Understanding heterogeneity in the job preferences of community-based healthcare workers: Applications from Ethiopia and Ghana

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ABSTRACT

It is recognised that a better understanding of the job preferences of health workers is needed to inform policies intended to retain them in their roles. This has led to a growing interest in advancing and applying methods to study preference heterogeneity in order to acknowledge differences in health provider characteristics that are known to affect their labour market choices. Many countries dealing with human resource shortages depend on community-based workers to improve healthcare coverage. This thesis analysed the job preferences of community-based healthcare workers in Ethiopia and Ghana, to understand heterogeneity in their preferences and how it can be modelled using multiple methods.

Primary data were collected to qualitatively explore the job preferences of community health workers in Ethiopia. Secondary datasets with unlabelled discrete choice experiments reproducing the roles of community health workers in Ethiopia and community volunteers in Ghana were analysed to elicit stated preferences for financial and non-financial job attributes. Sources of heterogeneity in preferences were explored by incorporating individual characteristics and psychological constructs in choice models. The difference between decision making heuristics and preference heterogeneity in the analysis of discrete choices was also examined.

Community health workers in Ethiopia were found to strongly prefer non-financial incentives in their jobs, and motivation was found to be an important source of preference heterogeneity. The need for characterising well-defined and relevant attributes in a DCE was also highlighted, to ensure that heuristics in decision making do not get confused with preference heterogeneity. Similarly, in Ghana, non-financial incentives were also found to be very important to respondents. Three groups of health workers with heterogeneous job preferences for role incentives were identified in the dataset.

This thesis contributes to the limited evidence on the job preferences of community-based healthcare workers, alongside sources and ways to model preference heterogeneity. This knowledge is important to inform policies in resource-constrained settings that rely heavily on lay workers for primary healthcare delivery.

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TABLE OF CONTENTS

DECLARATION BY THE CANDIDATE 2
ABSTRACT 3
ACKNOWLEDGEMENTS 4
LIST OF ABBREVIATIONS 10
PART 1 - INTRODUCTION 11
CHAPTER 1 12
INTRODUCTION 12
1.1. Health worker shortages in Sub-Saharan Africa 12
1.2. Investigating the job preferences of community-based healthcare workers 14
1.3. Scope of the thesis 15
1.4. Structure of the Thesis 16
REFERENCES 18
CHAPTER 2 21
REVIEW OF LITERATURE 21
2.1. Human resources for health shortages 21
2.2. Models of labour supply 23
2.3. Non-wage job incentives 24
2.4. Health worker motivation for non-wage job incentives 25
2.5. Methods to study preferences 26
2.6. DCE: analytical approach 28
Accounting for preference heterogeneity in DCEs 29
REFERENCES 31
CHAPTER 3 35
STUDY SETTING 35
3.1. Country profile: Ethiopia 35
The health extension program 36
3.2. Country profile: Ghana 38
The rural response system (RRS) 38
Community-based action teams (COMBATs) 39
REFERENCES 40
CHAPTER 4 41
STUDY OBJECTIVES, CONCEPTUAL FRAMEWORK, AND METHODS 41
4.1. AIM AND OBJECTIVES 41
4.2. THESIS CONCEPTUAL FRAMEWORK 42
4.3 OVERVIEW OF METHODS USED IN THIS THESIS 44

4.3.1 Methods used ... 44
4.3.2 Description of the data used ... 45
4.3.3. Methods for data analysis ... 49
4.4. REFLECTIONS ON THE CHANGES MADE TO MY PROPOSED RESEARCH ... 50
REFERENCES ... 52
PART II – RESEARCH PAPERS ... 53
INTRODUCTION TO THE RESEARCH PAPERS ... 54
CHAPTER 5 ... 56
Research paper 1: Understanding the importance of non-material factors in retaining community health workers in low-income settings: a qualitative case-study in Ethiopia ... 56
Overview ... 56
CHAPTER 6 ... 64
Research paper 2: The stated preferences of community-based volunteers for roles in the prevention of violence against women and girls in Ghana: a discrete choice analysis ... 64
Overview ... 64
CHAPTER 7 ... 88
Research Paper 3: Linking health worker motivation with their stated job preferences: a hybrid choice analysis in Ethiopia ... 88
Overview ... 88
CHAPTER 8 ... 117
Research paper 4: Discrete choice analysis of health worker job preferences in Ethiopia: separating attribute non-attendance from taste heterogeneity ... 117
Overview ... 117
PART III – DISCUSSION ... 144
CHAPTER 9 ... 145
DISCUSSION AND CONCLUSIONS ... 145
9.1. Summary of key findings ... 145
9.1.1. Objective 1 ... 145
9.1.2. Objective 2 ... 146
9.1.3. Objective 3 ... 147
9.2. Overall contribution of the Thesis ... 148
9.2.1. Contribution to empirical findings ... 148
9.2.2. Contribution to methods ... 149
9.3. Strengths and limitations of the thesis ... 150
9.3.1. Reflections on the use of DCEs ... 151
9.3.2. Reflections on the change in empirical approach due to fieldwork disruptions ... 152
9.4. Implications for research ... 153

9.4.1. The need for data on lay health workers 153
9.4.2. Generalisability to other contexts 154
9.5. Implications for policy and practice 155
9.5.1. Evidence-based policy making on HEWs in Ethiopia 155
9.5.2. The use of a hybrid choice approach for policy making 155
9.6. Conclusion 156
REFERENCES 157
APPENDIX 160
Appendix 1: LSHTM ethics approval for thesis 160
Appendix 2: Thesis ethics approval from Addis Ababa University, Ethiopia 161
Appendix 3: Ethical approval for DCE data from Ethiopia 162
Appendix 4: Ethical approval for DCE data from Ghana 162
Appendix 5: Interview Topic Guides for qualitative data collection 163
Appendix 6: Consent forms for qualitative interviews 168

LIST OF FIGURES

Chapter 3

Figure 1: Left: Boundary of Ethiopia in the map of Africa. Right: Map showing the 11 regions in Ethiopia with the four study regions 35

Figure 2: Right: Regional boundary of Ghana in the map of Africa. Left: The four study regions of Ghana 38

Chapter 4 42

Thesis conceptual framework

Chapter 5

Figure 1: A framework of relationships between motivational factors, motivation, and CHW work behaviour 60

Chapter 6

Figure 1: Example DCE choice task 74

Chapter 7

Figure 1: Example Choice task 97

Figure 2: Study hybrid choice model structure 99

Figure 3: Association between intrinsic motivation and a higher than average salary 106

Figure 4: Association between intrinsic motivation and a heavy workload 106

Figure 5: Association between extrinsic motivation and higher than average salary 107

Figure 6: Extent of variation in preferences explained by the three latent variables 107

Chapter 8 108

Figure 1: Example choice task 113

LIST OF TABLES

Chapter 1

Table 1: Outline of thesis 16

Chapter 3

Table 1: List of health extension program interventions 36

Chapter 4

Table 1: Description of the study sample for qualitative interviews 46

Table 2: List of final attributes and levels used in the DCE 47

Table 3: Final list of attributes included in the DCE 48

Chapter 5

Table 1: Interviews conducted per informant study 61

Chapter 6

Table 1: DCE attributes and levels 73

Table 2: Participant socio-demographic characteristics 77

Table 3: MMNL results 78

Table 4: Model goodness of fit results 80

Table 5: Estimation results for the three-class LCM 81

Table 6: Estimation results for the three-class LCM 82

Table 7: MNL Results 88

Chapter 7

Table 1: Respondent characteristics 95

Table 2: DCE attributes and their levels 96

Table 3: Motivation statement included 102

Table 4: Goodness of fit, MNL and MMNL 103

Table 5: Estimation results of the HCM 104

Table 6: Factor analysis of the motivation measure 116

Table 7: MNL estimation results 116

Table 8: MMNL estimation results 117

Chapter 8

Table 1: DCE attributes and their levels 113

Table 2: Goodness of fit results 127

Table 3: Likelihood ration test results 128

Table 4 : Estimation results for ANA-MMNL, for HEWs 129

Table 5 Estimation results of ANA-MMNL, for other cadres 130

Table 6: Rates of ANA captured in different ANA models 130

LIST OF ABBREVIATIONS

AIC	Akaike information criterion
ANA	Attribute non-attendance
BIC	Bayesian information criterion
CHW	Community Health Worker
COMBAT	Community-based action teams
CV	Contingent valuation
DCE	Discrete choice experiment
ETB	Ethiopian Birr
FGD	Focus group discussion
GP	General practitioner
HEP	Health extension program
HEW	Health extension worker
HRH	Human resources for health
LCM	Latent class model
LMIC	Low-and-middle-income-country
LSHTM	London School of Hygiene & Tropical Medicine
MMNL	Mixed multinomial logit
MNL	Multinomial logit
QI	Quality improvement
RRS	Rapid rural system
VAWG	Violence against women and girls
WHO	World Health Organisation

PART 1 - INTRODUCTION

CHAPTER 1

INTRODUCTION

1.1. Health worker shortages in Sub-Saharan Africa

In 2021, the World Health Organisation (WHO) projected a shortfall of 18 million health workers (doctors, nurses, and midwives) by 2030, with the highest relative shortage projected in the African region (WHO, 2021). While the supply of health workers can be increased by training more in the region, this comes at a substantial cost. For example, it was estimated that training 1.5 million more doctors in Africa by 2030 would require a threefold increase in the capacity of medical schools, at an estimated cost of over US$ 17 billion for construction alone (Liu et al., 2017) – the equivalent of Burkina Faso's GDP (World Bank, 2022). Although further investments in medical education programmes for doctors are essential, depending on these alone to improve the pool of available health workers is neither sufficient nor does it guarantee that all of those trained would stay in public sector jobs. Different approaches are therefore necessary to increase the number of health workers who are urgently needed for the delivery of healthcare of adequate quality. These approaches are also needed to address the disparities in the distribution of health workers in Africa. For example, of the 973 doctors said to be working in the public sector in Ethiopia in 2008, 360 (37%) were working in the national capital, Addis Ababa, home to only 4% of the population (Central Statistical Agency, 2008). Similarly in Angola and South Africa, only 15% and 17% of health workers, respectively, work in rural areas where approximately half the population resides (Singh and Sachs, 2013, UNAIDS, 2017).

To reduce the ill-effects of a long-lasting shortfall of health workers, many governments in resource-poor settings have invested in expanding healthcare coverage at lower cost through the use of community health providers (Olaniran et al., 2017, Schneider and Lehmann, 2016, Schneider et al., 2016, Perry et al., 2014, Kok et al., 2015a). Comprising a wide range of role characteristics and relevant training in the interventions that they are mandated to deliver, these workers include community health workers, volunteers, nutrition counsellors, and traditional birth attendants, among others (Lewin et al., 2005, Kok et al., 2015a, Kumar et al., 2019). Depending on the context and policy, these workers, henceforth referred to as community-based healthcare workers, deliver a wide range of preventative, promotive, and curative healthcare services to communities in which they are local. Recent evidence from randomised controlled trials and costing studies show that these workers can be effective and cost-effective in expanding service coverage in certain contexts and clinical areas (Torres-Rueda et al., 2020, Björkman Nyqvist et al., 2019, Karuga et al., 2019, Ferrari et al., 2022).

For example, in Ethiopia, where the majority of the research in this thesis was conducted, a supply-side healthcare reform – the Health Extension Programme – was rolled out by the government in 2003 to address the shortage of healthcare workers and improve the delivery of primary healthcare services in the country. It deployed community health workers called health extension workers (HEWs) who deliver basic preventative, promotive and select curative services, especially in rural areas (Tilahun et al., 2017). HEWs are salaried, full-time health workers delivering healthcare services through established health posts located in villages, serving approximately 2500 people each. The Ethiopian government spends close to 21% of recurrent health expenditure on HEW salaries alone (Wang et al., 2016). Though large numbers of HEWs were initially deployed, current policy initiatives are hampered by a dearth of empirical evidence on what influences HEWs to remain in or leave the health system (Tekle et al., 2022). Specifically, evidence is lacking on HEW preferences towards workplace incentives, the determinants of their job choices, and the implications of these dynamics on their retention in this workforce. A nationally representative study researching the extent of attrition of HEWs since the implementation of the program shows that the cumulative lifetime attrition within the cadre has been just over 20% (Tekle et al., 2022). Since significant domestic public resources are devoted to the salaries of these health workers, attrition within this workforce fuels the existing human resources shortages hindering the attainment of basic healthcare needs at the population level.

In contrast to the Ethiopian health extension worker model, in Ghana Community-Based Action teams (COMBAT) consist of unpaid volunteers providing healthcare interventions for the prevention of violence against women and girls (VAWG) at the community level. COMBATs undertake sensitisation activities to mobilise the community about the ill effects of VAWG, provide individual counselling to people affected by VAWG, and carry out referrals to state agencies where necessary. COMBATs comprise male and female volunteers nominated by local communities and their leaders and are trained and supervised by a non-governmental organisation called the Gender Centre in Ghana. COMBATs are paid a small per-diem during training, however, once the training is complete, they work as unpaid volunteers in their communities. Trials studying the economic value of the COMBAT program have deemed it highly effective and cost-effective in reducing VAWG in Ghana (Torres-Rueda et al., 2020, Ogum Alangea et al., 2020, Ferrari et al., 2022). This evidence suggests that established community-based interventions such as the COMBAT program warrant consideration for scale up to prevent VAWG in similar African contexts. Worker retention is key in any programme seeking to scale up, and therefore understanding the factors driving their decisions to stay in their roles or not is important to inform programmers and policymakers on how to retain volunteers for the sustainable delivery of such programs.

1.2. Investigating the job preferences of community-based healthcare workers

Although challenges around retention are not unique to community worker programs, research on their working conditions and preferences for job characteristics is particularly limited. The role they play as intermediary between communities and the health system often becomes even more challenging as evidence has shown that they are less likely to be integrated into the health system, less educated and have fewer support structures available to them than other professional, formal cadres of healthcare workers such as doctors and nurses (Kok et al., 2015b, Gilmore and McAuliffe, 2013, Cometto et al., 2018). These challenges can be aggravated by poor working conditions, particularly in remote areas due to infrastructural difficulties, as well as the lack of career progression, dearth of training opportunities, and low wages (If any) (Kumar et al., 2019).

At the same time, there is increasing evidence that the determinants of their labour supply include factors other than just wages and leisure, as normally assumed by standard models of labour supply. This is particularly due to the possible role played by pro-social behaviour and intrinsic motivation – themes which emerge from the field of Psychology and its insights into other-regarding behaviour which have become the focus of mainstream economic research (Kallander et al., 2015, Grant, 2008, Akintola and Chikoko, 2016, Okuga et al., 2015, Alhassan et al., 2016, Saran et al., 2020, Arora et al., 2020).

