, km	18.3	**7.2**	15.9	**32.4**
Housing and transport service				
EA has access to bicycle or motorcycle, yes=1	0.16	0.14	0.19	0.15
EA received housing from the government, yes=1	0.22	**0.18**	0.15	**0.33**
If no housing received, does EA live outside kebele, yes=1	0.72	**0.85**	0.73	**0.53**
Farmer Training Centers (FTC) and FTC resources				
Kebele has an FTC, yes=1	0.88	**0.92**	0.89	**0.81**
FTC has demonstration plot, yes=1	0.81	**0.88**	0.83	**0.70**
FTC has ICT tools, yes=1	0.15	**0.23**	0.13	**0.07**
FTC has training materials, yes=1	0.52	0.51	0.55	0.50
FTC has own budget, yes=1	0.36	**0.41**	0.38	**0.28**
Educational opportunity				
EA enrolled in continuing education (CEP), yes=1	0.36	0.33	0.38	0.37
If CEP enrolled, government sponsored, yes=1	0.43	**0.60**	0.48	**0.23**
Educational opportunity after some years of service, yes=1	0.46	**0.50**	0.46	**0.40**
Observations	761	261	252	248

Source: Author's calculation based on Digital Green's EA survey, 2019.
Note: Differences that are statistically significant are shown in bold

The descriptive analysis of our main variables of interest in Table 2 clearly indicates that EAs are dissatisfied with their current job and the vast majority believes that their job is worse than other public and private jobs open to candidates with similar education levels. This could be partly because EAs work in locations that are relatively remote, i.e., far from district capitals and markets, and which lack basic amenities and services, like electricity, water, transportation, and housing. The latter often forces EAs to live outside of their working kebeles, even though, in principle, they are expected to reside in proximity to the farmers they serve. The frustration of EAs about their current job seems also to emanate from inadequate facilities to effectively perform their jobs. As shown in Table 2, about half of Farmer Training Centers (FTC), which are supposed to serve as training and demonstration centers, do not have proper training materials and demonstration plots. EAs also have limited opportunity to advance their careers through continuing education programs. The results in Table 2 also show that EAs in the most remote locations (farthest tercile) have a relatively poorer work environment compared to less remote areas (nearest tercile).

[7] Remoteness is defined based on distance between the center of the kebele in which an EA is posted and the capital of the local woreda. 'Nearest tercile' represents kebeles closest to the woreda capital.

3. CHOICE EXPERIMENT DESIGN AND ANALYTICAL FRAMEWORK

Various research methods have been used to investigate the factors determining the labor supply choices of EAs. The most common is the use of cross-sectional survey data to measure outcomes for EAs, such as job satisfaction, motivation, and organizational commitment, and to evaluate the extent to which these outcomes are correlated with various individual and job characteristics (Davis et al. 2009; Kassa & Abebaw 2004; Kassa et al. 2012). These studies have identified a range of factors, such as low salary, poor housing, job insecurity, lack of transparent remuneration scheme, and unavailability of resources to run the FTCs, that constrain the performance of EAs. While this method produces valuable insights, it provides weak evidence on the relative importance of the various constraints EAs face.

An alternative method is to employ longitudinal data on labor supply choices of EAs – a revealed preferences approach. This method, based on panel data, can be helpful in providing robust evidence on the relevance of policy interventions in labor markets. However, to date, it has mainly been used in developed countries (Frijters et al. 2009; Shields 2004). The extensive data it requires are often not available in developing countries. This is particularly the case for EAs due to their high turnover.[8]

The Discrete Choice Experiment (DCE) method presents a valid alternative to counter the shortcomings of using cross-sectional and longitudinal data. DCE has become increasingly popular to elicit preferences for attributes of differentiated goods and services. It is particularly helpful for examining the stated preference of workers for job attributes that are not easily observable in the market or for which markets do not exist. Since it is based on workers' choices from among hypothetical job scenarios, it also allows an assessment to be made of the responsiveness of workers to potential policy interventions. An additional advantage of DCE is that it allows analysts to disentangle the contribution of each of the attributes to overall utility. In revealed preference data, it is not possible to isolate the contribution of the attributes due to the strong correlation among them, e.g., housing and location of work. In the design of choice experiments, the experimental method allows the researcher to exogenously vary the attributes (Hensher & Greene 2006; Mangham & Hanson 2008; Train 2009).

Although DCE shares the basic features of hedonic wage analysis, contingent valuation methods (CVM), and conjoint rating, it improves on and goes beyond these methods since it allows estimation of a consistent marginal rate of substitution for both existing and prospective traits (Hensher, Rose, & Greene 2005; Louviere, Hensher, & Swait 2010; Train 2009). While application of choice experiment surveys to elicit preferences is common in the environmental, health, marketing, and transport literatures, its application to evaluate employees' preferences for job attributes is nascent. The handful of existing application of DCE to job preference are limited to health care occupations (Chomitz et al. 1998; Hanson & Jack 2008; Kolstad 2011; Kruk et al. 2010; Scott 2001) and youth employment (Assy et al. 2019). To the best of our knowledge, this study is the first to apply DCE to elicit the job preferences of agricultural EAs.

The choice experiment design

The DCE outlines a hypothetical setting in which respondents are asked to repeatedly choose from a limited number of alternatives. Each alternative is described by a number of attributes that take

[8] A credible econometric method is difficult to establish mainly because the use of panel data implies such analysis is based on those that remained employed. This would result in biased estimates as those that remained employed would constitute a systematically different sample from those that left the industry (Angrist & Pischke 2009; Heckman 1979).

on different levels.[9] Representing job alternatives as bundles of attributes allows assessment of changes in individual choices as one or more of the attributes vary (Lancaster 1966).

In our study, EAs were presented with a series of choice situations, each of which contained a pair of job profiles with six attributes and an opt-out option. The EAs were asked to choose which of the two jobs (or neither) they preferred. The choice of the selected attributes (Table 3) is based on an extensive literature review of the factors that are perceived to be important in job choices of EAs in Ethiopia and beyond (Berhane et al. 2018; Dufera et al. 2017; Gebru, Asayehegn, & Kaske 2012; Haile & Abebaw 2012; Kelemu et al. 2014; Mangham & Hanson 2008; Ragasa et al. 2016). We verified the appropriateness of these attributes and their respective levels based on series of discussions with national and regional extension coordinators, focus group discussion with EAs, and pre-survey piloting.

The number of selected attributes is in line with previous empirical studies. The attributes and their respective levels need to be realistic enough to provide relevant policy prediction regarding the effect of potential interventions. At the same time, the design needs to not be too complicated in order to minimize fatigue and cognitive burden on the respondents (Kuhfeld 2010; WHO 2012).[10] The chosen attributes alongside their respective levels are shown in Table 3. During the interviews, these attributes and their levels were carefully explained to respondents. Explicit information was also included regarding potentially relevant excluded attributes and attribute levels. Respondents were asked to assume that all unstated characteristics of jobs are the same for the two jobs.