In 1759, Adam Smith presented evidence in favour of human behaviours being driven by kindness towards others alongside self-interest:

> *"How selfish so ever man may be supposed, there are evidently some principles in his nature, which interest him in the fortune of others, and render their happiness necessary to him, though he derives nothing from it, except the pleasure of seeing it." (Smith, 1759)*

These values can be seen to echo those of community-based health workers in African settings, including in this thesis:

> "*Most of the time in our environment, the mothers don't use contraceptives, they don't give birth in health centres and they don't get antenatal care. The mothers normally give birth in their home with a traditional birth attendant. Because of this, many mothers die. When I saw these types of problems in my community, I decided to become a HEW*" – *Health Extension Worker, Ethiopia* (Arora et al., 2020)

> "*Nowadays, life is simply expensive and there is no employment" yet he said that he would continue to volunteer as a CHW because, "It is a promise*." *community health volunteer, Ethiopia (Maes, 2015)*

The interplay between work motivation and preferences for incentives is multifaceted and there is growing recognition that a better understanding of the preferences of health workers is needed to address their current misdistribution and shortage (Vujicic and Zurn, 2006). In the case of community-based healthcare workers, there is evidence that altruistic behaviour may be crowded out by financial incentives (Frey and Jegen, 2001, Bénabou and Tirole, 2006, Strachan et al., 2015), while financial incentives can also be seen as a sign of appreciation, particularly if they are not tied to performance (Bénabou and Tirole, 2003, Maes et al., 2010). A review of literature on community-based healthcare provider programs suggests that both, financial and non-financial factors can affect their motivation. Findings from Saran et al (2020), for example, showed that community health workers in Western Kenya, many of whom were volunteers, strongly valued community appreciation for their work while also having strong preferences for monetary incentives.

An additional feature that maybe useful in understanding the circumstances under which job incentives can be effective is preference heterogeneity. This can be defined as the extent to which individual tastes and preferences for those incentives can vary across individuals (Price et al., 1989). A key focus of researchers in health economics has therefore been to recognise that preferences vary across individual decision makers, that understanding the average preferences for service and treatment attributes is not sufficient alone, and that preference heterogeneity needs to be explored fully (Hess et al., 2021). To inform the design of policy levers that can motivate and retain community-based healthcare workers, this research presents a theoretical and empirical exploration of the financial and non-financial drivers of their labour market decisions, using multiple methods. This thesis also adds to the evidence on choice modelling methods used to understand the incentive structures of health workers in low-income countries, particularly analysing the heterogeneity in their preferences. It is the first application of a hybrid choice approach in health economics for studying the link between health worker motivation and job preferences. It is also a contribution to the nascent body of work recognising heuristics in decision making within choice modelling, and the need to separate them from respondent's heterogenous preferences to avoid misinformed welfare estimates.

1.3. Scope of the thesis

The aim of this thesis is to understand heterogeneity in the job preferences of community-based healthcare workers in Ethiopia and Ghana, and how it can be modelled, with a view to inform policy interventions to improve retention.

Their long-term supply is defined as the number of adequately trained community-based workers who are available to work in a given health system. Since this is mainly driven by system-level factors that are more regulatory in nature, such as other government policies and healthcare budgets, we focus on studying the short-term supply of these workers where these macro-level factors remain fixed. This allows us to focus on the individual decisions made by community-based healthcare workers based in Ethiopia and Ghana, who are already qualified to be in the workforce, about what sorts of roles they want to work in.

1.4. Structure of the Thesis

This is a research paper style thesis and includes published and unpublished work, linked by supporting material.

The thesis has three parts, as shown in Table 1 alongside their submission status. The first part contains the introduction and literature review along with the description of the study setting and an overview of the methods used to address the research questions. Part 2 comprises four research papers, together with linking material connecting them all. The third part discusses the research findings, the strengths and limitations of the methods used, and suggests some policy implications of this work, concluding with the scope for future research.

Table 1: Outline of thesis including chapter submission and publication status

Part	Chapter	Title	Submission Status
Part 1	1	Introduction	Unpublished, for thesis only
	2	Literature review	Unpublished, for thesis only
	3	Study setting	Unpublished, for thesis only
	4	Study objectives and methods	Unpublished, for thesis only
Part 2	5	Research paper 1 - Understanding the importance of non-material factors in retaining community health workers in low-income settings: a qualitative case-study in Ethiopia	Published - *BMJ Open*
	6	Research paper 2 – The stated preferences of community-based volunteers for roles in prevention of violence against women and girls in Ghana: a latent class analysis	Not yet submitted
	7	Research paper 3 – Linking health worker motivation with their stated	Published - *Social Science and Medicine*

		job preferences: a hybrid choice analysis in Ethiopia	
	8	Research paper 4 - Discrete choice analysis of health worker job preferences in Ethiopia: separating attribute non-attendance from taste heterogeneity	Published - *Health Economics*
Part 3	9	Discussion and conclusion	Unpublished, for thesis only

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CHAPTER 2

REVIEW OF LITERATURE

In this chapter I review theoretical and empirical research mostly in labour economics and health economics to situate my research in these fields and to guide my analysis of the job preferences of health workers in LMICs. I begin with an overview of the empirical literature on human resources for health, particularly in sub-Saharan Africa, followed by theoretical literature on the models of labour supply. Then, I summarise literature on the role of non-financial incentives in driving labour market decisions of health workers and the theoretical frameworks behind their motivation for valuing such incentives. I then present literature on the methods used to study health worker preferences in health economics, focussing on discrete choice experiments and their theoretical underpinnings.

2.1. Human resources for health shortages

Human resources for health (HRH) are of critical importance to health systems. There is a positive correlation between the density of healthcare providers in a country and the coverage of important health interventions such as immunization or skilled attendance at delivery, although this evidence remains observational (Anand and Bärnighausen, 2004, Speybroeck et al., 2006, Lagarde and Blaauw, 2009). The severe shortage and marked maldistribution of health workers across the world has been identified as one of the most critical constraints to attaining health and development goals (World Health Organisation, 2022). In the last decade, these shortages have become more acute due to demographic changes and epidemiologic shifts (Crisp and Chen, 2014). It has nearly been two decades since the release of the first global report on HRH, 'Human Resources for Health; Overcoming the Crises', in which WHO acknowledged a global health workforce crisis. It found that nearly all countries were facing health worker shortages, skill mix imbalances, negative work environments and maldistribution of health workers. A threshold of 2.28 healthcare workers per 1,000 people was found to be associated with higher skilled birth attendance, on the basis of which WHO recommended this minimum threshold of health workers to be necessary to achieve the Millennium Development Goals (Chen et al., 2004).

More than 57 countries facing critical shortages in health workers were identified based on the threshold, out of which the majority (63%) were in Sub-Saharan Africa (WHO, 2006). It was estimated that the African workforce would need to be nearly doubled in order to meet this threshold (Chen et al., 2004). At the time, the primary cause of the shortage was believed to be the chronic underproduction of health workers, particularly doctors (WHO, 2008). Thus, early responses in recognition of these findings led many African countries to invest in considerably expanding the production of doctors. Studies show that the majority (76%) of all known medical schools in the region reported higher enrolment of students in 2009 in comparison to 2004 (Mullan et al., 2011). The University of Bamako in Mali, for example, increased its number of medical graduates from 50 per year in 1998 to 350 in 2007 (Van Dormael et al., 2008). Further, 33 new medical schools were established in the region between 2000 and 2009 (Mullan et al., 2011).

These initial country efforts and reports had been driven by the assumption that greater training of doctors would mitigate health worker shortages, leading to increased service provision. These ideas were too simplistic and refuted in the *Global Strategy on Human Resource for Health: Workforce 2030* (WHO, 2016), which recommended alternative policies to improve service provision that address not just the inflows but also the outflows of health workers. These include strategies to reduce the migration of qualified health workers from LMICs, improve productivity and performance of health workers and retain the existing workforce. Additionally, the report shows a renewed focus on task shifting and investment in a diverse skill mix in the health workforce, calling for a greater role to be played by health workers without medical degrees such as community-based health workers with necessary skills to provide large-scale preventative healthcare interventions.

The health economics literature on health worker shortages is further nuanced and acknowledges another important factor: health workers are economic actors with preferences and behaviours, working in national, regional as well as international labour markets. With this in mind, to understand the determinants of health worker labour supply, there has been a move towards consulting theoretical frameworks based on labour economics (Vujicic and Zurn, 2006, Scott, 2001, Scott and Farrar, 2002, McPake et al., 2014, Andalón and Fields, 2011, McPake et al., 2013). These frameworks show that the labour force participation rate of health workers, particularly sectoral participation rate (whether individuals are willing to work in the health sector), depends on, among other things, their individual preferences for the jobs available. Age, gender, and reservation wages[1] are examples of factors based on which job preferences are known to vary among health workers (Vujicic and Zurn, 2006). An overview of the normative models of labour supply that are relevant in building an understanding on some of the determinants of health workers' labour supply, contributing to the theoretical basis of this thesis is given in the next section.

2.2. Models of labour supply

The neoclassical model of labour supply (King, 1990) is set in the context of a perfectly competitive labour market, in which jobs are homogenous and there is perfect information. It assumes that

[1] The lowest wage at which an individual is willing to work.

individuals choose between allocating their time to work and leisure, such that the level of utility attached to an individual is given by:

$$U = (H, L) \quad (1)$$

Where H is the number of hours worked by the individual to be able to consume a certain amount of goods, and is determined by a given wage rate, and L leisure time. In this theoretical framework, the quantity of labour supplied is exclusively determined by financial considerations, including the wage rate (W) and other possible non-labour income of the individual such as the spouse's income. A corollary to the above can be that a worker's utility from working is given by:

$$U_L = (H_L, W_L) \quad (2)$$

Such that $\frac{\partial U}{\partial H} < 0 \; and \; \frac{\partial U}{\partial W} > 0$.

Because of the importance given to wages, this approach assumes that individuals choosing between different job opportunities in the job market simply compare the wages offered in each job and pick the one that offers higher wages. However, a large body of evidence exists contradicting these predictions of labour supply. For example, Adam Smith's theory of compensating wage differentials posits that jobs are not identical and usually differ in the working and living conditions they offer to the workers:

> *"The wages of labour vary with the ease or hardship, the cleanliness or dirtiness, the honourableness or dishonourableness of the employment. Thus in most places, a journeyman tailor earns less than a journeyman weaver. His work is much easier. A journeyman weaver earns less than a journeyman smith, his work is not always easier but it is much cleaner(.. .). The most detestable of all employments, that of public executioner, is, in proportion to the quantity of work done, better paid than any common trade whatever''. Book I, Chapter X, Part one - Inequalities arising from the Nature of the Employments themselves* (Smith, 1776)

Rosen formalized Smith's theory and showed that labour markets tend to ensure that the net advantage from jobs is equalised, such that the wages proposed by a job depend on job characteristics that are desirable (Y) and undesirable (X) (Rosen, 1986, Rosen, 1974):

$$W = f(Y, Z) \;\; (3)$$

The theory of compensating wage differentials, thus, says $\frac{\partial w}{\partial Z} > 0 \; and \frac{\partial w}{\partial Y} < 0$, suggesting that higher wages can be expected from jobs with poor working conditions and lower wages from jobs where the conditions are good. The compensating wage differential approach departs from the earlier approach by suggesting that workers do not only consider salaries when making labour market choices, but other job characteristics as well. Stated formally, the utility derived from working can now be modelled as:

$$U_L = (W_L, H_L, Y_L, X_L). \quad (4)$$

It is normally assumed that the marginal utility attached to wage and other pleasant working conditions is positive, while the marginal utility of effort and unpleasant working conditions is negative. While this framework is more holistic, including factors other than wages in a worker's utility function, it still puts significant emphasis on financial remuneration by assuming that wages can adequately reflect variations in working conditions i.e., wages will rise as working conditions become more unpleasant, and decrease as they improve. However, there is imperfect information on working conditions and often restricted wages in the public sector in the health labour market, especially in LMICs (Lagarde and Cairns, 2012, Lagarde and Blaauw, 2014). The actual wage offered does not always reflect the equilibrium wage that workers should be getting paid based on their working conditions, or the health worker's willingness to be compensated for the negative working conditions. Further, while financial incentives such as wages are known to influence health worker preferences and decisions about which jobs to consider (WHO, 2000, Zurn et al., 2011), it has long been recognised that health workers do not only care about earnings and consumption and that non-financial factors, such as patient health outcomes, also factor in the utility function of their jobs (Ellis and McGuire, 1990). The existence of non-pecuniary motivations which can be affected by non-wage incentives is thus key when seeking to understand the determinants of the labour market choices of health workers. The following section reviews literature on non-wage incentives, followed by literature on health workers' non-pecuniary motivation.

2.3. Non-wage job incentives

Health worker incentives, defined as a form of remuneration which is intended to achieve some specific change in behaviour (WHO, 2000), can generally be categorised into financial and non-financial, and combined into a package for the workers (Mandeville et al., 2016a). Due to the limited fiscal capacity, among other factors, many sub-Saharan African countries have turned to using non-financial incentives, defined as those which hold little or no monetary value compared to the direct or indirect monetary transfer of financial contributions (Mathauer and Imhoff, 2006). These incentives are normally combined with wages and/or other financial incentives leading to a broader definition of the "compensation" offered by employers in a labour market (McPake et al., 2013). Examples include better supervision and management, availability of good work infrastructure, clear career progression, and opportunities for training. Although such incentives have low monetary value for an individual health worker, there is growing awareness across the social sciences that they can be equally, if not more, important in motivating (Gopalan et al., 2012, Chin-Quee et al., 2016, Bhattacharyya et al., 2001), retaining (Madede et al., 2017, Rockers and Bärnighausen, 2013) and improving health worker performance (Sayinzoga and Bijlmakers, 2016, Madede et al., 2017). There is also growing literature in behavioural economics that deals with the motivations behind individual decision processes for non-wage job incentives, and borrows many concepts from psychology (Fehr and Falk, 2002, Rebitzer and Taylor, 2011, Rockers et al., 2012, Lagarde et al., 2012, Lagarde et al., 2015, Lagarde and Blaauw, 2009, Saran et al., 2020, Quaife et al., 2021). The next section reviews some of these concepts.

2.4. Health worker motivation for non-wage job incentives

Literature in behavioural economics recognizes the importance of sources of motivation other than income, and concepts from psychology have been used to provide more insight into economic models estimating the utility function of workers. Pro-social and intrinsic motivation are often terms used to understand the other, non-pecuniary aspects of work, jobs and roles that matter in explaining economic behaviour (Fehr and Camerer, 2007, Fehr and Falk, 2002, Frey and Jegen, 2001, Frey, 1997). Evidence of this goes back to 1759, where Adam Smith in his Theory of Moral Sentiments mentions other-regarding behaviour:

> *"And hence it is, that to feel much for others and little for ourselves, that to restrain our selfish, and to indulge our benevolent affections, constitutes the perfection of human nature; and can alone produce among mankind that harmony of sentiments and passions in which consists their whole grace and propriety." - (Smith, 1759)*

Deci and Ryan in their seminal theory on self-determination describe an approach to human motivation and personality, where they define intrinsic motivation as motivation that is driven by the task itself, resulting from the human tendency to seek out novelty and challenges, to exercise and extend one's capacities, to explore and to learn. The opposite of this is extrinsic motivation, which tends to be driven by external rewards (Ryan and Deci, 2000). Similar to intrinsic motivation, Benabou and Tirole describe actions that are defined as beneficial to other people, despite costs for the self as 'pro-social' (Bénabou and Tirole, 2006).

This literature aligns well with the literature in health economics about health workers deriving utility from not just income but also, for example, patients' health status (Ellis and McGuire, 1990) and gained importance in the 1970s and 1980s in the context of the theory of supplier-induced demand and the principal–agent relationship, explaining the differing motivations of doctors and patients (McPake et al., 2014). Other non-pecuniary attributes such as the availability of training opportunities and better career progression have also been proposed to exist in health workers' utility function (Scott and Farrar, 2002, Lagarde et al., 2015, Mandeville et al., 2014). It has been assumed that health workers with a relatively low marginal utility of net income attach a higher marginal utility to other aspects of work, including intrinsic features of medical practice, altruism, and improving patients' health (Banuri et al., 2018). A qualitative study using in-depth interviews, for example, was done with nurses and doctors in Benin and Kenya aiming to assess the role of non-financial incentives in influencing motivation (Mathauer and Imhoff, 2006). Health workers in both countries recognized that they were frequently demotivated and frustrated, and identified the roots of these problems as an inability to meet their professional goals given features of their environment that make that difficult. The relative importance of these factors will thus likely influence the response to incentives and therefore the design of remuneration packages for different health worker cadres. An understanding of health worker preferences for job incentives is thus important.

2.5. Methods to study preferences

Health economists have used a range of methods for analysing the preferences of health workers and why they behave the way they do. A simple methodology is the use of cross-sectional survey tools that can measure outcomes such as work motivation, job satisfaction, intention to leave, to investigate job characteristics that are correlated with those measures (Hayes et al., 2006, Coomber and Barriball, 2007). While a range of factors that influence the job choice of health workers have been identified by such studies, including personal work ethic, working conditions, remuneration, career opportunities, these data provide weak evidence on the relative importance of individual factors (Lagarde and Blaauw, 2009).

A second approach is to use longitudinal datasets, often available in high income countries, to undertake econometric analysis of the determinants of labour market decisions made by health workers during their careers. Information gathered from observing real-life behaviour is categorised as revealed preference data. While revealed preference data is useful in the analysis of the relative importance of different job characteristics that can shape the preferences of health workers, and thus inform human resource policy interventions, such longitudinal data on health personal in LMICs are hardly ever available (Lagarde and Blaauw, 2009).

A third approach which involves the use of the 'stated preferences methods' has become more popular in health economics. The two key methods which could be used in this context are contingent valuation and discrete choice experiments. Contingent valuation (CV) requires asking respondents for their willingness to pay, or willingness to accept given conditions (Klose, 1999). It normally uses open-ended questions or categorical questions, both of which inquire about the amount a respondent maybe willing to pay for a good or service in a straightforward manner, although dichotomous choice tasks or bidding games have also been used (Champ et al., 2003). CV is most widely applied in transport and environmental economics though some studies in health related contexts also exist (Klose, 1999). However, a large body of evidence suggests that hypothetical bias in CV can lead to a substantial overstatement of willingness to pay values (Harris et al., 1989). Importantly for this thesis, CV may not be the right tool for measuring the preferences of health workers where the utility of jobs is substantially driven by non-pecuniary incentives.

Discrete choice experiments (DCEs) are by far the most popular stated preference elicitation method in health economics literature (de Bekker-Grob, 2009, Ryan et al., 2001) and well suited to examine health worker job preferences and also to explore sources of preference heterogeneity. This is a quantitative method used to evaluate the importance of different attributes or characteristics of a given good or service that can influence the choice behaviour of an individual.

Kelvin Lancaster's seminal work (Lancaster, 1966) challenged the neoclassical economic theory of consumer demand which was based on the assumption that goods are non-devisable, intrinsically valuable and that consumers gain utility from the consumption of goods as a whole. Lancaster suggested an extension to the neoclassical theory by arguing that the utility attached to goods is a sum of the utility derived from the individual characteristics of a good, i.e. it is the characteristics of a good that gives rise to utility, not the good *per se*. By doing so, Lancaster's theory allowed economists to explore trade-offs made by consumers between goods that have different combinations of characteristics, as characteristics can be shared by more than one good. For example, two different bikes can have the same price but different colours, brand, and performance, which would imply that a consumer's choice between equally priced bikes is based on the utility derived from other non-price characteristics. Additionally, if an analyst can estimate the shadow price or the value consumers attach to certain characteristics of goods, it is possible to predict the demand for new goods with similar characteristics before they are even released in the market.

Similar to any other good or service that can provide utility, healthcare jobs can be characterised in terms of multiple attributes, and healthcare workers positioned as making choices among different jobs that have utility attached to them. DCEs can be used to model the effects of policy interventions in the absence of actual data so that policy initiatives can be tailored to the job preferences of health workers for their improved retention (Lagarde and Blaauw, 2009).

Further, the analysis of DCE is based on Lancaster's consumer theory (Lancaster, 1966) and allows the modelling of demand using disaggregate level data, meaning that they are normally applied to data where each data point represents an individual choice situation, and the sum of the choices combine to produce information about the overall demand (Hensher et al., 2005). A detailed description of the analytic framework of DCEs is given below.

2.6. DCE: analytical approach

In DCEs, respondents are asked to choose between hypothetical alternatives of goods or services, in which each alternative of the good or service is described by a set of characteristics or "attributes". The attributes chosen to characterise a good or service (or a health worker's job in this instance) are chosen carefully based on study objectives and formative research (Mangham et al., 2009, Coast et al., 2012).

Methods used to obtain attributes in a DCE include: literature review, professional recommendations, theoretical arguments from the literature, existing outcome measures, qualitative focus groups and interviews, key informant interviews, and patient surveys. It is, however, highly recommended by experts in the field that qualitative work, using focus group discussions and key informant interviews, is conducted during attribute development (Coast, 1999, Coast et al., 2012). In the final experiment, respondents are shown multiple scenarios comprising of the same attributes with different levels, many times, to create a panel dataset for each respondent making it possible to infer how different individuals trade off between different attributes.

DCEs are analysed using the standard random utility framework proposed by McFadden (McFadden, 1974) which assumes that individuals choose alternatives which offer them the highest benefit or utility. In the case of a choice between two jobs, j and k, this can be given by the following equation:

$$prob\left[Y_j = 1 \mid X_i\right] = prob\ [U_j > U_k] \quad (5)$$

where Y_j is the choice variable that equals 1 when job A is chosen by individual i and U_j and U_k represent the utility derived from jobs j and k, respectively. Further, the utility of a job alternative j, at time situation t, can be partitioned into two separate components – observed or the modelled component, V_{ijt}, and an unobserved or un-modelled component ε_{ijt} such that,

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} \quad (6)$$

Where V_{ijt} , the observed component of the utility, can further be given by:

$$V_{ijt} = f\left(x_{ijtm}, \beta\right) \quad (7)$$

Where x_{ijtm} is a vector of k attributes describing alternative j and β is the vector of parameters to be estimated.

Using this general framework, DCE analysis can use different regression techniques to model respondents' choices as a function of the scenario attributes. The most commonly used regression techniques include multinomial-logit models (MNL), or probit or conditional logit models (de Bekker-Grob et al., 2012, Ryan, 2004). While studies have traditionally focussed on estimating the preferences of a sample assuming that they are homogenous, within a given population preferences may in fact be heterogenous. Typically, preference heterogeneity means that different individuals can exhibit different preferences, leading them to make different decisions in the same choice situations (Vass et al., 2022, Hess et al., 2021). Interest in accounting for preference heterogeneity has increased in choice modelling literature over recent years (Soekhai et al., 2019) and more advanced models that provide better behavioural fit by accounting for random heterogeneity in preferences of respondents are increasingly being used (Quaife et al., 2018, Mandeville et al., 2016b, Saran et al., 2020, Soekhai et al., 2019).

Accounting for preference heterogeneity in DCEs

A recent online survey of health researchers and systematic review of studies exploring the analytical methods used to account for preference heterogeneity in DCEs showed that most sampled health preference researchers (86%) agreed that accounting for preference heterogeneity enables a richer interpretation of the data, and the majority (63%) agreed that not explicitly accounting for it during analysis can lead to bias in preference elicitation (Vass et al., 2022). In DCEs, differences among decision makers in the utilities are often explained by focusing on deterministic (or observed) heterogeneity, e.g. though interactions with observable characteristics such as sex, age in an MNL. However, all decision makers of that particular stratum are assumed to have the same preferences, not uncovering all possible sources of preference variations (Hensher et al., 2005). This remaining preference heterogeneity which cannot be explained by observable correlates, could be due to latent factors that may be difficult to measure, or to complex relationships between observable characteristics that are not well understood. Methods to account for random heterogeneity are thus more widely being used in healthcare (Mandeville et al., 2016b, Soekhai et al., 2019, Hess et al., 2021, Lancsar et al., 2017, Kløjgaard and Hess, 2014). These models allow the parameter estimates to be drawn from some underlying distribution, which can be continuous or discrete in nature. Just more than half of the studies in the above mentioned systematic review reported using a mixed logit with continuous distributions (51%) and almost a third conducted latent class analysis (32%), specifying a discrete distribution of parameters (Vass et al., 2022). Moreover, an increasing number of studies across different fields are using a new class of choice models known as hybrid choice models or integrated choice and latent variable models that incorporate the role of attitudes and motivations in decision making, which can also be responsible for variation in preferences (Santos et al., 2011, Kim et al., 2014, Ben-Akiva et al., 2002, Buckell et al., 2021, Kløjgaard and Hess, 2014).

Further, the analysis of DCEs by default posits that when faced with choice situations individuals deem all attributes and alternatives to be relevant to them and use a compensatory decision rule to arrive at a choice (Hensher and Rose, 2009). However, there is now sufficient literature in behavioral research that demonstrates that individuals make use of heuristics and information processing strategies to simplify preference construction and make their choices (Collins, 2012, Hensher et al., 2005). Multiple decision strategies and heuristics that can be employed by respondents have been identified by economists (Payne et al., 1988). In health economics literature, analysts have focused on investigating heuristics that violate the axiom of continuous preferences – meaning that respondents take into account all available information, and trade-off between all presented attributes, before making their choices (Lagarde, 2013). The majority of this work in health economics has focused on detecting a particular form of discontinuous preferences: the existence of dominant preferences to see if respondents systematically choose the alternative with the best level of a particular attribute in DCEs (Scott and Farrar, 2002, Ryan and Farrar, 2000, McIntosh, 2006). Most of these studies have found that a large proportion of respondents do in fact have dominant preferences. Failing to account for dominant preferences in the analysis of DCEs could result in biased results and thus flawed policy recommendations.

The identification of dominant preferences only provides partial understanding of respondent's discontinuous preferences, as they could be 'trading off' only a subset of attributes and levels, ignoring different combinations of the remaining attributes. This information processing strategy is referred to as attribute non attendance (ANA) and is in direct violation of the assumption of continuity of respondent's preferences. Failing to account for ANA may lead to biased coefficient estimates and a skewed understanding of respondent preferences (Heidenreich et al., 2018, Hole et al., 2013). However, assuming that the respondent's choice to not consider all attributes is always non-attendance, when it could reflect heterogeneity in preferences, can also result in the wrong cost-benefit ratios and distorted welfare estimates. The following sections of this thesis describe this research undertaken in detail, starting with a description of the study setting.

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CHAPTER 3

STUDY SETTING

This research took place in two sub-Saharan African countries: Ethiopia and Ghana. A detailed country profile, along with descriptions of specific health worker programs studied in both countries are given below.

3.1. Country profile: Ethiopia

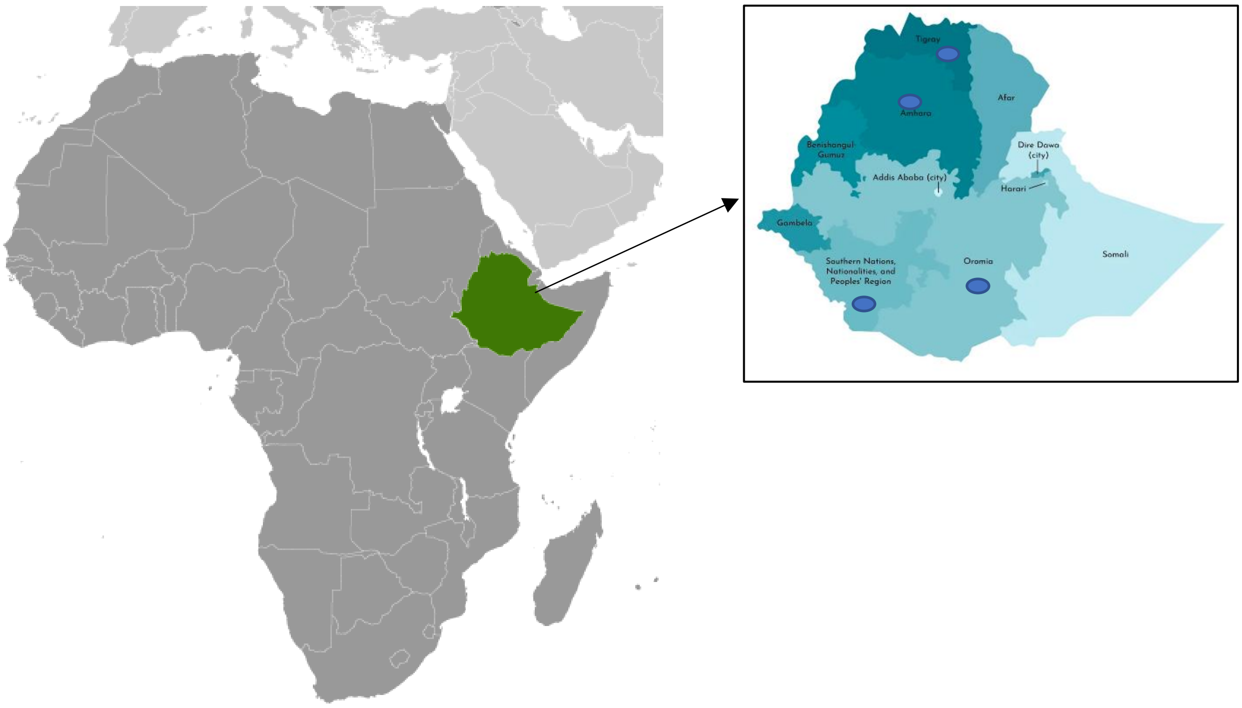

Figure 1 Left : Boundary of Ethiopia in the map of Africa. Source greenminigrid.afdb.org. Right: map showing the 11 regions in Ethiopia with the four study regions; Tigray, Oromia, SNNPR and Amhara, marked with purple circles.