Table 3. Job attributes and attribute levels used in the choice experiment

Attribute	Definition	Attribute Levels
Location	Whether location of work has reliable mobile coverage, electricity, and piped water (advanced) or not (remote)	(1) Advanced, (2) Remote
Net Monthly salary	Net salary at job (reference: current net average salary)	(1) Plus 100%, (2) Plus 50%, (3) Plus 25%, (4) Minus 25%
Provision of Housing	Provision of government housing at kebele of work for residence of the extension agent and her family.	(1) Available, (2) Not available
Extension tools at Farmer Training Centers (FTC)	Adequacy of FTC resources to effectively deliver extension service to farmers (e.g. demonstration plot, adequate budget to run the FTC, adequate teaching materials)	(1) Adequate, (2) Inadequate
Transportation facilities at FTC	Availability of transportation facility at the FTC (bicycle, motorcycle, or horse)	(1) Available, (2) Not available
Education opportunities	Availability of education opportunities after 2 year of service	(1) Available, (2) Not available

Source: Constructed by authors.

In the survey, we presented respondents with a series of pairs of jobs and asked them to choose the one they prefer from each pair, or none. Theoretically, there are 128 (= 2*4*2*2*2*2) distinct jobs characterized by the six attributes, and, hence, 8,192 (=128*128/2) distinct job pairs. From among these distinct job pairs (called full factorial design), we identified and presented to the respondents 16 different choice sets based on main effects fractional factorial design. This is a D-optimal hypothetical choice design based on the covariance matrix of a multinomial logit model with all the coefficients set equal to zero. The design[11] offers an efficient combination of orthogonality, level balance, and minimum overlap (Kuhfeld 2010)[12]. The 16 choice sets were randomly divided into two blocks in order not to exhaust the respondents. Each respondent thus

[9] For an excellent review of this method, please see Hensher et al. (2005); Louviere et al. (2010); and Train (2009).

[10] In comparable public sector human resource applications, the suggested number of attributes ranges between 2 and 24, with a mode of 6 (De Bekker-Grob et al. 2008; WHO 2012)

[11] Operationalized with SAS analytical software.

[12] In order to generate unlabeled experimental designs suitable for our purpose, SAS choice modelling macros, %MktRuns, %MktEx , %ChoicEff and %MktBlock are used. While there are other popular tools that could be used to generate experimental designs including Stata, Sawtooth, Ngene and R, these SAS macros are also well suited to find good, efficient, and realistic designs (Kuhfeld 1997, 2010).

made eight binary choices. Table A3 in the Appendix presents the instructions given to the respondents and an example of the question set-up.

Analytical framework

The analytical framework of the choice experiment data is based on random utility theory, which assumes that a representative individual is rational and, in a given choice situation, selects the alternative that yields the highest level of utility (McFadden 1973). The individual is assumed to know her or his preferences, but a component of these preferences is unobservable to the researcher. Therefore, assuming a linear indirect utility functional form, the utility (U) of an individual i, for alternative j, in choice situation t, is expressed as a sum of a systematic (observable) component V_{ijt}, and a stochastic (unobservable) component, ε_{ijt}.

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, \qquad j = 1,2, \dots \dots, m \tag{1}$$

In line with Lancaster's (1966) theory of demand, which argues that the overall utility an individual generates from a good or service can be decomposed into the sum of separate utilities derived from its constituent characteristics, the systematic part of the utility function can be expressed as: $V_{ijt} = \alpha + x'_{ijt}\beta_i$. After replacing this for,V_{ijt}, equation (1) becomes:

$$U_{ijt} = \alpha + x'_{ijt}\beta_i + \varepsilon_{ijt} \tag{2}$$

where β_i is a vector of individual specific coefficients, X_{ijt} is a vector of observed attributes relating to individual i, and alternative j, in a choice situation t. In this model – a random parameter logit model (RPL) – ε_{ijt} is a random term that is assumed to be an independently and identically distributed extreme value type I[13]. Consistent with a utility function that is linear in parameter, the probability that an EA i, chooses alternative j, from among *m* alternatives in a choice situation t, takes a conditional logit specification (McFadden 1973):

$$L_{ij}(\beta_i) = \frac{exp\,(x'_{ijt}\beta_i)}{\sum_{l=1}^{m} exp\,(x'_{ilt}\beta_i)} \tag{3}$$

The specification in (3) assumes that ε_{ijt} is the only source of randomness and that the taste parameter of each EA, β_i, is known to the researcher and fully explained by only using its means. In reality, β_i is unknown to the researcher, and, hence, it is not feasible to condition on β_i (McFadden & Train 2000; Train 2009). Instead, β_i is assumed to be normally distributed with population mean β and covariance Σ_β, and the unconditional probability that an EA will choose alternative j is estimated by integrating the conditional probabilities over all values of each of β weighted by its density function. That is:

$$P_{ijt} = Pr[y_i = j] = \int L_{ij}(\beta_i)\, f(\beta_i|\theta) d\beta_i$$

$$= \int \frac{exp\,(x'_{ijt}\beta_i)}{\sum_{l=1}^{m} exp\,(x'_{ilt}\beta_i)} f\left(\beta_i \middle| \beta, \Sigma_\beta\right) d\beta_i \tag{4}$$

In equation (4), $f(\beta_i|\theta)$ is multivariate normal density for β_i with mean β and covariance Σ_β. The integral is multidimensional with dimension given by the number of components of β_i that are random with non-zero variance (Cameron & Trivedi 2005). For simplicity, we assume that the components are uncorrelated and, hence, the off-diagonal elements of Σ_β are zero. With respect to β and Σ_β, the Maximum Likelihood Estimation (MLE) now maximizes:

[13] When $\beta_i \sim lnN(\beta, \Sigma_\beta)$, for parameters whose sign is known a priori, this model is also known as a mixed logit model (Cameron & Trivedi 2005).

$$lnL_N(\theta) = \sum_{i=1}^{N}\sum_{j=1}^{m} y_{ijt} lnP_{ijt} \quad (5)$$

Since the integral in (4) does not have a closed form, the expression in (5) cannot be analytically solved. Instead, simulated probabilities are inserted into the log-likelihood function to give a simulated log likelihood (Cameron & Trivedi 2005; Hensher & Greene 2006; Train 2009) of the form:

$$\widehat{lnL_N}(\beta, \Sigma_\beta) = \sum_{i=1}^{N}\sum_{j=1}^{m} y_{ijt} ln \left[\frac{1}{S}\sum_{s=1}^{S} \frac{exp\,(x'_{ijt}\beta_i^{(s)})}{\sum_{l=1}^{m} exp\,(x'_{ilt}\beta_i^{(s)})}\right] \quad (6)$$

where y_{ijt}=1 if the EA chooses alternative j in choice set t, and zero otherwise; and $\beta_i^{(s)}$, with s=1, 2, …, S, are random draws from $f(\beta|\theta)$[14]. Parameter estimates, $\beta^s \; and \; \Sigma_\beta^{(s)}$, represent the mean and standard deviation generated from equation (6) using maximum simulated likelihood (MSL) at r^{th} draw (Cameron & Trivedi 2005; McFadden & Train 2000).