Source: istockphoto.com

Ethiopia is a landlocked country in the horn of Africa, located to the East of the continent (Figure 1). It borders Djibouti, Eritrea, Kenya, Somalia, South Sudan, Sudan, and Somaliland. With a population of close to 115 million, Ethiopia is the second-most populous country in Africa (World Bank, World Bank, 2017). The vast majority of its population (>80%) lives in rural areas (Wang et al., 2016). Ethiopia ranks 173 out of 189 countries on the human development index, a summary measure of three dimensions: length of healthy life, access to knowledge, and a decent standard of living (UNDP, 2021).

The country is divided into eleven regions and two city administrations, where more than 80 ethnic groups with very diverse cultural backgrounds and languages reside. In every region, districts or *woredas* are administrative units, managed by decentralised councils of elected members. The lowest unit of administration is a *Got* or village.

The health extension program

Development of frontline and middle-level health professionals has been one of the eight priorities of Ethiopia's health policy since 1993 and a key component of successive health sector development programmes since then (Abebe Alebachew, 2015). The health sector development programme provides situational assessments of the health sector and decides on upcoming priorities for healthcare delivery in the country, every 20 years. Despite these early reforms, in 2006, when WHO identified a health workforce threshold of 2.3 per 1000 population to achieve high coverage of healthcare with essential interventions, Ethiopia only had 0.3 doctors, nurses and midwives per 1000 population (WHO, 2006, Yigzaw et al., 2015). One study estimated that Ethiopia would have needed to devote close to 53% of its GDP to health in order to reach WHO's target of health workers, if it was to include only doctors, nurses and midwives (Yigzaw et al., 2015).

In 2003, the government of Ethiopia launched the Health Extension Program (HEP) – a flagship primary healthcare delivery program implemented to improve health outcomes in the country, particularly by increasing the number of health workers who can equitably deliver healthcare to all regions, and improve healthcare access for mothers, children and families. Focus was accorded towards the delivery of 16 essential healthcare packages, targeted at rural communities, under four major programmatic areas: disease prevention and control; maternal and child health services; hygiene and environmental sanitation; and health education and communication (Wang et al., 2016). The full list of HEP interventions is provided in Table 2.

Table 1: List of Health Extension Program interventions. Source: Federal Ministry of Health, Ethiopia

Disease Prevention and Control of	**Hygiene and Environment Sanitation**
• HIV/AIDS and other sexually transmitted infections • Tuberculosis • Malaria • First-aid emergency measures • Family health	• Excretion disposal • Solid and liquid waste disposal • Water supply and safety measures • Food hygiene and safety measures • Healthy home environment • Personal hygiene • Rodent control
Maternal and child health	**Health Education and Communication**

• Family planning • Immunization • Nutrition • Adolescent reproductive health	Contains cross cutting themes across all interventions

Since the roll out of the program, the country has since trained and deployed a workforce of close to 40,000 community health workers called health extension workers (HEWs), who are salaried, full-time civil servants tasked to transfer knowledge and skills to families they serve so that households can have better control over their own primary health (The Federal Democratic Republic of Ethiopia Ministry of Health, 2015). These workers are mostly women, recruited on the basis of a nationally consistent set of criteria, which includes being resident in the village from where they are hired, having knowledge of the local languages, and being a high school graduate. All selected HEWs go through a year-long training, which includes practical training at health centres (World Bank, 2012). Two HEWs are then paired to serve 3,000 to 5,000 people in a district, based at health posts, where much of their time is devoted to home visits and outreach activities. The health extension program is mainly financed by the government and a comparison of the payroll bill for HEWs with the overall government health expenditure shows that their salaries account for 21 percent of the recurrent health expenditure (Wang et al., 2016). This reform has resulted in a major increase in human resources for health; with the inclusion of HEWs, Ethiopia had 1.1 health workers per 1000 population in 2011 (Abebe Alebachew, 2015).

While strong emphasis has been given to deploying HEWs in large numbers to improve the delivery of primary healthcare, not much focus has been accorded on their retention. According to a nationally representative study estimating the extent of HEW attrition over the lifespan of the health extension program, their cumulative attrition was estimated to be close to 21% since the start of the program, which is substantial in comparison to other similar country contexts (Tekle et al., 2022, Walt et al., 1989, Emukah et al., 2008). To better address issues around retention, it is crucial to develop policy interventions that can adequately incentivise them. There is therefore need to further investigate the job attributes that can positively affect the job-satisfaction of HEWs.

3.2. Country profile: Ghana

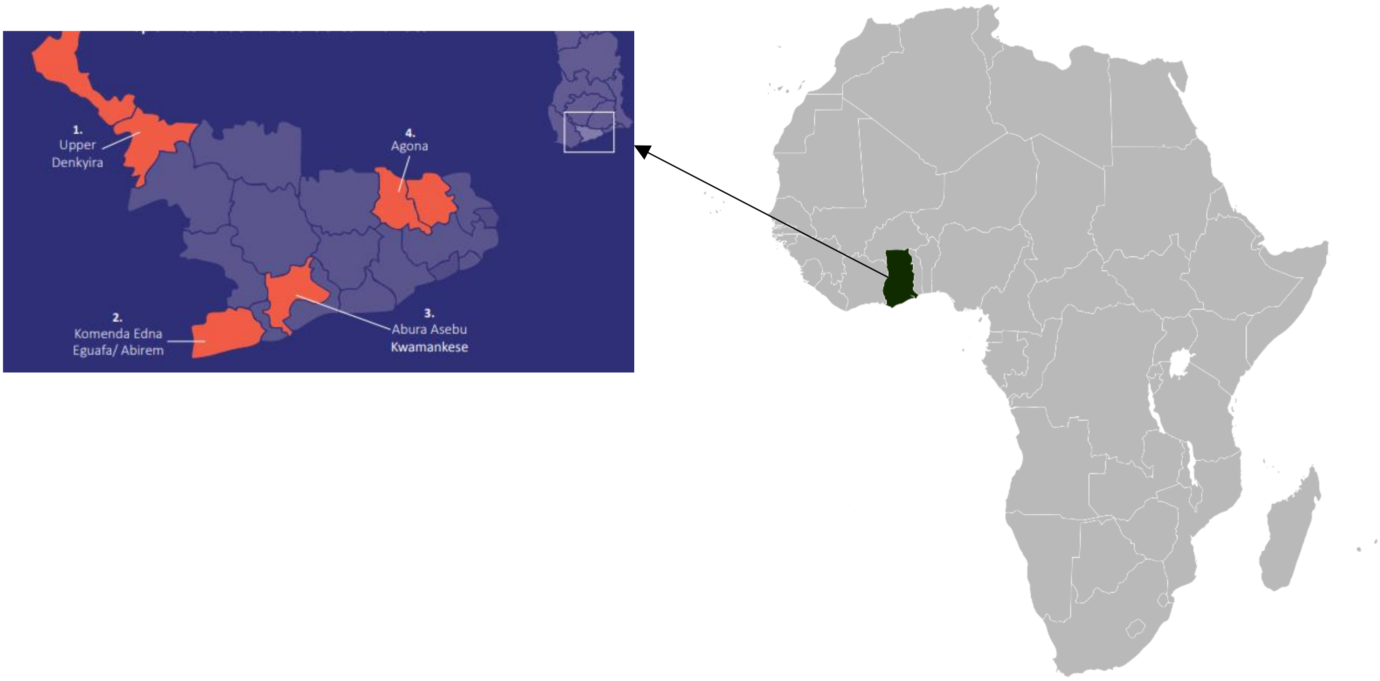

Figure 2: Right: Regional boundary of Ghana in the map of Africa. Source: Shutterstock.com. Left: The four study regions: upper denkiyra, Agona, Abirem, Abura Asebu Kwamenkese, of Ghana

Source: What Works, Ghana

Geographically, Ghana is located in West Africa, bordering Togo, Cote d'Ivoire and Burkina Faso. It is home to close to 30 million people (World Bank, 2022). Although Ghana is a relatively small country in terms of its area and population, due to its natural wealth it is one of the leading economies in the continent. There are about 50 different ethnic groups in Ghana, each with their own customs and languages (World Bank, 2022).

The rural response system (RRS)

Globally, one in three women face physical or sexual violence at least once in their lifetime (World Health Organisation 2021). In Ghana, the prevalence of violence against women and girls is even higher with prevalence recorded at 45% by UN women and other studies, and incidence of 28% of one or more type of violence experienced in the past 12 months (UKaid, 2018, Asante and Premo-Minkah, 2016). Further, there is now global evidence that community-led interventions led by local actors are crucial in challenging patriarchal attitudes that can underpin VAWG. In response to this background, the community-based action teams (COMBAT) programme was started in 2002 by the Gender Studies and Human Rights Documentation Centre (henceforth Gender Centre) in Ghana, to give the community some ownership of violence prevention activities, build trust and address context specific needs of the people so that violence prevention activities can be more sustainable and targeted. The COMBAT program developed a rural response system (RRS) to mobilise community members, state agencies and other key actors to respond to and prevent VAWG in rural communities in Ghana. It was first piloted in only three communities and then later scaled up to 15 communities in three years, to the Eastern region, Ashanti Upper East and Upper West regions of the country between 2005-2008. The three main aims of the COMBAT program are: A) to mobilise people about the causes and consequences of VAWG and women's rights that can change harmful social norms and practices that perpetuate violence; B) respond to violence within communities by coordinating efforts of community members, state agencies, and other key actors; and C) create referral systems for the survivors of violence so they can access support services. The key vehicles of delivery for this program are community based action teams or COMBATS.

Community-based action teams (COMBATs)

The intervention uses a community response model and is responsible for the recruitment and training of COMBATs who undertake sensitisation activities to mobilise the community about the ill effects of VAWG, provide individual counselling to people affected by VAWG, and liaise with state agencies and carry out referrals where necessary. COMBATs comprise male and female volunteers, are nominated by local communities and their leaders, and are trained and supervised by the Gender Centre (The Prevention Collaborative, 2020). They are paid a small per-diem during training, however once the training is complete, COMBATs work as unpaid volunteers. They are reimbursed for costs incurred during intervention activities, such as transportation costs during sensitization visits, but don't receive regular payment for their work. Staff at the Gender Centre provide technical support and supervision, however, this can often be irregular. There are no known studies on the extent of attrition among this cadre, however, focussing on the retention of these volunteers is important for sustained delivery of interventions on the prevention of violence against women and girls in Ghana.

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CHAPTER 4

STUDY OBJECTIVES, CONCEPTUAL FRAMEWORK, AND METHODS

4.1. AIM AND OBJECTIVES

The overall aim of this thesis is to investigate the job preferences of community-based healthcare workers in the public sector in sub-Saharan Africa, to understand heterogeneity in their preferences and how it can be modelled, with a view to inform policy interventions for improving retention. There are three main objectives of this thesis:

Objective 1: To understand the importance of financial and non-financial incentives in retaining community-based healthcare workers in their jobs

Objective 2: To explore sources of heterogeneity in the preferences for job characteristics of community-based healthcare workers

- Studying the role of individual characteristics in understanding the job preferences of community health volunteers in Ghana
- Defining differences in motivation as a source of heterogeneity in the preferences of community health workers in Ethiopia

Objective 3: To extend the existing methods of choice modelling to distinguish the heterogenous preferences of community-based healthcare workers from decision making heuristics

Four research papers make up the results section of this thesis. Paper one addresses objective one; papers two and three address objective two; and finally objective three is addressed by paper four. A summary of the research questions addressed in each research paper along with the research papers forms Part 2 of this thesis.

4.2. THESIS CONCEPTUAL FRAMEWORK

"When we think about how people work, the naive intuition we have is that people are like rats in a maze. We really have this incredibly simplistic view of why people work and how the labour market looks like…." (Ariely, 2012)

The conceptual framework of this thesis draws primarily on the models of labour supply, presented in the review of literature in Chapter 2. It is worth noting that this thesis only considers the short-term labour supply of community-based healthcare workers, driven by their individual decisions around job choices. It excludes the larger determinants of their supply, for example, the demand for these health professionals. Further, this framework only considers individuals who are eligible and have chosen to participate in the public health sector and are choosing between jobs.

Figure 1 illustrates the two main questions raised by this PhD around the determinants of labour supply of community-based healthcare workers:

1. Which wage and non-wage factors drive the labour market decisions of community-based healthcare workers?
2. Which individual characteristics are associated with heterogeneity in their job preferences, and how can this be modelled?

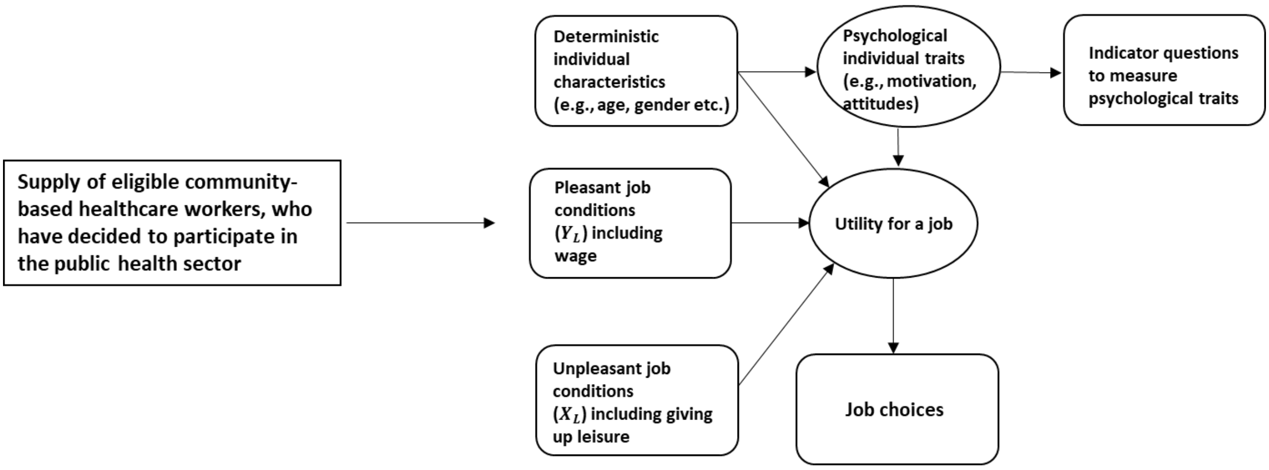

Figure 1: Thesis conceptual framework

The constructs in oval boxes are unobservable characteristics which include the utility attached to a job and psychological traits such as attitudes and motivations. The characteristics in rectangular boxes are assumed to be observed such as the respondent's deterministic characteristics, the different wage and non-wage job characteristics which can be pleasant or unpleasant, as well as their job choices. Psychological traits are not easily observed and are usually measured using indicator questions about the traits. Linking the two is not straight forward and requires specific econometric treatment which is described in detail in Chapter 7.

This section synthesised some of the key ideas included in the previous chapters to present a conceptual framework that can explain the drivers of the labour market decisions of community-based healthcare workers in sub-Saharan Africa. Importantly, it shows that non-wage incentives also add to the utility for a job and illustrates how potential sources of heterogeneity can be linked to the job preferences of community-based healthcare workers.

4.3 OVERVIEW OF METHODS USED IN THIS THESIS

This section presents a summary of the methods used to address my research objectives, listed at the beginning of this chapter. While each research paper provides details on the methodology used to answer the specific research questions, here I give a brief overview of the methods used, followed by a description of the datasets from Ethiopia and Ghana. Finally, I provide a broad summary of the strategy used to analyse the different data sources.

4.3.1 Methods used

Semi-structured interviews

The interview is the most widely used method to produce data in qualitative health research (Green and Thorogood, 2018). As a technique, interviews can be described as conversations with research subjects directed by the researcher's need for certain data. They can be *structured,* which requires the data to be collected quite tightly following a specified set of questions, in a specific order, for each respondent to generate comparable responses from each respondent. At the other end of this spectrum, interviews can also be *informal* which are like natural conversations in which data are gathered more or less opportunistically. While qualitative researchers are increasingly advocating for the use of informal interviews to produce more naturalistic data, some suggest that these types of interviews can have challenges around trying to remember and faithfully document long exchanges of conversation which can lead to mis-remembering important data (Swain and King, 2022). The most commonly used types of interviews in qualitative research, however, are *semi-structured*, *narrative* or *in-depth* interviews which are guided by a pre-determined set of topics to be covered in the interview but provide leeway to the researcher to formulate questions on the topic based on the respondents' answers, rather than following a list of pre-set questions (Green and Thorogood, 2018). For Paper 1, to understand which financial and non-financial job incentives are most valued by HEWs and how these can affect their labour market choices, I used semi-structured interviews. This method allowed me to guide the topics covered, while also letting the responses from the interviews inform the emerging topics of enquiry and the relative importance of each of them.

Discrete choice analysis

As mentioned in the literature review in Chapter 2, DCEs are the most popular method of stated preference elicitation in recent health economics literature (de Bekker-Grob et al., 2012, Ryan and Gerard, 2003). They require respondents to pick one of two or more alternatives, described by a set of chosen characteristics. Respondents are presented with multiple choice tasks and this panel dataset is used to analyze choices made, to estimate preferences for these characteristics, as given by a particular utility function (Hensher et al., 2005). Estimates are then used to analyze how different respondents trade off between different characteristics. To analyse job preferences and to explore sources of heterogeneity in these preferences for COMBATs in Ghana (Paper 2) and HEWs in Ethiopia (Papers 3 and 4), I used stated preference methods, particularly DCEs.

4.3.2 Description of the data used

Qualitative data from Ethiopia

For paper 1, I collected qualitative data from three key populations: active HEWs, those who had left HEW positions, and key informants. Key informants included HEW supervisors, senior officials at district health offices, HEW experts at district levels, HEW coordinators at regional levels and a senior official at the HEP directorate, Federal Ministry of Health. Table 1 gives a description of the study sample. Separate topic guides were drafted for each study population, informed by literature on factors affecting the motivation and labour choices of community health workers in LMICs, and a theoretical framework selected *a-priori.* The main topics covered in the interviews included reasons for choosing their jobs, motivating factors and challenges faced in their roles, as well as preferences towards job attributes. Leavers of HEW positions were additionally asked about their reasons for leaving. Topic guides were pre-tested and piloted with 5 HEWs, not included in the final sample. Semi-structured interviews were conducted with the study population in four districts: Raya Azebo and Saharti Samra districts in the Tigray region, and Dilla Zuria and Silte in the Southern Nations Nationalities and People's Region (SNNPR), between May and July 2019. The two regions, Tigray and SNNPR, were purposively sampled to capture variations in working conditions and perspectives among HEWs as historically, Tigray had been a region with better health indicators in comparison to SNNPR. Respondents were located in a mix of urban and rural contexts in both regions. Research assistants with experience in qualitative research, trained by me on the topic guides, were hired by Addis Ababa University to interview respondents until saturation was attained in the themes emerging from interview data. A total of 47 semi-structured interviews were conducted. The mean age of respondents across all three study groups was 31 years, ranging from 24 to 40 for leavers, 20 to 49 for HEWs and 26 to 48 for the key informants. The mean time worked in the health system was 6 years for HEWs, ranging between 1 and 13 years and 7 years for key informants, with a range of 0.5 to 8 years. Leavers had spent on average 6 years in their jobs, ranging between 1 and 9 years.

Table 1: Description of the study sample for qualitative interviews

Study population	Active HEWs	Leavers of HEW positions	Key informants
Sample size	16 (8 per region)	20 (10 per region)	11 (5 per region, plus one from Federal Ministry of Health)
Gender	All female	All female	3 female, 8 male
Purpose of inquiry	To capture their perspective on factors affecting HEW motivation and labour choices	To understand factors influencing their decisions to leave	To capture the perspective of key stakeholders and identify policy levers that could be modified to improve HEW retention
Sampling technique	Maximum variation sampling - for diversity of age, geographical location and years of experience	Snowball sampling	Purposive sampling, with variation in administrative levels, seniority and level of engagement with HEWs

DCE data on COMBAT job preferences from Ghana

For paper 2, I collaborated with researchers from the *What Works* (What Works, 2022) project at LSHTM, who gave me access to DCE data on the role preferences of COMBAT volunteers in Ghana. I was not involved in the collection of this data. *What Works* is a multi-country study generating evidence on interventions to prevent violence against women and girls in low-and middle-income countries, funded by UKAID. As part of this project in Ghana, an intervention was implemented in two districts – KEEA and Agona - in the Central region in 2018, alongside a cluster randomised controlled trial to assess the effectiveness and cost-effectiveness of the RSS/COMBAT program, (Torres-Rueda et al., 2020, Ogum Alangea et al., 2020) which is described in detail in Chapter 3.

To identify potential attributes and levels for the DCE, the research team critically appraised the peer-reviewed literature on financial and non-financial incentives that have been offered to community health workers and volunteers by governments in sub-Saharan Africa. A focus group discussion (FGD) topic guide was then developed, with probes exploring the most commonly offered incentives obtained from the literature review, to capture DCE attributes along with the possible levels for these attributes. Two FGDs (n=8 and n=5) were carried out in June 2018 with a total of 13 COMBAT volunteers in the Brong-Ahafo region in Ghana. The discussion was recorded and transcribed in one group, and detailed notes were taken in the other. FGD transcripts and notes were thematically coded and analysed, identifying several themes. The final DCE represents these themes using five attributes with three levels each. The attributes were: financial remuneration (per diem) offered for each sensitization activity, frequency of sensitization activities undertaken per month, reimbursement of transportation expenses incurred during volunteering, training type offered per year, and the frequency of supervision visits made by the management team per year. These attributes are shown in Table 3 along with their levels. More information on the development and design of the DCE is given in Paper 2.

Table 2: List of final attributes and levels used in the DCE

Attribute	Levels
Financial remuneration (per diem) per sensitization activity	1. 0 Cedis 2. 10 Cedis 3. 20 Cedis
Frequency of volunteering activities undertaken per month	1.1 2. 4 3. 8
Reimbursement of transportation expenses incurred during volunteering	1. No reimbursement 2. Half reimbursement (50%) 3. Full reimbursement (100%)
Trainings offered per year	1.No training offered 2.Training on volunteering offered 3. Professional training offered
Frequency of supervision visits per year	1. No supervision offered 2. Supervision every 3 months 3. Supervision every 6 months

Note: 1 Ghanaian Cedi = USD 0.16 (As on 23rd February, 2022)

DCE data on HEW job preferences from Ethiopia

For Papers 3 and 4, I collaborated with researchers at the IDEAs project at LSHTM (IDEAS, 2021), who gave me access to DCE data on HEWs from Ethiopia. I was not involved in the collection of this data. The DCE was included in the endline data collection of a survey conducted as part of a process evaluation of a quality improvement (QI) program implemented by IDEAS and the Federal ministry of health in Ethiopia in 2018. Data were sampled from four out of the nine Ethiopian regions for the QI study. Using a random number generator, research assistants randomly selected one QI programme woreda per region from Oromia, Amhara, Southern Nations, Nationalities, and Peoples' Region (SNNPR) and Tigray. An additional randomly selected district was added in Amhara since the first randomly selected district had too few health facilities to reach the sample size. Two additional districts were purposively sampled from Oromia and SNNPR (Bunno Bedelle and Chencha, respectively) where other evaluative work was also taking place. For each of the seven QI programme districts chosen for data collection, one matched district was chosen from the same region which was not subject to QI activities, resulting in 14 districts in total. The districts were matched using service utilization data from the last three Ethiopian Demographic Surveys (2005, 2011, 2016) (USAID, 2022).

In each district, 30 participants across a range of health worker and management cadres were interviewed, where the latter included facility heads alongside district and regional health office managers. Senior non-patient-facing staff in each woreda were not randomly sampled due to their small number, but staff at primary hospitals, health centres and health posts were randomly sampled. The heads or clinical directors of each district (one), primary hospital (one) and health centre (three) were interviewed. Four maternal and child health clinical care workers and two from each health centre were interviewed in the hospital. One HEW was interviewed from each health post under each health centre.

The endline survey was conducted in June 2019 with a cadre stratified sample of 404 health workers including 202 HEWs (50%); 40 non patient facing staff (10%), and 162 mid-level healthcare providers (40%). A team of seven trained research assistants from the authors' institute implemented a face-to-face survey administered in English, Amharic and Oromifa languages using Open Data Kit (https://opendatakit.org) software on tablet computers. Informed consent was obtained from all participants before data were collected.

The DCE had 6 attributes identified after a thorough review of literature on health workforce choice experiments done in the East African context (Blaauw et al., 2013, Mandeville et al., 2016, Rockers et al., 2012). Ten potential attributes were selected and then short listed to 6, based on discussions with the study team and a qualitative study in Ethiopia (Wang et al., 2016). Table 2 gives a final list of the attributes included in the DCE along with attribute levels. Further details about the DCE are given in Papers 3 and 4.

Table 3: Final list of attributes included in the DCE

Attribute	Attribute levels
Salary	1. 20% below average 2. Average earnings 3. 20% above average
Training	1. No training available 2. 5 days per year dedicated training time (improving work-related and transferable skills) 3. 10 days per year dedicated training time (improving work-related and transferable skills)
Workload	*1.* Light: more than enough time to complete duties *2.* Medium: enough time to complete duties *3.* Heavy: barely enough time to complete duties
Management style	1. Management is supportive, and makes work easier 2. Management is not supportive, and makes work more difficult

Health facility quality	1. Your workplace is good: it has reliable electricity and other services, supplies are always available 2. Your workplace is basic: it has unreliable electricity, whilst supplies you need are not always available
Opportunities to improve health outcomes	1. Your work will have a large impact on improving health in the local community 2. Your work will have a small impact on improving health in the local community

4.3.3. Methods for data analysis

Analysis of qualitative data

Transcripts from audio recordings of the semi-structured interviews were analysed using an iterative, inductive-deductive approach (Braun and Clarke, 2006) in NVivo (Version 12) (QSR International Pty Ltd., 2018). Themes were identified by reading and re-reading the transcripts and making notes on relevant issues, followed by listing out emerging issues in the form of a codebook and then attaching codes to relevant sections of the transcripts. I then wrote narrative summaries of relevant themes and sub-themes that emerged most frequently and were appropriate to my study, which were used to write my results. Further details of the analysis strategy are given in Paper1.

Analysis of DCE data

DCEs are analysed using the discrete choice modelling framework as proposed by McFadden (McFadden, 1986) and explained in the literature review in Chapter 2.

Four discrete choice model frameworks were used in this thesis: multinomial logit, mixed multinomial logit, latent class, and hybrid choice. These models and their estimation are described fully in each paper containing DCE data (Papers 2-4), alongside their comparative advantages and disadvantages, and are not duplicated here. In Paper 4, semi-parametric mixtures of latent class models were used to account for ANA in the dataset and to disentangle successfully inferred non-attendance from the lower taste sensitivities of health workers.

4.4. REFLECTIONS ON THE CHANGES MADE TO MY PROPOSED RESEARCH

Through this statement, I hope to review my decisions and decision making processes during the period of this PhD, particularly the choices that were made between March and December 2020 to overcome the disruptions to my fieldwork caused by the COVID-19 pandemic followed by the civil war in Ethiopia.

My proposal at the start of this PhD, which was examined at upgrading, was to undertake a quantitative analysis of the health extension program in Ethiopia to inform human resource policy interventions, particularly those targeting the retention of HEWs. As data required to answer my research questions did not exist in the public domain, I had planned to collect primary data from Ethiopia to answer these questions. Prior to starting my PhD at LSHTM I was working for the Africa Region Gender Innovation Lab at the World Bank based out of Ethiopia, which is where I learnt about the health extension program; a commended flagship program implemented by the Ethiopian government to mitigate health worker shortages in the country by focussing on task shifting to community health workers. It was heralded as a success by the government and a large proportion (21%) of the recurrent health expenditure was being invested towards the salaries of HEWs. My proposed research, which focussed on understanding the job preferences of HEWs to improve retention, was novel as no such research had previously existed. It was also well timed as HEP was due to be redesigned using findings from an evaluation commissioned to analyse its current status as well as existing peer reviewed literature.

I upgraded on April 11th 2019, as per schedule, and had planned to conduct a DCE with HEWs to understand their preferences for financial and non-financial incentives, and a dictator game to evaluate altruistic traits in them, early next year. My PhD was on track; I had completed my formative qualitative work for the DCE by the end of June 2019, analysed the qualitative data and developed DCE attributes and levels by September 2020, prepared a manuscript for submission (now Paper1) by October 2020. By March 2020, I had received the necessary ethics approvals, developed and coded my data collection instruments and was ready to administer the DCE and dictator game to HEWs in four regions in Ethiopia. Like various other academic projects globally, my research was impacted by the COVID-19 pandemic which hit Ethiopia around March 2020 when I was getting ready for fieldwork. Keeping my safety in mind, I was asked by LSHTM to delay fieldwork until the SARS-CoV-2 cases declined in Ethiopia. In the coming months, the pandemic worsened and the country started a tragic civil war. I knew then that I could no longer wait to travel to Ethiopia and had to make contingency plans.