Besides its relevance to capture unobserved heterogeneity, RPL is preferable because it allows possible correlations between the selected alternatives and choice tasks. That is, the model relaxes the strict assumption of independence of irrelevant alternatives (IIA) (Hensher & Greene 2006; McFadden & Train 2000; Train 2009). More importantly, our preferred specification allows estimation of the respondents' marginal rate of substitution for different attributes. When one of the attributes is salary, this produces the willingness to pay (WTP) of EAs for location and different work attributes. For any non-monetary attribute, x^{nm}, the willingness to pay of EA i, could be calculated as:

$$WTP_{ix^{nm}} = \frac{\frac{\partial U_i}{\partial X^{nm}}}{\frac{\partial U_i}{\partial W}} = -\left(\frac{MU_{x^{nm}}}{MU_w}\right) \quad (7)$$

where $MU_{x^{nm}}$ and MU_w represent marginal utility of attribute x^{nm} and salary, respectively. One issue with estimation of the WTP as ratios of the estimated random coefficients of non-monetary attributes to the marginal utility of salary is that it involves dividing distributions on distributions (Hensher & Greene 2006; Train 2009; WHO 2012). Depending on the choice of parameter distributions, this results in WTP distributions which are heavily skewed or distributed with no defined moments (Scarpa, Thiene, & Train 2008; Train & Weeks 2005). Commonly, empirical studies circumvent this problem by assuming that the monetary coefficient is fixed. However, this assumption might be unrealistic as marginal utility of income tends to vary depending on sociodemographic characteristics (Layard, Nickell, & Mayraz 2008).

In this study, we adopt a novel approach suggested by Train and Weeks (2005) and directly estimate the WTP in a WTP space. This approach, which involves deriving the WTP estimates directly by reformulating the mixed logit model, appears to better fit the data (Scarpa et al. 2008) and produce more realistic WTP estimates (Train & Weeks 2005) than the conventional method. For the sake of illustration, we rewrite the utility function in equation (2), differentiating between monetary (W_{ijt}) non-monetary (Z_{ijt}) attributes.

$$U_{ijt} = \eta_i w_{ijt} + z'_{ijt}\varphi_i + \varepsilon_{ijt} \quad (8)$$

where η_i and φ_i are individual specific coefficients for monetary, i.e. salary, and non-monetary attributes of the job and ε_{ijt} is the random term. Dividing both sides of equation 8, we get:

[14] We report results obtained using 100 Halton draws. However, the results remained robust to alternative number of draws.

$$U_{ijt} = \eta_i[w_{ijt} + z'_{ijt}\gamma_i] + \varepsilon_{ijt} \quad (9)$$

where $\gamma_i = {}^{\varphi_i}/_{\eta_i}$ represents the WTP for the non-monetary attributes. This specification – called model in WTP space – allows direct estimation of the coefficients corresponding to the non-monetary attributes as WTP estimates by using MSL (Train 2009).

4. RESULTS

In this section, we report estimation results that is based only on the elicited preference of 761 EAs. Initially, the choice experiment included 763 EAs. However, two respondents who provided non-rational choices were excluded from the analysis.[15] We also report results based only on estimation of the RPL model. To assess the pertinence of the RPL model, we initially estimated a conditional logit (CL) model and tested the assumption of independence of irrelevant alternatives (IIA). The Hausman test rejected the IIA assumption, implying that the CL model is not appropriate.[16]

Preferences for job attributes

Table 4 presents the simulated likelihood estimates of the RPL model. It is important to note that the coefficients of the parameter estimates do not have absolute interpretation. This is because the utility represented in the framework merely describes ordinal dependence (Train 2009). However, the sign of the parameter estimates indicates whether the respondents view the attributes positively and their relative magnitude indicates how strongly they do so relative to the alternative attributes.

The findings provide several insights. First, there is a general dissatisfaction with current job characteristics among EAs, as indicated by the constant term of the model. The constant term, which represents EAs preference for their current job, is negative and statistically significant. This implies that EAs evidently prefer the two hypothetical job choices associated with differing attribute levels than their current job and its respective attributes. Second, even though salary increases appear to be highly valued, as one would expect, they do not come as the top incentive for EAs. Instead, our results suggest that the availability of educational opportunities is by far the most important factor affecting EAs job choices. Whereas we are not able to interpret the absolute magnitude of the coefficients in column 1 of Table 4, the relative magnitude of the parameter estimates clearly point to the value that EAs place on educational opportunities. To put this in context, availability of educational opportunities comes out as more important than even a 100 percent increase in salary.

Availability of housing, transportation services, adequately equipped FTCs, and access to better infrastructure (access to mobile telephone network, road, and electricity) are also found to be significant factors in the decision process. More generally, the statistical significance of all the selected attributes indicates the availability of a wide range of interventions to policy makers in order to improve the attractiveness of public service jobs in rural areas of Ethiopia.

[15] To assess whether the EAs understood the setup of the questions and were able to make an informed decision between the alternatives, we included a question where one of the choices is superior to the other and asked them to make a choice. Of the 763 EAs, only two EAs selected a strictly dominated alternative. These two EAs were not included in the final sample.

[16] The estimation result of the CL and the conducted test is available from the authors upon request.

Table 4. Simulated likelihood estimates of the random parameters' logit model

	1	2	3	4
	Structural parameters		Standard deviation of parameter distributions	
Variables	Coefficient	SE	Coefficient	SE
Location is advanced, yes=1	0.848***	0.073	0.953***	0.090
Housing, yes=1	0.498***	0.060	0.399***	0.125
Transport service, yes=1	0.685***	0.061	0.663***	0.096
Adequate Farmer Training Center, yes=1	0.745***	0.062	0.788***	0.082
Educational opportunity, yes=1	2.039***	0.093	1.331***	0.086
Salary (ref: current basis salary)				
Salary increment of 100%, yes=1	1.753***	0.139	1.536***	0.137
Salary increment of 50%, yes=1	0.991***	0.135	-0.049	0.127
Salary increment of 25%, yes=1	0.376***	0.127	0.019	0.160
Salary reduction by 25%, yes=1	-0.727***	0.160	-1.069***	0.131
Constant	-0.101*	0.056		
Respondents, no.	761			
Observations, no.	18,264			
Log-likelihood	-3420.7			
LR Chi^2 (9)	457			
McFadden-R^2	0.48			
Halton draws	100			

Source: Authors' analysis.
Note: standard error given in parenthesis; ***, **, and * represent statistical significance at 1%, 5%, and 10% level. SD in Columns 3 and 4 represent standard deviations indicating preference heterogeneity.

Column 3 of Table 4 presents the standard deviation associated with each of the mean coefficient estimates of the random parameters calculated over the 100 Halton draws. Except for the intermediate salary increments, the standard deviation coefficients are statistically significant, indicating considerable preferences heterogeneity among EAs. Later in this section, we explore the source of the heterogeneity in preferences for these attributes across EAs based on their socio-demographic characteristics.

Willingness to pay

The most important and informative output of the econometric analysis of choice experiment data for policy purposes is the marginal analysis and the related policy impact analysis. The marginal analysis indicates the rate at which EAs are willing to substitute one attribute for another. When the reference attribute is salary, this produces the willingness to pay (WTP) of EAs for a non-pecuniary job attribute. As highlighted in the methods section, we adopt a novel approach suggested by Train and Weeks (2005) and directly estimate the WTP in a WTP space. This approach, involving deriving the WTP estimates directly by reformulating the mixed logit model, appears to better fit the data (Scarpa et al. 2008) and produce more realistic WTP estimates than the conventional method. Conceptually, estimation based on the WTP space is more appealing as it avoids an arbitrary choice of the WTP distribution resulting from dividing distributions on distributions (Hensher & Greene 2006; Hole & Kolstad 2012).