Given my proposed study population of HEWs and inclination to collect my own data, I decided to modify my research objectives to also study the influence of the pandemic on the work of HEWs, and proposed a time and motion study to understand the change in their work responsibilities as a result of the pandemic. I piloted this study remotely from London with the help of data collectors based in and local to the study regions. Piloting showed that the study was robust and feasible, however, the ethics committee at LSHTM did not approve it due to the remote nature of the proposed work and concerns around data validity. This proposed piece of work had to be abandoned, and I had to start from scratch to look for another contingency plan. Since this had taken up a substantial amount of time out of my PhD already, to buy some more time I applied to and was offered a Secondment Fellowship by the Wellcome Trust. For 6 months as a secondment fellow I enjoyed working with the OECD on a project on mental health and wellbeing while also searching for secondary datasets to continue my PhD research.

Thanks to the support of my supervisors, I was finally able to get access to a DCE dataset on HEWs in Ethiopia which captured their preferences for job incentives and so was very similar to my initial proposal. I decided to explore preference heterogeneity in the dataset using a hybrid choice model and since I needed some guidance on my econometric analysis, we requested Dr Romain Crastes dit Sourd from the School of Business at the University of Leeds to join the supervisory team. My work on this dataset eventually resulted in Papers 3 and 4.

Later in 2021, through research contacts at LSHTM, I gained access to another DCE dataset capturing the incentive preferences of COMBAT volunteers in Ghana. My work on this dataset resulted in Paper2.

To sum up, my research has evolved substantially over the last four years due to factors not in my control and I have tried to create a coherent and useful body of work, despite multiple disruptions to my initial proposal.

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PART II – RESEARCH PAPERS

INTRODUCTION TO THE RESEARCH PAPERS

This part presents the research undertaken within the thesis in the form of four research papers. These papers analyse the job preferences of community-based healthcare workers in Ethiopia and Ghana, with a view to understand the heterogeneity in their preferences and how it can be modelled. The four papers are:

1. Understanding the importance of non-material factors in retaining community health workers in low-income settings: a qualitative case-study in Ethiopia
2. The stated preferences of community-based volunteers for roles in prevention of violence against women and girls in Ghana: a discrete choice analysis
3. Linking health worker motivation with their stated job preferences: a hybrid choice analysis in Ethiopia
4. Discrete choice analysis of health worker job preferences in Ethiopia: separating attribute non-attendance from taste heterogeneity

Paper 1 uses primary data from qualitative in-depth interviews with HEWs, leavers of HEW positions, and policy makers to identify various financial and non-financial factors driving their decision to leave or stay in their jobs. This paper uses the social identity approach to explain the social behaviour and pro-social preferences of HEWs and how that can influence the way they trade-off between different job characteristics.

Paper 2 estimates the preferences and heterogeneity in preferences for job characteristics of COMBATs in Ghana. These volunteers represent the perspectives of community-based healthcare workers for incentive structures alternative to HEWs, mostly as they are not remunerated for their work. Using secondary data from a DCE conducted with COMBAT volunteers in Ghana, this paper examines their stated preferences for financial and non-financial incentives that could feasibly be offered in their roles. It extends this enquiry to examine the association between individual characteristics and job preferences for different sub-groups of the study population, to explore preference heterogeneity in the dataset.

Paper 3 uses secondary data from a DCE with HEWs and a hybrid choice approach to link stated job preferences with their motivation, as illustrated in the conceptual framework of this thesis, to understand if psychological constructs such as motivation can be a source of preference heterogeneity. Normally, a key methodological concern in linking the two is the risk of introducing endogeneity bias and measurement error in model estimation. Paper 2 is the first application of the hybrid choice approach in this context, which models the link between motivation and the job preferences of HEWs.

Finally, Paper 4 explores the presence of ANA in the dataset from Ethiopia. Failure to account for ANA can lead to biased DCE estimates and incorrect policy recommendations. However, ANA can also be confused with preference heterogeneity when respondents have low taste sensitivities towards certain attributes, which can lead to the over-estimation of ANA and wrong welfare estimates. Thus, its important to distinguish one from another. This paper uses a cadre stratified sample of community-based healthcare workers from the same survey as that used in Paper 3, including HEWs, non-patient facing staff and other frontline workers in Ethiopia and contributes to the growing body of evidence on the use of heuristics and information processing strategies by respondents in choice modelling.

CHAPTER 5

Research paper 1: Understanding the importance of non-material factors in retaining community health workers in low-income settings: a qualitative case-study in Ethiopia

Overview

This paper undertook a qualitative assessment of the job preferences of active HEWs and leavers of HEW positions using semi-structured interviews in two regions in Ethiopia. While this research had been undertaken as formative work for the development of a new DCE focusing on understanding HEW job preferences to improve retention, the COVID-19 pandemic followed by the civil war in northern Ethiopia made the roll out of the DCE impossible. Thus, using the rich qualitative data on the heterogenous job preferences of HEWs and leavers of their positions, I developed this manuscript to show which financial and non-financial job incentives influence their labour market decisions.

I use the social identity approach to explain how the social behaviour and pro-social preferences of HEWs' can influence the way they trade-off between different job characteristics and suggest that the job preferences of HEWs, and similar community-based health workers, can be driven by their strong social identity. This is further influenced by their social standing and acceptance by the community and supervisors, a lot more than monetary factors such as salaries. Thus, appealing to their social needs may represent a relatively more acceptable, potentially cost-effective complementary strategy to the traditional approach of using financial incentive packages for improving retention of health workers, particularly in resource-constrained settings.

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RESEARCH PAPER COVER SHEET

Please note that a cover sheet must be completed for each research paper included within a thesis.

SECTION A – Student Details

Student ID Number	1406216	**Title**	Ms.
First Name(s)	Nikita		
Surname/Family Name	Arora		
Thesis Title	Understanding heterogeneity in the job preferences of community-based healthcare workers: Applications from Ethiopia and Ghana		
Primary Supervisor	Professor Kara Hanson		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

Where was the work published?	BMJ Open		
When was the work published?	October 8th, 2020		
If the work was published prior to registration for your research degree, give a brief rationale for its inclusion			
Have you retained the copyright for the work?*	**Yes**	Was the work subject to academic peer review?	**Yes**

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Where is the work intended to be published?	
Please list the paper's authors in the intended authorship order:	

Stage of publication	Choose an item.

SECTION D – Multi-authored work

For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	Conceptualised the study, trained data collectors to conduct interviews with study respondents, analysed the data, wrote first draft, incorporated co-author's comments, submitted manuscript to journal, responded to reviewers' comments.

SECTION E

Student Signature	[redacted]
Date	04.07.2022

Supervisor Signature	[redacted]
Date	4th July 2022

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Understanding the importance of non-material factors in retaining community health workers in low-income settings: a qualitative case-study in Ethiopia

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ABSTRACT

Objectives The motivation and retention of community health workers (CHWs) is a challenge and inadequately addressed in research and policy. We sought to identify factors influencing the retention of CHWs in Ethiopia and ways to avert their exit.

Design A qualitative study was undertaken using in-depth interviews with the study participants. Interviews were audio-recorded, and then simultaneously translated into English and transcribed for analysis. Data were analysed in NVivo 12 using an iterative inductive-deductive approach.

Setting The study was conducted in two districts each in the Tigray and Southern Nations, Nationalities and People's Republic (SNNPR) regions in Ethiopia. Respondents were located in a mix of rural and urban settings.

Participants Leavers of health extension worker (HEW) positions (n=20), active HEWs (n=16) and key informants (n=11) in the form of policymakers were interviewed.

Results We identified several extrinsic and intrinsic motivational factors affecting the retention and labour market choices of HEWs. While financial incentives in the form of salaries and material incentives in the form of improvements to health facility infrastructure, provision of childcare were reported to be important, non-material factors like HEWs' self-image, acceptance and validation by the community and their supervisors were found to be critical. A reduction or loss of these non-material factors proved to be the catalyst for many HEWs to leave their jobs.

Conclusion Our study contributes new empirical evidence to the global debate on factors influencing the motivation and retention of CHWs, by being the first to include job leavers in the analysis. Our findings suggest that policy interventions that appeal to the social needs of CHWs can prove to be more acceptable and potentially cost-effective in improving their retention in the long run. This is important for government policymakers in resource constrained settings like Ethiopia that rely heavily on lay workers for primary healthcare delivery.

Strengths and limitations of this study

- ► To the best of our knowledge, this is the first study to report the perspective of leavers of community health worker (CHW) positions, to understand the drivers of their decisions.
- ► We provide an understanding of non-material factors influencing the retention of CHWs, which is important for policymakers to manage attrition among these workers in a cost-effective manner especially in resource constrained settings.
- ► We employed an iterative inductive-deductive style of analyses to allow for relevant themes to be selected, while also allowing unexpected themes to be reflected in participant narratives.
- ► Participants were recruited from within the country so a limitation of the study was our inability to capture the perspectives of leavers who had migrated out of Ethiopia.

INTRODUCTION

With 24% of the global burden of disease and only 3% of the global health workforce, countries in sub-Saharan Africa are struggling to attain universal health coverage and meet the Sustainable Development Goals by 2030.[1] In this context, over the last two decades, a large body of evidence has emerged on the importance of community health workers (CHWs) in overcoming workforce shortages and improving population health, particularly in previously underserved communities.[2–6] Although the model and scope of CHW programmes vary, these health workers are mostly female, trained for a short period on the interventions they will deliver, and usually reside in communities where they work.[7] The significance of CHWs has also been recognised in two recent reports: a WHO guideline on optimising CHW programmes[8] and the CHW Assessment and Improvement Matrix[9]—both of which recommend strategies to optimise the functioning of CHW programmes in health systems, especially in low- and middle-income countries (LMICs).[10]

Although now seen as critical to a well-functioning health system, poor motivation and increased attrition among CHWs remains a challenge. While there is some limited evidence of effective interventions to address poor motivation and retention,[11–14] existing research has typically only explored how different, material incentive packages could improve performance.[15–17] Importantly, studies have not explored the role that community culture and group identification play in influencing CHWs' preferences, motivation and retention in the long term. In particular, no study to date has studied CHWs who have left the health system to understand why they left, and what could have averted their exit.

In 2003, Ethiopia launched the health extension program (HEP), a primary healthcare delivery strategy designed to make up for the low number of doctors, nurses and midwives. HEP has focussed on delivering essential healthcare services using lay CHWs called health extension workers (HEWs), mainly targeting agrarian communities.[18] HEWs complete a year-long training in delivering primary healthcare interventions like family planning services, latrine construction and basic preventive and curative services for communicable and non-communicable diseases.[19] Unlike CHWs in many other countries, HEWs are salaried government employees with currently more than 40 000 workers deployed in the country.[18 20 21] HEP has recently been recognised by WHO as a role model for global CHW programmes, due to its focus on integrating CHWs in the health system as civil servants; training HEWs for a significant period of a year before deployment; and offering educational opportunities to upgrade to higher levels of the health workforce.[8]

A recent, national evaluation of HEP had found the overall job satisfaction of HEWs to be quite low. More than half of the study sample reported to be unsatisfied with their current posts, suggesting that their retention could be affected in the long run. These apprehensions were substantiated by data indicating a gradual rise in the rate of attrition among HEWs over the programmatic lifetime of HEP, between 2005 and 2019. The average annual rate of attrition was reported to be close to 3%, with overall attrition since the start of the programme being 21%.[22] This showed a clear rise in HEW attrition since the last national assessment of HEP published in 2011, which estimated overall attrition in the cadre for the period between 2005 and 2010 to be 6.5%.[23]

HEWs take up a large proportion of the Ethiopian health budget; 21% of the recurrent health expenditure in 2010/2011 was spent on HEW salaries,[21] and so it is critical to make sure that experienced HEWs are retained over time to use this budget efficiently but also to sustain the delivery of quality healthcare. Yet, to date few studies have researched why HEWs leave their posts. Most research has sought to identify financial and non-financial incentives, which motivate HEWs.[24–29] Some ethnographic accounts of HEWs have also studied the context in which they work,[30–32] and more broadly, research has been conducted on contextual factors influencing the performance of CHWs.[26]

While material incentives that align with the preferences of CHWs are relevant to studying retention, behavioural theories like the social identity approach have seldom been applied to empirical findings, to account for the social behaviour of health workers. This approach studies the social identity, context in which they work, along with self-efficacy and outcome expectancies that could influence their labour choices to stay in or leave their jobs. Further description of this approach is provided in the discussion section. Moreover, previous studies have never researched the perspective of CHWs who have left these positions ('leavers'), to capture the drivers of their decisions.

This study identifies factors influencing the labour market decision of CHWs in Ethiopia to leave or stay in their jobs, taking the perspectives of current HEWs, leavers and the health system. Furthermore, we use the data generated from qualitative interviews to demonstrate how group identification can also influence the social behaviour and preferences of HEWs towards working conditions that ultimately influence retention in the health workforce. This evidence makes an original contribution to the global literature on retention of CHWs, as countries gear towards strengthening their own CHW programmes.

METHODS

We conducted this study between January and August 2019. In the first stage, we undertook a literature review to identify conceptual frameworks that link motivational factors to health worker retention. We adapted the conceptual framework by Ormel *et al* 2019,[33] shown in figure 1 which critically analyses the use of a mix of incentives and their relationship with CHW motivation and work behaviour, to include the role that pro-social preferences play towards prioritising non-material incentives. This model was most in line with our study objectives and thus selected to inform our interview topic guides and

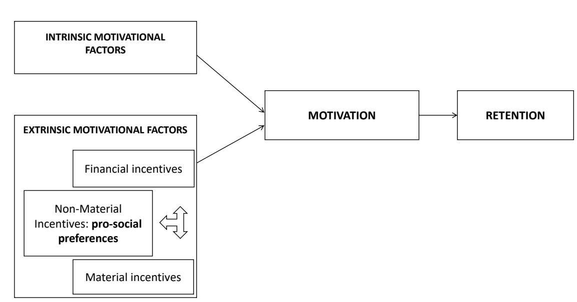

Figure 1 A framework of relationships between motivational factors, motivation and community health worker work behaviour. Modified from Ormel *et al*.

Table 1 Interviews conducted per informant type

Study population	Active HEWs	Leavers of HEW positions	Key informants
Sample size	16 (8 per region)	20 (10 per region)	11 (5 per region, plus one from Federal Ministry of Health)
Gender	All females	All females	3 females, 8 males
Marital status	10 married, 4 single, 2 divorced	8 married, 1 divorced, 1 single	10 married, 1 single
Purpose of inquiry	To capture their perspective on factors affecting HEW motivation and labour choices	To understand factors influencing decisions to leave	To capture the perspective of key stakeholders and identify policy levers that could be modified to improve HEW retention
Sampling technique	Maximum variation sampling from a list of HEWs working in study districts, for diversity of age, geographical location and years of experience	Snowball sampling	Purposive sampling, with variation in administrative levels, seniority and level of engagement with HEWs

HEW, health extension worker.

categorise our qualitative data described in the section below. Following this, we conducted qualitative narrative research with HEWs, leavers and policymakers.