The WTP estimates in Table 5 provide clear indications about the relative importance that EAs attach to education opportunities.[17] On average, EAs are willing to pay 2,530 ETB in order to obtain education opportunities after two years of service rather than no further educational opportunities. Given that the average salary is about 3,000 ETB per month, this represents an extraordinarily strong preference for continuing education opportunities. EAs require to be paid an

[17] Note that these estimates are generated by converting the categorical salary variable to cardinal values based on the median monthly salary of EAs in Ethiopia, which was 2,500 ETB in 2018. In January 2018, 1 USD = 27.34 ETB.

additional 1,190 ETB in order to be willing to work in remote areas rather than locations that are more connected and equipped with basic amenities. This is consistent with the notion of paying extra amounts for people working in difficult conditions. Similarly, the average WTP for transport services and housing is 880 ETB and 690 ETB, respectively.

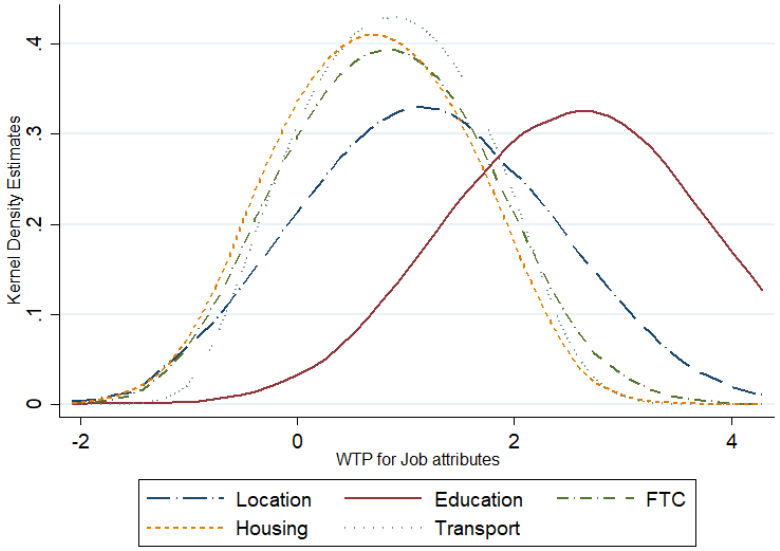
Table 5. Willingness to pay (WTP) estimates for job attributes, '000 ETB

Variables	Coefficient	SE	95-percent confidence interval	
			Lower level	Upper level
Mean of estimates				
Location is advanced, yes=1	1.19***	0.08	1.03	1.36
Housing, yes=1	0.69***	0.07	0.56	0.83
Transport service, yes=1	0.88***	0.08	0.73	1.03
Adequate Farmer Training Center, yes=1	0.83***	0.08	0.68	0.99
Educational opportunity, yes=1	2.53***	0.11	2.30	2.75
Standard deviation of estimates				
Location is advanced, yes=1	1.40***	0.10	1.21	1.59
Housing, yes=1	0.93***	0.11	0.71	1.16
Transport service, yes=1	0.75***	0.10	0.56	0.94
Adequate Farmer Training Center, yes=1	1.06***	0.09	0.89	1.24
Educational opportunity, yes=1	1.46***	0.11	1.24	1.68
Respondents, no.	761			
Observations, no.	18,264			
Chi-squared (df = 6)	711.6			
Log-likelihood	-3452.3			

Source: Authors' analysis.
Note: ***, **, and * represent statistical significance at 1%, 5%, and 10% level.

We note that EAs have strong intrinsic motivation to deliver quality extension service, as signaled by the large and statistically significant WTP for adequately equipped FTCs. An average EA is willing to sacrifice 830 ETB in order to work in an FTC that is adequately equipped. Although we are not aware of any other study that computed the WTP estimates for agricultural extension agents with which to compare, our results are comparable to studies of health professionals (e.g., nurses, laboratory technicians, clinical officers) in middle and low income countries (Hanson & Jack 2008; Kolstad 2011; Mangham & Hanson 2008; Rockers et al. 2012).

Figure 1. Estimated kernel densities of individual willingness to pay estimates for trait parameters



Source: Authors' analysis.

The kernel density plot in Figure 1 provides further evidence of the strongly positive, yet notably heterogeneous, preferences for these job attributes. While a small fraction of the distribution falls in in the negative quadrant, the means fall substantially in the positive for all included attributes. This is particularly the case for location and education opportunities, for both of which the distribution mass lies far to the right.

Policy impact

Another salient output of DCE is the policy impact analysis. Calculated by differentiating the probability function with respect to changes in job attributes, this analysis indicates how effective alternative policy interventions are to improve the attractiveness of an EA job. It shows how the preference for or the probability of taking the baseline job changes due to a change in the level of one of the job attributes (Train 2009). The baseline job is represented by the reference category for all dummies, i.e., location is remote; no housing; no transportation service; FTC is inadequate and no educational opportunity, and the average monthly salary level.[18]

Table 6. Simulated preferences under potential policy changes

Variable	Change in probability	Standard error	P>|z|	95% confidence interval	
Location is advanced, yes=1	0.40	0.03	0.00	0.34	0.46
Housing, yes=1	0.24	0.03	0.00	0.19	0.30
Transport service, yes=1	0.33	0.03	0.00	0.28	0.38
Adequate Farmer Training Center, yes=1	0.36	0.03	0.00	0.30	0.41
Educational opportunity, yes=1	0.77	0.02	0.00	0.73	0.81
Salary (ref: current basic salary)					
Salary increment of 100%, yes=1	0.70	0.04	0.00	0.64	0.77
Salary increment of 50%, yes=1	0.46	0.05	0.00	0.35	0.56
Salary increment of 25%, yes=1	0.19	0.06	0.00	0.07	0.31
Salary reduction by 25%, yes=1	-0.35	0.07	0.00	-0.49	-0.21

Source: Authors' analysis.
Note: Coefficients and related statistics are calculated with the *nlcom* command in Stata, based on the 'delta method'.

Table 6 shows that increasing salary by 25, 50, and 100 percent increases the propensity of EAs to accept a remote job posting by 19, 46, and 70 percentage points, respectively. This reiterates that upward salary adjustment is a powerful tool to improve the attractiveness of an EA job in remote areas. Two additional points are noteworthy. First, our results are consistent with loss aversion (prospect) theory.[19] While reducing salary by 25 percent reduces the propensity of taking up the baseline job by 35 percentage points, a 25 percent increase in salary only results in a 19-percentage point increase in probability of employment. Second, the results show that the potency of pecuniary incentives to improve the attractiveness of an EA job diminishes as salary increases. While increasing salary by 50 percent increases the probability of taking up the baseline job by 46 percentage points, increasing it by 100 percent (an additional 50 percent increase from the baseline) increases probability of take up only by an additional 24 percentage points.