Study setting

Qualitative indepth interview data were collected from four districts in two Ethiopian regions, between May and July 2019. Raya Azebo and Saharti Samra districts were covered in Tigray, and Dilla Zuria and Silte in Southern Nations Nationalities and People's Republic (SNNPR). HEWs were located in a mix of urban and rural backgrounds. The regions were purposively sampled to capture the varying extent of HEP implementation and thus HEW retention in different regions, which was likely to differ due to the political set up in Ethiopia. Historically, Tigray has been a better performing region on health indicators, in comparison to SNNPR, and so we expected variation in perspectives from staff working in the two regions.

Sampling and participants

Data were collected from three key populations: active HEWs, leavers and key informants (KIs). Key informants were policymakers at the national, regional and district level. Details on sampling and respondents per region are presented in table 1.

We interviewed respondents until sufficient saturation was attained in the themes emerging from interview data. A total of 47 semi-structured interviews were conducted. The mean age of respondents across all three study groups was 31 years, ranging from 24 to 40 for leavers, 20 to 49 for HEWs and 26 to 48 for KIs. The mean time worked in the health system was 6 years for HEWs, ranging between 1 and 13 years and 7 years for key informants, ranging from 0.5 to 8 years. Leavers had spent on average 6 years in their current jobs, ranging from 1 to 9 years. Key informants included HEW supervisors, senior officials at district health offices, HEW experts at district levels, HEW coordinators at regional levels and a senior official at the HEP directorate, Federal Ministry of Health.

Conduct of the interviews

Separate topic guides were drafted for each study population, informed by literature on factors affecting the motivation and labour choices of CHWs in LMICs, and the framework by Ormel *et al*.[33] Key topics covered in the interviews included reasons for choosing the HEW profession, motivating factors, challenges faced in their jobs and preferences towards job attributes. For leavers, we additionally inquired about their reasons for leaving. Topic guides were piloted and pre-tested with interviewers and members of the study populations. Research assistants experienced in qualitative research conducted interviews after receiving 2 days' training on study aims, topic guides, ethics of research and its conduct. Training included how to identify and reduce social desirability tendencies in respondents. All research assistants were Ethiopian women between ages 24 and 35 years. Respondents above the age of 18 and willing to participate were approached by research assistants through telephone calls. Principles of confidentiality and informed written consent were upheld during interview administration, in compliance with the ethical approval conditions of the project. Each interview was conducted in the language local to that region, in private spaces—normally at the back side of the health post where the respondent and interviewer could be left alone. As much as possible, the research assistants held interviews when HEWs were comparatively less busy with work, and took on average forty-five minutes to complete. All interviews except two were audio-recorded, translated and transcribed in English by interviewers, who also took notes and discussed in daily debriefing sessions between researchers. For the two interviews where audio recording was not possible due to respondent refusal, research assistants took down detailed notes which were later used for analysis. Each interview was assigned a unique alphanumeric identification code during analysis, and personally identifiable information was removed from transcripts during coding.

Data analysis

Transcripts from the audio recordings were analysed using an iterative, inductive-deductive approach[34] in NVivo 12.[35] Themes were identified by 1: reading and re-reading the transcripts and making notes on relevant issues 2 ; listing out these issues in the form of a codebook and attaching codes to relevant sections; and 3 writing narrative summaries of relevant themes and subthemes that emerged most frequently and/or were appropriate to the study.[36]

Patient and public involvement

This study focussed on capturing the perspectives of CHWs and policymakers, and was undertaken without the involvement of patients.

RESULTS

Since leavers were the key population of interest in the study, we first describe the jobs that they were engaged in at the time of interview and summarise factors that sped up their exit from HEW positions. Key factors influencing HEW motivation and labour choices are then presented in detail.

Leavers' destinations

We found significant variation in the type of employment that the leavers were currently engaged in. Migration to non-health jobs in the Middle East due to better pay was a particularly unanticipated finding. Notably, no participant reported leaving or wanting to leave Ethiopia to work in a health system abroad, perhaps because HEWs are relatively low skilled by international standards.

> Most HEWs think about going to foreign countries. Like Arab countries. The salary in Arab country is relatively good in comparison with HEWs. […] They think, here the workload is very high and the salary is very low so, why don't I go to an Arab country? And why don't I change my life in a short time? - Active HEW, SNNPR

A significant number of leavers reported to have become full-time homemakers. 'I raise my children, I am a housewife 'said a leaver from Tigray. Some women were currently self-employed and owned small businesses highlighting increased earnings and autonomy. 'I have my own grocery. If you are an excellent worker, it provides higher income. It also has freedom; nobody can come and shout at you ' reported a leaver from Tigray. Other respondents remained working in different health system roles, including as lab technicians and administrators in government health facilities.

Catalysts influencing exit: pro-social preferences

While HEWs did not generally anticipate leaving their jobs, they did leave when they felt they had lost the appreciation of their community or supervisors. These were the two main reasons for leavers to finally quit their jobs, despite other challenging working conditions reported by active HEWs and leavers alike. We call these factors *catalysts,* or the triggers that sped up the process of attrition.

Failure to receive support and validation from supervisors and senior staff

Conflict with supervisors and senior managers was the main reason why leavers claim to have quit. These 'conflicts' often seem to have started with a senior official disrespecting the HEW, resulting in a negative shift in their status, social standing and esteem and thus in their identity as a HEW. Supportive supervision, with appropriate acknowledgement and validation from their managers was identified as a critical factor in the retention of HEWs in Ethiopia.

> …the director came to my home and insulted me when I was very sick. He said this institution is neither your mother's nor father's; either perform your job appropriately or leave. I immediately left my job, and didn't even take my monthly salary - Leaver, Tigray

Reduced acceptance and validation from the community

Another key element for retention was receiving respect, acceptance and validation from the community for whom the HEWs worked. Despite tough working conditions, the opportunity to improve community health attracted many to their jobs. A negative shift in their social identity, due to low community acceptance, influenced working conditions and status and their exit.

> There is no appreciation from the people in my woreda (district)… always they will criticise the HEW and service delivery… they are fault finders. - Leaver, SNNPR

Key factors influencing HEW motivation and retention

Numerous factors reported by HEWs, leavers, and KIs were identified as those influencing HEW motivation, and retention in the workforce. Using our conceptual model from figure 1, we classified these into two categories: Extrinsic and Intrinsic.

Extrinsic motivational factors

Financial incentives

Financial incentives in the form of salaries or wages were found to be important among active HEWs as well as leavers. Current salaries were not considered to be commensurate with workload, their compensation not being enough to cover monthly household expenditure.

> HEWs do many overlapping tasks, but salary doesn't balance the work we do…the salary does not reflect living conditions of HEWs. Since we don't have

additional income, and spend all our time at work, it's difficult to live on our existing salary. - Active HEW, SNNPR

Key informants, including HEW supervisors and senior officials at health centres unanimously agreed that HEW salaries were inadequate. HEWs cater to a large population, often in topographically difficult terrains and on foot, so physical strain due to their job came up as a common theme and a constraint to their motivation. 'I still remember how horrible it was…the 4-hour walk in the mountains. It rains over us, and the sun burns so bad', remembers a leaver from SNNPR.

Material factors

Material factors were also seen as being important in influencing HEW motivation and retention. These were often driven by whether adequate drugs, equipment and infrastructure were available at the health post. Such factors were found to be critical not only to support their daily work, but important to sustain the rapport and confidence the community had in them by managing to do the tasks entrusted to them. Sometimes facilities were perceived so lacking that faith was the only answer:

> Sometimes I support the labouring mothers by praying to Gebriel (Angel), because what we learn is different from what we apply. The materials that we have are inadequate; we only have delivery kit, which contains scissor, and cord tie. When a mother delivers at hospital, many things are provided to her and her baby, but here we have nothing to give her. - Leaver, Tigray

In addition, HEWs and leavers suggested that material incentives such as motorcycles for transportation should be provided as part of their work package, to decrease their physical burden.

Furthermore, the gender of HEWs results in a double burden, as many mothers with infants mentioned that it was hard for them to do their daily tasks as a HEW, alongside caring for their infants.

> It is very difficult having a child. I leave from my home early morning at 6 am […] I may stay up to 6 pm, sometimes I don't even have time to drink water after coming back from field work. So, imagine doing all things having a baby - Leaver, Tigray

For HEWs with young children, the absence of childcare was a disincentive to continue in their jobs after giving birth.

HEWs also mentioned not always feeling safe in travelling to rural areas. 'Facilities like motor for transportation should be fulfilled. This security issue also needs attention since in rural areas females can be abused,' stated a leaver from Tigray.

Non-material factors

Most importantly, HEWs and leavers mentioned highly valuing the non-material factors such as appreciation from their communities and supervisors. The opportunity to improve community health, especially that of mothers and children, and gain their community's trust, respect and acceptance, was unanimously described as the top factor motivating them to stay in their jobs.

> When I get the acceptance of healthy mothers and children, I am satisfied. Otherwise, the salary is not enough; the high workload is as I told you before. - Active HEW, SNNPR

Sometimes HEWs were not as easily accepted by their community, which demotivated them. Often respondents claimed that these demand-side barriers existed because of low levels of education and awareness among community members, which also led them to reject healthcare interventions such as family planning and latrine construction.

> The community's behaviour is difficult. For example, when we go to their home to educate them about environmental hygiene, they may close their door and leave from home. They say, oh! She is coming! When I enter through the front door, they will leave the house from the back door. It is for them but they do not understand. To teach them about something we will take many days. They have a shortage of knowledge. - Leaver, Tigray

Other non-material demotivating factors were things that HEWs and leavers identified as lacking in HEW jobs. For example, the placement of HEWs in health posts, often far away from their hometowns where their husband and children are based, limited their motivation and retention. All three study populations agreed that the absence of opportunities to transfer to a facility closer to their family was frustrating, unfair and led HEWs to leave their positions. 'This was my main reason to leave my job… Imagine that you can't meet with your husband as well as your children for a long time because there is no transfer (opportunity)', mentioned a leaver from Tigray.

In addition, respondents reported concerns around the ways in which they could progress in their careers. The majority of HEWs are currently hired as level 3 (nowincreasingly level 4) health workers and according toHEP, HEWs have the opportunity to upskill to the nextlevel after taking a competitive exam. After this, based onopportunities available and skills needed in the district,HEWs can further upgrade to diploma level courses insubjects like midwifery, and even complete a master'sprogramme in public health from government universities. Two key issues around career progression were identified. First, HEWs that were keen to upskill to the next level had to take this competitive exam in English—a language they are not generally proficient in and do not normally use in their jobs, and on topics in which they had not received enough training. The success rate for these exams was thus found to be low. HEWs complained that while many of them are excellent field workers with many years of experience in delivering healthcare, their inability to do well in an exam should not be the sole determinant of career progression.

The second key issue was for HEWs who did manage to upgrade to the next level, but despite upskilling, were expected to return to their old jobs at the health post. Many HEWs agreed that while after upgrading, their remuneration increased (or was expected to increase in the following months), they were expected to undertake the same tasks in the same health post as before.

> After we get back from our level 4 study, we will be placed to the same kebele (village) as before. We need to be refreshed, be in a new place! Alongside with transfer, we should also be assigned to health centres (promoted to a higher health facility). - Active HEW, SNNPR

Another reason why HEWs and leavers felt de-motivated was the lack of support, oversight and acknowledgement from supervisors and managers, who said that supervision was based on a model of faultfinding, not mentorship.

> …[…]. I was so tired that night that I could not clean all the blood and every mess (after single- headedly doing a delivery at the health post). Next morning the woreda (district) officials showed up and insulted me without considering what I have been through. It was so painful not to be understood to this level. - Leaver, SNNPR

Intrinsic motivational factors

Many HEWs mentioned that the key reason for joining the profession was to serve the community where they were raised.

> Most of the time in our environment, the mothers don't use contraceptives, they don't give birth in health centres and they don't get antenatal care. The mothers normally give birth in their home with a traditional birth attendant. Because of this, many mothers die. When I saw these types of problems in my community, I decided to become a HEW. - Active HEW, SNNPR

Some HEWs also insisted that financial incentives were less important than intrinsic factors and that the profession requires women to be truly dedicated to the community's health improvement, to survive in their jobs.

Many leavers mentioned having left their jobs out of frustration with challenging conditions but confessed to have really enjoyed working towards improving community health. ' Regarding the profession, health extension work itself has no concerns. I believe as a HEW you get to serve or work for the community which is great… it's the working conditions that are problematic,'said a leaver from Tigray.

DISCUSSION

Our study findings from two regions in Ethiopia contribute new empirical evidence to the global knowledge and debate on factors influencing the motivation and retention of CHWs in LMICs. It is the first study to include the perspectives of those who had left their posts. Since we wanted to capture the individual experiences and behaviour of all three respondent groups, we refrained from conducting focus group discussions and committed to using in-depth interviews. Moreover, we believe that reasons why people leave their jobs or things they find unsatisfying are of a sensitive nature, unlikely to be disclosed in a group of peers.

Many of the extrinsic motivational factors we identified, such as wages and allowances, were similar to those identified for CHWs in other settings.[11 24 27 33 37 38] For example, a study in Bangladesh reported lack of time to attend to their own children and other household responsibilities, insufficient profit/salary and their families' disapproval as reasons cited by CHWs for leaving their posts.[39] In Nigeria, village health workers reported low work satisfaction due to the lack of career advancement opportunities, low salaries and poor supervision.[40]

Our study offers a number of new perspectives that we believe are valuable in Ethiopia and in other LMICs. Discussion around an adequate career path for CHWs in LMICs is ongoing.[8 33 37] Despite WHO's repeated recommendations on a set career ladder for CHWs to be established in individual country contexts,[8] the uptake has been low by governments. For example, in Ethiopia, there is evidence that the majority of HEWs are keen to take on more responsibility and upgrade to become nurses, pharmacy technicians and health administrators[41] but no such career path is offered to them. In another study, access to and provision of upgrading and promotion opportunities was identified as one of top five measures that can motivate HEWs and improve HEP services.[42] The need for, and the value of, career progression among CHWs to improve job satisfaction was also a key topic of discussion at an international symposium on CHWs in 2019.[43] Moreover, the lack of educational opportunities and poor career development seems to be a bigger cause of concern in Ethiopia, as similar factors also drove up the rate of attrition for higher level professionals like doctors and nurses by nearly three times, in comparison to other allied health professionals lower in the hierarchy [23].