However, salary regulation alone may not be the most efficient way to retain and incentivize EAs. In line with what was observed in previous sections, offering possibilities for further education after two years of service proves to be more effective than increasing salary by 100 percent. Investing in essential rural infrastructure is another effective policy instrument to make remote areas more attractive to EAs. The results in Table 6 show that investment in basic infrastructure increases the probability of taking a remote job by 40 percentage points. Sufficiently equipping

[18] While this baseline job may appear as a worst-case scenario, it rather closely resembles a typical employment condition of EAs in remote areas in Ethiopia. See, for instance, Davis et al. (2010); and Kassa, Karippai, Alemu, Deressa, & Yousuf (2012).

[19] Prospect theory argues that downside changes are far more powerful than upside changes (Ang, Chen, & Xing 2006; Kahneman & Tversky 1979; Schindler & Pfattheicher 2017).

FTCs, providing transportation facilities, and providing housing increase the propensity of attracting and retaining an EA in remote areas by 36, 33, and 24 percentage points, respectively.

Heterogeneity in preferences

As highlighted in previous sections, the estimated standard deviation of the random parameters suggests that EAs exhibit significant preference heterogeneity for all the job attributes, i.e., not all EAs attach equal weights to the different job attributes. More precisely, the combination of the estimated means and standard deviations of each of the random taste parameters provides information about the proportion of the respondent population that has a positive or negative preference for the job attributes (Train 2009; WHO 2012).[20] The result shows that more than three-quarters of the respondents favor well connected locations, housing, transportation service, adequate FTCs, and education opportunities. In the latter case, an overwhelming 94 percent of the respondents exhibit a strong preference for availability of education opportunities. Preference is even less homogenous for upward salary adjustment. While 87 percent of the EAs prefer a 100 percent increment in salary, 13 percent prefer a less sizable increment.

In this section, we assess the sources of the preference heterogeneity by re-estimating equation (5) for the sub-samples based on gender, work experience, current salary level, and remoteness of place of work. Table 7 presents the results. The differences between the subgroups that are statistically significant are indicated in bold. Columns 1 and 2 show that female EAs are less sensitive to pecuniary incentives compared to their male counterparts. That is, increasing salaries over a certain level is less effective in retaining or incentivizing female EAs. On the other hand, female EAs appear to be more responsive to the provision of transport services. Perhaps, this is related to security and safety issues, as travelling on foot in sparsely populated area is considered relatively less secure for female than for male EAs.

Educational opportunities remain a powerful instrument to attract, retain, and motivate EAs. This is particularly the case for relatively young and newly employed EAs. Columns 3 and 4 of Table 7 show that, relative to more experienced EAs, younger EAs (those with less than 3 years of experience as EA) have a weaker preference for salary adjustments. Instead, they show a stronger preference for education opportunities, as well as housing and transport services. The existing incentive structure might explain this. Every two years, evaluation of the performance of EAs are conducted by the woreda Bureau of Agriculture in order to nominate EAs for promotion (Dufera 2018). Younger and more newly employed EAs thus might show stronger motivation in early periods of their employment. Gradually, work burdens and frustrations catch up to them and they tend to become responsive principally to short term pecuniary incentives. Alternatively, the results might be explained by life-cycle effects, where older workers value monetary returns higher than non-pecuniary ones simply because they need to sustain their families and are generally less flexible in terms of income generation.

[20] The proportion of the respondent population that has a positive preference for the job attribute (%POS) is calculated as:%POS=ø(β⁄(SD)), where β and SD represent the estimated means and standard deviations of each of the random taste parameters, respectively and ø is the standard normal cumulative distribution function.

Table 7. Preferences for job attributes, sub-sample analysis

	1	2	3	4	5	6	7	8
	Gender		Worked 3 years or less as EA		Salary is above median for EAs		Remote place	
	Female	Male	No	Yes	No	Yes	No	Yes
Location is advanced, yes=1	0.685***	0.884***	0.810***	0.956***	***0.738***	**0.867***	0.794***	0.987***
	(0.131)	(0.087)	(0.078)	(0.187)	(0.099)	(0.101)	(0.080)	(0.177)
Housing, yes=1	0.404***	0.560***	**0.452***	**0.701***	*0.609***	0.410***	**0.435***	**0.812***
	(0.112)	(0.072)	(0.066)	(0.160)	(0.087)	(0.082)	(0.066)	(0.155)
Transport services, yes=1	0.694***	0.661***	**0.643***	**0.838***	*0.766***	0.565***	0.690***	0.566***
	(0.116)	(0.070)	(0.064)	(0.157)	(0.085)	(0.080)	(0.066)	(0.137)
Adequate Farmer Training Center, yes=1	0.619***	0.779***	0.797***	0.737***	*0.695***	0.806***	0.764***	0.666***
	(0.107)	(0.073)	(0.069)	(0.163)	(0.089)	(0.086)	(0.069)	(0.133)
Educational opportunity, yes=1	**1.805***	**2.069***	**2.010***	**2.528***	***2.191***	**1.832***	**1.955***	**2.304***
	(0.172)	(0.113)	(0.105)	(0.263)	(0.141)	(0.127)	(0.101)	(0.234)
Salary (ref: current basic salary)								
Salary increment of 100%, yes=1	**1.405***	**1.944***	**1.905***	**1.165***	**1.417***	**2.113***	**2.019***	**0.841**
	(0.255)	(0.169)	(0.154)	(0.339)	*(0.198)*	(0.197)	(0.158)	(0.336)
Salary increment of 50%, yes=1	**0.789***	**1.080***	**1.138***	**0.243**	**0.598***	**1.361***	**1.207***	**-0.036**
	(0.247)	(0.161)	(0.148)	(0.344)	*(0.194)*	(0.188)	(0.150)	(0.337)
Salary increment of 25%, yes=1	0.357	0.403***	**0.488***	**-0.080**	**0.060**	**0.752***	**0.594***	**-0.634**
	(0.231)	(0.153)	(0.140)	(0.324)	*(0.185)*	(0.173)	(0.143)	(0.312)
Salary reduction by 25%, yes=1	-0.434	-0.811***	**-0.643***	**-1.301***	-0.902***	-0.502**	-0.460***	-1.930***
	(0.281)	(0.196)	(0.177)	(0.409)	*(0.231)*	(0.225)	(0.175)	(0.433)
Constant	-0.160	-0.086	-0.134**	-0.014	0.031	-0.229***	-0.170***	0.211
	(0.104)	(0.066)	(0.062)	(0.135)	*(0.079)*	(0.079)	(0.062)	(0.131)
Respondents, no.	191	570	619	142	378	383	626	135
Observations, no.	4,584	13,680	14,856	3,408	9,072	9,192	15,024	3,240
Chi-squared (df = 5)	81	358	373	94	203	236	384	60
Log-likelihood	-919.1	-2504.1	-2781.4	-628.9	-1682.6	-1725.1	-2805.8	-602.7
Pseudo-R^2	0.042	0.067	0.063	0.069	0.057	0.064	0.064	0.047

Source: Authors' analysis.
Note: Standard error given in parenthesis; ***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively. The differences between the subgroups that are statistically significant are in bold.

The response of EAs also appear to differ significantly based on current salary level. The higher the current salary level, the more sensitive EAs are to salary adjustments. This is intuitive as salary adjustments in the choice experiment are proposed as a percentage of the current salary level. It is well known that the same amount of money will present a different value depending on the baseline income level. Demand for better infrastructure also interacts positively with the current salary level. On the other hand, availability of government provided housing and transportation services are not very effective to motivate top earning EAs. This perhaps emanates from the fact that better earning EAs could afford to rent housing and transportation services on their own. That is, since salaries of EAs are based mainly on work experience and most experienced EAs work in relatively advanced locations close to the district capital, they often have their own housing or the opportunity to rent decent housing in these locations. It is, however, interesting to note that EAs that earn above average salary tend to have a weaker preference for further education. This might speak to the high unemployment among graduates and the low return to education in the country (Desalegn 2018). Leaving a reasonably well-paying job to pursue further education for which a return is not guaranteed might not be appealing.

To examine the difference in preferences based on location of work, we introduce an indicator of remoteness. The kebele where an EA serves is considered remote if the distance between the kebele and the district capital is larger than the 80th percentile of the distance distribution.[21] Columns 7 and 8 of Table 7 show that EAs in remote locations show stronger preference for government provided housing as well as educational opportunities. This can be explained by the relatively thin house rental market in remote areas as well as the lack of adequate transportation facilities for daily commuting from workplace to residences located outside of the kebele. On the other hand, EAs in more connected areas show strong preferences for salary adjustments. This can be explained by the relatively higher cost of living in more connected areas.

5. DISCUSSION

The results of the choice experiment indicate that the six selected job attributes are statistically significant, implying that EAs are willing to trade pay raises for improved living and working conditions. Preferences for further education and infrastructure are particularly strong. Given that improvement in the education of the EAs and in infrastructure are beneficial not only to retain the EAs but also, indirectly, for the productivity of farmers, these appear to be worthwhile investments for the government. These findings are quite pragmatic in low income country settings where wage improvement possibilities are limited because governments lack the required fiscal space, especially since salary adjustments for one group of public sector employees are likely to trigger similar demands from other groups.

However, to develop concrete policy recommendations, supplementary studies are needed. The role of qualitative information in this regard can be important. To partly address this, we analyze responses from three open ended questions: (1) the perception of EAs regarding factors that hinder effective extension delivery, (2) factors that motivate EAs in their extension work, and (3) changes EAs suggest to make extension delivery more effective. Table 8 asserts that investment in infrastructure, or the lack thereof, is a considerable impediment to effective extension service in rural Ethiopia.

[21] See Abate et al. (2019) and Minten, Koru, and Stifel (2013) for similar definitions of remote kebeles.

Table 8. Reported challenges, motivation factors, and changes suggested by Extension Agents for effective agricultural extension

Panel A: Challenges faced in conducting extension service	% EAs
Poor infrastructure (drinking water, food, electricity, transportation, etc.)	62
Lack of housing	18
Poorly equipped Farmer Training Center (demonstration plots, ICT tools, budget, etc.)	39
Lack of education opportunities and short-term training	6
Low salary (low basic salary and no or inadequate allowance)	19
Workload (long working hours and long work week)	15
Farmers' resistance (low adoption, low attendance at meetings, etc.)	35
Management approach (poor incentive structure, obsolete extension system, etc.)	45
Extension Agents reporting, no.	722
Panel B: Factors that motivate Extension Agents in conducting extension work	
Nothing	35
On job training	5
Management support (recognition, fair promotion, etc.)	10
Desire to change farmers' lives	49
Active participation of farmers (attentiveness, attendance in meetings, etc.)	14
Interest in agricultural extension (love for profession)	9
Extension Agents reporting, no.	764
Panel C: Suggested changes to make agricultural extension more effective	
Improve infrastructure (improve road quality, provide motorcycles or bicycles, etc.)	65
Provide housing	30
Equip Farmer Training Centers for effective extension	44
Provide educational opportunities, regardless of current level of education	27
Upgrade salary structure to reflect living cost and job market	67
Reduce workload (less frequent reporting, free weekends, etc.)	8
Modify management approach (upgrade extension system, create transparent incentive structure)	46
Extension Agents reporting, no.	718

Source: Authors' calculation based on the 2019 Digital Green's extension agents' survey data.

It is also important to underline that improvement in identified attributes are helpful primarily in reducing EA turnover and job demotivation, but not to spur performance. Factors related to working conditions, i.e., infrastructure, housing, transport service and FTC materials, and to the package of benefits EAs receive, i.e., salary and educational opportunities, are extrinsic to the job. Consequently, their improvement can only partially increase job motivation. According to Herzberg (1987), there are additional factors that lead to work motivation, which are intrinsic to the job. These include love for the profession, desire to make a difference through the job, and desire to advance (through training). Table 8 shows that this is indeed the case for EAs in Ethiopia. Close to half (45 percent) of the EAs indicated that the desire to change farmers' living conditions through extension service is their motivating factor. Other important factors include acceptability of their trainings among farmers, support from management, the work itself, and access to training (panel B of Table 8). This suggests that, in the long run, motivating EAs and, hence, improving their performance requires interventions that are designed and targeted to make extension work more productive and responsive to the demands of farmers. Disengaging EAs from non-extension duties, e.g. tax collection, kebele administration, promoting political views, etc., and equipping FTCs with adequate materials, e.g., ICT tools, demonstration plots, training materials, etc., are examples of changes in the right direction (Table 8). This is consistent with findings from other studies (Berhane et al. 2018; Ragasa et al. 2016).

That said, further experiments that include additional attributes from this qualitative assessment would offer additional insights of value. The six attributes we considered represent only a subset of many possible attributes that affect the job choices of EAs (Table 8). Table 8 clearly shows that, to

most EAs, workload, management practices, and farmers' interest in extension (meetings) are hurdles to effective extension dissemination that require meaningful improvement. While we acknowledge the importance of these remaining attributes and that further research on these attributes would be valuable to inform policy, our basic conclusion regarding the included attributes remains valid. The experimental design we used ensures valid trade-off among the included attributes, assuming that all relevant excluded attributes remain the same between alternatives (Chomitz et al. 1998; Scott 2001).[22]

Future research can also estimate interaction effects of attributes beyond the main effects of attributes. Our analysis focused only on the estimation of main effects, i.e., the independent effect of each attribute level on the preference of the EAs. Results from interacting attributes might produce interesting insights regarding synergies in multiple interventions. For instance, it might be the case that preferences for government provided housing is determined by the location of work. Unfortunately, estimation of such interaction terms requires a larger number of choice sets to be presented to the respondents (a full factorial design). In this study, we opted to use a fractional factorial design and present eight choice sets to each EA to minimize fatigue and the cognitive burden on respondents. While this design is simple, it is realistic enough to provide relevant policy prediction regarding the effect of policy interventions under the selected attributes (De Bekker-Grob et al. 2008; Kuhfeld 2010; WHO 2012). In describing the preferences of employees for job attributes, the main effects are argued to explain most of the variation in preferences (De Bekker-Grob et al. 2008; WHO 2012).

The hypothetical nature of the questions in choice experiment might be unconvincing as respondents may over- or under-state their true preferences systematically. This potential bias is often magnified by poor survey administration, including in the selection and training of enumerators, the discussions held with key informants, and pre-testing. While we cannot entirely rule out the possibility of respondent bias, our survey was subjected to a rigorous preparation process to minimize such bias. For studies in which the experimental design was carefully constructed, the stated preferences of respondents were found to closely resemble their revealed preferences (De Bekker-Grob et al. 2008; Johnston et al. 2017; Lusk & Schroeder 2004; WHO 2012).

6. CONCLUSION

Lower labor productivity in rural areas, especially in remote locations, is a considerable hurdle to overcome for successful poverty reduction in developing countries. Low labor productivity in remote locations also exacerbates spatial imbalances in welfare. Agricultural extension agents (EAs) could contribute to reducing this spatial imbalance by promoting the use of modern technologies and production methods, thereby increasing agricultural productivity. However, studies consistently show that farmers' access to extension service is limited in such locations. Extension offices are often understaffed and the quality, motivation, and effort level of EAs are dubious, particularly in more remote areas.

In this study, we designed a choice experiment that would be useful to inform policy interventions to abate the high turnover of EAs and mitigate geographical imbalances in the number and quality of EAs. For data analysis, we employ a random parameter logit model (RPL). The use of RPL in conjunction with the choice experiment data allows statistical flexibility and avoids the limitations of using cross-sectional and repeated revealed preference data that are susceptible to endogeneity and selection issues.

[22] Each respondent was explicitly informed to assume that all unstated characteristics of jobs are the same for the presented alternatives (see Table A3).

We find that offering continuing education opportunities after two years of service is one of the most powerful incentive instruments available to policy makers. Increasing salaries and offering decent housing and transportation facilities are also effective incentives to EAs, but not as much as offers of further educational opportunities. Good infrastructure, including improved access to electricity and mobile telephone networks in the kebeles in which EAs are posted, as well as equipping Farmer Training Centers (FTC) are also interventions to which EAs are highly likely to respond.

The sub-sample analysis shows that the preferences of EAs for job attributes vary considerably based on gender, age, current salary level, and place of work. In general, male and experienced EAs, as well as those in more connected areas strongly prefer increased salaries. On the other hand, less experienced EAs and those in remote locations have stronger preferences for further educational opportunities. Overall, these results highlight the importance of accounting for EA sociodemographic factors when designing policy intervention designed and targeted to attract, retain, and motivate EAs.

The cost effectiveness of the alternative interventions should be factored in before concrete policy recommendations are made. To this end, future studies might estimate the cost of the different interventions and combine that information with computed elasticities to assess the cost-effectiveness of each intervention. This is crucial for determining both the effectiveness of the interventions and their efficacy.

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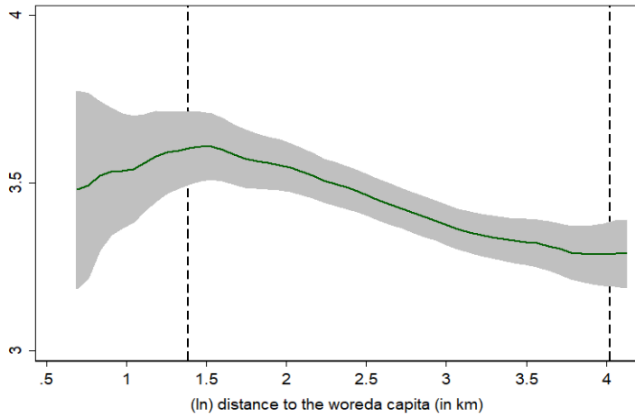
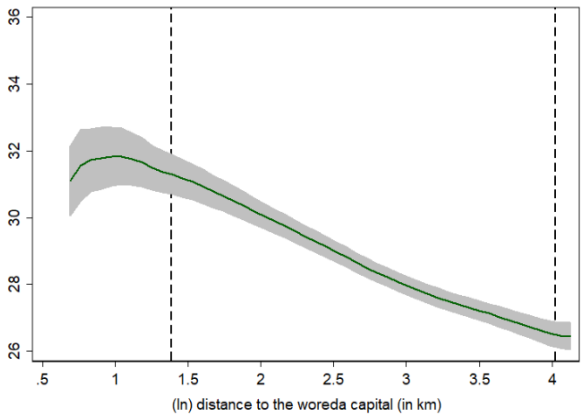
APPENDIX

Figure A1. Characteristics and effort levels of Extension Agents, by remoteness

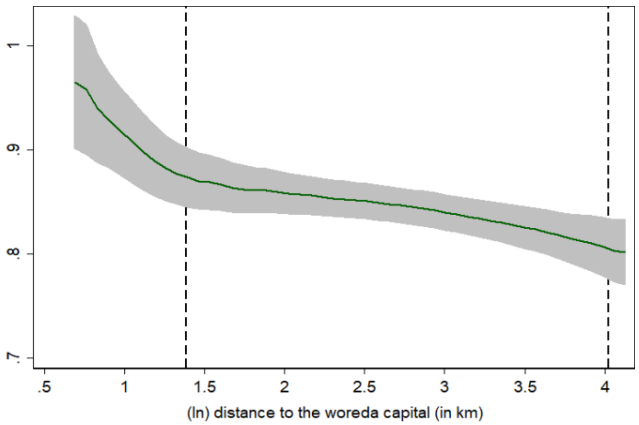
a) Extension Agents in kebele, number



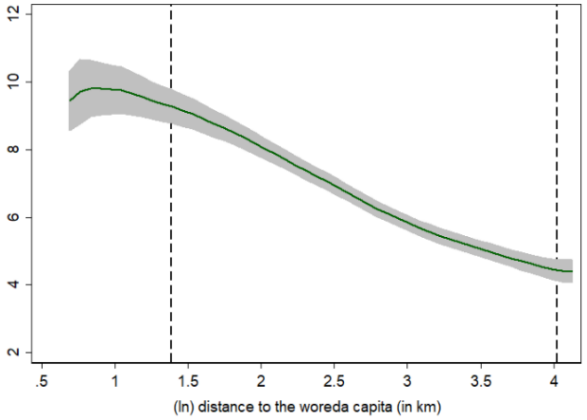
b) Average age of Extension Agents in kebele, years



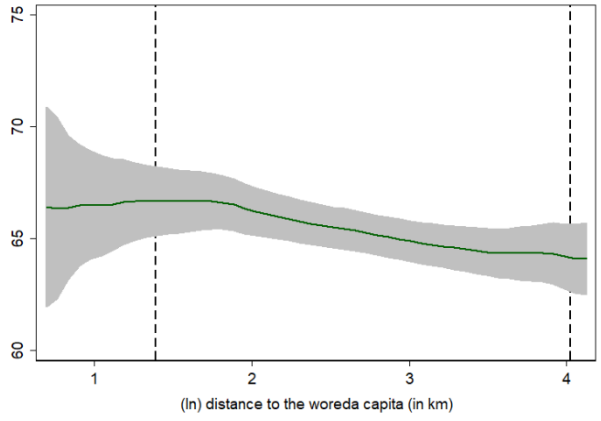
c) Extension Agents with Diploma or higher educational attainment, share



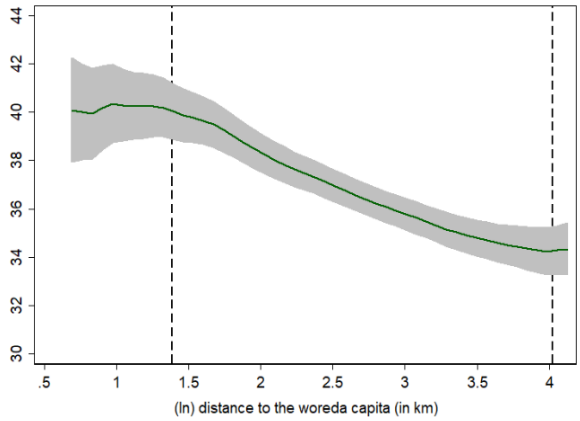
d) Average work experience of Extension Agents, years



e) Technical knowledge of Extension Agents on agricultural practices, average score



f) Working hours per week of Extension Agents, average



Source: Authors' calculation based on Digital Green's EA survey, 2017, 2018 & 2019.

Table A1. Sociodemographic characteristics of agricultural Extension Agents in study sample, over survey rounds

Characteristics		2017	2018	2019	All
Male		0.75	0.77	0.75	0.76
Age, years		27.8	28.8	29.3	28.6
Years working as an EA		5.59	6.72	7.27	6.48
Years working in current kebele		1.88	2.53	2.6	2.31
Education:	Certificate, yes=1	0.25	0.17	0.03	0.16
	Diploma, yes=1	0.54	0.55	0.7	0.6
	Degree, yes=1	0.2	0.28	0.27	0.25
Computer literate, yes=1		0.46	0.41	0.5	0.46
Mobile with internet access, yes=1		0.37	0.48	0.62	0.48
Spent childhood:	In working kebele, yes=1	0.09	0.1	0.09	0.09
	In working woreda, yes=1	0.6	0.61	0.64	0.61
	In working zone, yes=1	0.83	0.85	0.87	0.85
EAs in kebele, number		3.47	3.53	3.27	3.42
Farmers' field days organized, number		2.02	1.86	1.83	1.91
Working hours per week:	Planting season	51	49.6	46.1	49
	Harvesting season	40	36	33.5	36.7
	Slack season	26.1	22.4	23	23.9
	Average	39	36	34.2	36.5
Knowledge score:	Teff		68.4	72.3	70.3
	Maize		65.1	69.7	67.4
	Wheat		62.1	68.9	65.5
	Average		65.2	70.3	67.7
Observations		896	781	763	2,440

Source: Authors' calculation based on Digital Green's EA survey, 2017, 2018 & 2019.
Note: Knowledge refers to EAs' work-related knowledge score (out of 100) obtained through quizzes. The knowledge questions focused on growing practices of teff, maize and wheat.

Table A2. Characteristics, knowledge, and effort level of Extension Agents, by remoteness

Outcome variable:	1 EAs in kebele, no.	2 Age of EAs, years	3 Work experience, years	4 Education level Diploma or higher, share	5 Test scores, percentile	6 Working hours per week	7 Field days organized, no.
Travel time to woreda from kebele center, minutes [Reference= First tercile]							
Middle tercile	-0.026	-2.255***	-2.202***	-0.032	-1.837**	-3.149**	-0.563***
	(0.125)	(0.589)	(0.539)	(0.028)	(0.815)	(1.353)	(0.209)
Farthest tercile	-0.459***	-3.099***	-2.959***	-0.068*	-2.796***	-3.104***	-0.670*
	(0.100)	(0.610)	(0.523)	(0.035)	(0.908)	(1.053)	(0.346)
Within-R^2	0.045	0.058	0.08	0.007	0.014	0.018	0.012

Source: Authors' analysis.
Note: Woreda fixed-effects used in all models. Observations: 781.
Standard errors clustered at the woreda level and reported in parenthesis. ***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively.

Table A3. Description of the choice experiment task

Instruction for choice experiment

[Interviewer: Please read the following aloud to the respondent]

Below I will present you with a number of jobs with features similar to current working conditions in rural Ethiopia. However, these jobs are hypothetical and do not necessarily reflect the working condition of any particular job. In each round, I would like to ask you to make a choice between two jobs based only on the information given corresponding to the jobs. Since, these jobs are hypothetical, you are not supposed to evaluate whether the jobs are realistic or not. Based only on the information given, you need only to choose which one of the two jobs (Job 1, Job 2, or neither) you prefer. Assume that all unstated characteristics of jobs are the same for the two jobs.

Description of the Attributes of the Jobs:

Location: Refers to quality of services at the location of work and distance from quality services and takes **two values**.

1. **Advanced location**: Location with reliable mobile telephone coverage, electricity, and piped water.
2. **Remote location**: Location with unreliable mobile telephone coverage, electricity, and piped water.

Pay (salary): This assumes **four values**.

1. **Minus 25%**: 25 percent less than the current net salary of the responding EA. That is, the current basic salary minus 25 percent of the current basic salary;
2. **Plus 25%**: Current basic salary plus 25 percent of current basic salary.;
3. **Plus 50%**: Current basic salary plus 50 percent of current basic salary;
4. **Plus 100%**: Twice current basic salary.

Housing: This assumes **two levels**

1. **No**: No housing;
2. **Yes**: Housing with basics enough for survival.

Farmer Training Centers (FTC): This stands for extension tools at FTC and assumes **two levels**:

1. **Inadequate**: Not enough resources to effectively deliver extension service to farmers, e.g., no demonstration plot, inadequate budget to run the FTC, inadequate teaching materials)
2. **Adequate**: Enough resources to effectively run the FTC as well as deliver extension service to farmers.

Transportation: This assumes **two levels:**

1. **No**: No transportation facility at the FTC (no bicycle, motorcycle, or horse)
2. **Yes**: FTC has own transportation facility (e.g. bicycle, motorcycle, or horses).

Educational opportunity: this assumes **two levels:**

1. **No**: No educational opportunities
2. **Yes**: Educational opportunity offered after 2 or more year of service

Do you have any question? Is everything clear?

Now, let us take the following as an example.
If you are given the opportunity to choose between **J1 and J2**, which job would you choose?

Block-1	Question-1	
Job profiles	Job 1 (J1)	Job 2 (J2)
Location	Remote	Advanced
Salary	Plus 25%	Plus 50%
Housing availability	Yes	No
Transport access	No	Yes
FTC tools/equipment's	Inadequate	Adequate
Educational opportunity	No	Yes
Answer choices: **1.** Job 1; **2.** Job 2; **3.** Neither job 1 nor job 2		

ABOUT THE AUTHORS

Mekdim D. Regassa is a PhD student in the Centre for Development Research (ZEF), Bonn University, Bonn, Germany. **Gashaw T. Abate** is a Research Fellow in the Markets, Trade, and Institutions Division (MTID) of the International Food Policy Research Institute (IFPRI), based in Addis Ababa, Ethiopia. **Zaneta Kubik** is a Senior Researcher at ZEF, Bonn University, Bonn, Germany.

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INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
1201 Eye St, NW | Washington, DC 20005 USA
T. +1-202-862-5600 | F. +1-202-862-5606
Email: ifpri@cgiar.org | www.ifpri.org | www.ifpri.info

POLICY STUDIES INSTITUTE
P.O. Box 2479, Addis Ababa, Ethiopia
T. +251.11-550-6066; +251-11-553-8633 | F. +251-11-550-5588
http://psi.gov.et/

IFPRI–ESSP ADDIS ABABA
P.O. Box 5689, Addis Ababa, Ethiopia
T. +251-11-617-2000 | F. +251-11-667-6923
Email: ifpri-essp@cgiar.org | http://essp.ifpri.info

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