Other material and non-material incentives affecting retention in this context were better living and working conditions that included their ability to live close to their family and have easy access to water, electricity at home and at work. According to a study published in 2007,[28] the living and working conditions of HEWs during early stages of HEP had not met basic standards. A more recent study suggested that many health posts were still missing basic infrastructure like water supply, electricity in 2012.[44] The mean availability of tracer items for basic facilities, infection prevention, malaria diagnosis and essential medicines at health posts was 37%, 29%, 52% and 47%, respectively, according to data from a service availability and readiness assessment, in 2016.[45 46]

Additionally, there is growing recognition of the importance of gender inclusiveness and equity in healthcare, which entails transforming the systems within which women work, such as highlighted in a recent report from the WHO's Gender Equity Hub.[47] In a Cochrane review, socio-cultural norms that restrict movement of female CHWs and govern acceptable male-female communications were also identified as barriers to doing their jobs successfully.[48] Jackson *et al*[49] apply a gender lens to HEP and to the role of HEWs and conclude that by changing gender norms and reducing constraints to gender equality, HEP could have more transformative outcomes not just for HEWs but for the communities they serve. Since the majority of HEWs in Ethiopia are women of reproductive age, providing them with childcare, particularly for when they are away for house visits, could be a step forward in gender transforming their work environment.

Social behaviour and preferences of HEWs

While our evidence supports the importance of material incentives, we also identified other influences on social preferences of CHWs, which could help understand how they prioritise across multiple factors. Such insights could inform the development of new interventions to motivate and satisfy CHWs and retain them in the long term.

In this context, while conventional models have identified motivation as intrinsic and extrinsic, our empirical results identified two further additions—pro-social preferences as a non-material motivator, and social identity as a factor that could influence how CHWs trade among attributes. The social identity approach demonstrates how processes within an individual that influence behaviour are dependent on interpersonal relationships and group memberships, as well as their perceived value and significance to the individual.[50 51] This approach states that when a person identifies as a member of a group, and when a given group identity is relevant to an individual, their behaviour becomes more focussed towards what is seen to be in the group's interest, rather than their own.[51 52]

Thus, when workers define themselves in terms of a personal identity it could be expected that individual motivators such as personal advancement and financial incentives may be more influential. However, when defining themselves in terms of a social identity, motivators that impact on the group one identifies with, such as their status, standing and acceptance in the group may become more influential,[53] like in the case of HEWs. This is a hypothesis that merits further empirical investigation. While the social identity approach is increasingly being applied in high-income countries,[11 53] it is less common in LMICs. To our knowledge, the inSCALE project, which operated in Uganda and Mozambique,[11] is the first to use the social identity approach in a LMIC context to address these constraints in motivation of CHWs. Our study drew on formative research results from the inSCALE study and applied the social identity approach for establishing links between identification and motivation[54 55] in the context of CHWs in Ethiopia.

It has already been recognised that non-material interventions to support CHWs can contribute substantially in creating a more satisfied health workforce that is able and willing to continue delivering quality healthcare to communities.[31 49 56 57] In the Ethiopian context, focus particularly could be accorded to improve not just the availability of strategic resources such as mentoring and supervision, but the quality of support offered by often male supervisors to these female workers. Addressing HEW aspirations to progress in their jobs by providing sufficient upgrading opportunities, tailored to their preferences and abilities, has good potential for improving their job satisfaction, reducing attrition. Clearly, positive community attitude towards HEWs is a key demand-side requirement for HEWs to stay motivated. We believe a good rapport between HEWs and the community often results when HEWs are capable of providing healthcare to the standards expected by the community, which is a function of having health posts equipped with adequate infrastructure as well as well-trained HEWs. Equally important is that HEWs are emotionally satisfied, not having to live apart from their families due to the lack of transfer opportunities.

Future research should explore the development of interventions that can create and maintain trust between CHWs and the community. It could further be evaluated if a bottom-up approach that is designed with the inputs of CHWs and the community, is better tailored to the needs and realities of both.[25] In addition to health outcomes, policymakers should also invest in studying outcome measures such as competencies and self-esteem of health workers as this can have direct effects on their retention and indirect effects on the sustainable delivery of population health.

CONCLUSION

Our study showed that CHW jobs in LMICs including Ethiopia continue to be challenging, and incentives that align with their preferences have the potential to improve their motivation, influencing retention. However, modifying material incentives alone might not improve retention in the long term. Using empirical data from our study and theories of CHW motivation from the literature, we have demonstrated that CHWs identify themselves as members of a group (in this case their community and team). Thus, appealing to their social needs may represent a relatively more acceptable, potentially cost-effective and complementary strategy to the traditional approach of using financial incentive packages for improving retention, particularly in the long run in resource-constrained settings. These non-material factors are important to be considered by government policymakers in resource constrained settings like Ethiopia that are struggling with critical health workforce shortages and inadequate health budgets. The voices of health workers can offer insights that may otherwise be missed and should thus be included while designing programmes to improve retention.

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Patient consent for publication Not required.

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CHAPTER 6

Research paper 2: The stated preferences of community-based volunteers for roles in the prevention of violence against women and girls in Ghana: a discrete choice analysis

Overview

In sub-Saharan Africa, a significant proportion of programs targeting the prevention and mitigation of violence against women and girls (VAWG), a significant public health concern, are run by unpaid community-based volunteers. In Ghana, where the proportion of VAWG is very high, an intervention to reduce VAWG is delivered by community-based volunteers called COMBATs. While this intervention has been proven effective and cost-effective by multiple trials, there is no evidence on the job preferences of these volunteers to ensure longer term retention and increased programmatic impact. This paper uses secondary data from a DCE with COMBATs in Ghana to estimate their average stated preferences for role characteristics, and a latent class analysis to capture how heterogeneity in job preferences between different sub-groups of the study population is associated with their individual characteristics.

This paper found that overall, the preferences of COMBATs were in line with expectations of pro-sociality in the behaviour of community-based healthcare workers, and that they value the non-material aspects of their roles the most, such as getting trained in volunteering skills and getting supervised regularly, over material factors such as remuneration. I also found heterogeneity in incentive preferences among respondents and identified three different sub-groups through the first use, to my knowledge, of a latent class model in this area of application within VAWG. Results showed that COMBAT volunteers with higher education cared most about receiving further training in voluntary skills, followed by three monthly supervision visits. In contrast, older, less educated COMBATs disliked these attributes of their jobs and preferred a higher frequency of sensitization visits and higher per-diems. The majority of COMBATs comprised the “balanced bunch” who gained more or less the same amount of utility from all the attributes included in the DCE. My findings present a step forward towards understanding the factors that would support the scale-up and sustained response of volunteers preventing VAWG in sub-Saharan Africa. I present evidence on how policy makers can leverage the use of non-financial incentives for the retention of these key volunteers.

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First Name(s)	Nikita		
Surname/Family Name	Arora		
Thesis Title	Understanding heterogeneity in the job preferences of community-based healthcare workers: Applications from Ethiopia and Ghana		
Primary Supervisor	Professor Kara Hanson		

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SECTION E

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THE STATED PREFERENCES OF COMMUNITY-BASED VOLUNTEERS FOR ROLES IN THE PREVENTION OF VIOLENCE AGAINST WOMEN AND GIRLS IN GHANA: A DISCRETE CHOICE ANALYSIS

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ABSTRACT

Interventions to prevent violence against women and girls (VAWG), often implemented at the community-level by volunteers, have been proven effective and cost-effective. One such intervention is the Community-Based Action Teams (COMBAT) programme in Ghana, a volunteer-run rural response system which sensitises the community about VAWG and provides counselling services. To increase programmatic impact and maximise the retention of these volunteers, it is important to understand their preferences for incentives.

We conducted a discrete choice experiment (DCE) among 107 COMBAT volunteers, in two Ghanaian districts in 2018, to quantitatively examine their stated preferences for financial and non-financial incentives that could be offered in their roles. Each respondent answered 12 choice tasks, and each task comprised four hypothetical volunteering positions. The first three positions included different levels of five attributes: amount of per-diem (payment) offered, number of sensitization activities undertaken in the community, reimbursement of transport expenses incurred during volunteering, trainings offered, and number of supervision visits made in the year. The fourth option was to cease volunteering as a COMBAT volunteer (opt-out). Data were analysed using multinomial logit, mixed multinomial logit, and latent class models.

We found that overall the majority of COMBAT volunteers gained varying magnitude of utility from all the DCE attributes, while caring most for receiving training in volunteering skills and frequent supervisions. A three-class latent class model fitted our data best, identifying subgroups of COMBAT

workers with distinct preferences for incentives. The younger 'go getters', comprising a third of the sample, were more educated on average and showed very strong preferences for training and supervision visits. The 'veterans' which included 15% of the sample, were older, more experienced at their jobs, and preferred to undertake a higher number of sensitisation visits as well as per diems while gaining disutility from other attribute levels. Lastly, the 'balanced bunch' encompassing the majority of the sample (51%), valued all aspects of their roles roughly equally.

This study was the first to quantitatively examine the preferences for incentives of VAWG-prevention volunteers using a DCE. Understanding preferences and how they vary between sub-groups can be leveraged by programme managers to improve volunteer motivation and retention.

1. INTRODUCTION

Violence against women and girls (VAWG), which includes physical, sexual and/or emotional forms of violence, is a threat to the human rights and wellbeing of women. Its consequences transcend the negative psychosocial, economic, physical and mental health outcomes of the victims, also impacting the nutritional and other long term life outcomes of their children (Chai et al., 2016).

Globally, one in three women experience violence by an intimate partner in their lifetime (World Health Organisation 2021). In sub-Saharan Africa, between 30% and 65% of women and adolescent girls over the age of 15 years, experience intimate partner violence (IPV) (Devries et al., 2013), making it the region with the highest burden of IPV in the world. Rates of VAWG in Ghana are high: 38.7% of ever-married women between ages 15-49 years reported having experienced physical, sexual or psychological violence perpetuated either by current or previous partners in their life times, and 28% of women report having experienced at least one type of domestic violence in the past year (Asante & Premo-Minkah, 2016).

While the majority of VAWG prevention interventions have historically focussed only on prevention (Abramsky, 2012), more recently there has been a shift in developing interventions that prevent VAWG by transforming gender norms and relations at the community level (Heise, 2011). In 2002, the Gender Studies and Human Rights Documentation Centre in Ghana (henceforth Gender Centre) developed one such intervention called the 'Rural Response System to Reduce Violence against Women' (henceforth RRS). The intervention uses a community response model and is responsible for the recruitment and training of Community Based Action Teams (COMBATs) who undertake sensitisation activities to mobilise the community about the ill effects of VAWG, as well as provide individual counselling to people affected by VAWG, liaise with state agencies and carry out referrals where necessary. COMBATs comprise male and female volunteers, nominated by local communities and their leaders, and are trained and supervised by the Gender Centre (The Prevention Collaborative, 2020). They are paid a small per-diem during training, however once the training is complete, COMBATs work as unpaid volunteers. They are reimbursed for costs incurred during intervention activities, such as transportation costs during sensitization visits, but they don't receive regular payment for their work. Staff at the Gender Centre provide technical support and supervision during the intervention, however, often it does not take place on regular intervals.

A recent trial evaluating the effectiveness of the RSS program showed a 9.3% reduction in women's past year experience of sexual IPV, a 15% reduction in emotional perpetration of IPV, and significant reductions in women's depression scores and reported male partner controlling behaviour in treatment areas in comparison to control areas (Ogum Alangea et al., 2020). In addition to effectiveness, the programme was also estimated to be cost-effective. Ferrari et al (2022) report that from a health sector perspective, the RRS program had a 52% probability of being cost-effective for women and men jointly, and 95% probability for women only, compared to Ghana's opportunity cost threshold of $497. Some studies report that community health worker programs that shift healthcare provision from health facilities to the community by engaging unpaid volunteers often appear more cost-effective from a health sector perspective than they are from a societal perspective (Kasteng et al., 2016). The RSS program, however, also had a 98% probability of being cost-effective under the societal perspective for both men and women (Ferrari et al., 2022).

The evidence thus suggests that established community-based interventions such as the RRS/COMBAT warrant consideration for scale up to prevent VAWG in similar contexts. It is sometimes assumed that the decision to volunteer, especially in African countries, is due to pro-social motives and reflects a negligible opportunity cost of workers. Understanding their actual motivation to volunteer, which is driven by the utility derived from different financial as well as non-financial incentives offered, and is thus important to inform programmers and policymakers on ways to retain these volunteers. Yet, no previous work has looked at the labour market preferences for VAWG-prevention volunteers. Discrete choice experiments (DCEs), a popular method to understand the determinants of choices among health workers, are increasingly used to determine the driving factors behind their incentive preferences without expensive trials or pilot studies. Based on Lancaster's theory of consumer behaviour (Lancaster, 1966), DCEs are able to capture how respondents trade off between different attributes of their jobs to reveal their marginal utility attached to different attribute levels. Although based on stated preferences, the trade-off design in DCEs resembles real-life decision making better than ranking and rating techniques sometimes used for policy analysis. A systematic review of DCEs aimed at eliciting job preferences of health workers in low-and middle income countries (LMICs) found 27 studies conducted with a range of health practitioners, including doctors, nurses, midwives, and medical and nursing students (K. L. Mandeville et al., 2014). While there is an increasing body of work on the stated Preferences of community health workers that are employed in the public sector to deliver primary healthcare (Gopalan et al., 2012; Lamba et al., 2021; Saran et al., 2020) (Abdel-All et al., 2019), there is only one study which quantitatively values the incentive preferences of unpaid volunteers in Africa (Kasteng et al., 2016) and none on VAWG-prevention volunteers.

Understanding incentive preferences and thus the motivation of VAWG-prevention volunteers to continue in their roles is important, especially since the RRS/COMBAT, as well as many other VAWG interventions in Africa, are run largely by unpaid volunteers (Heise, 2011; Torres-Rueda et al., 2020). This study will be the first to quantitatively examine the stated preferences of VAWG-prevention volunteers using a DCE. In addition, since it is important to acknowledge that different sub-groups of volunteers would have different incentive preferences, we also account for variation in their preferences in the analysis of our DCE.

2. DATA AND DCE DESIGN

The cohort of all 120 COMBAT volunteers based in two districts – KEEA and Agona - in the Central region of Ghana were contacted to participate in the DCE, as part of the Foreign, Commonwealth and Development Office (previously DFID) funded *What Works* project (UK Aid, 2019). The project was implemented in 2018, alongside a cluster randomised controlled trial to assess the effectiveness of the RSS/COMBAT program (Ogum Alangea et al., 2020; Torres-Rueda et al., 2020). The sample size was chosen in line with rules of thumb from previous health worker DCEs which indicated that a minimum sample size of 50 from each stratum (district) was sufficient to power the study (de Bekker-Grob et al., 2015). After the tasks had been explained by interviewers and respondent questions answered, respondents were asked to complete the DCE alone, though the data collector sat nearby in case the respondent had questions. Additional sociodemographic data were collected alongside the DCE, including personal characteristics listed in Table 2.

2.1. DCE development and design

To identify potential attributes and levels for the DCE, we reviewed peer-reviewed literature to study the range of financial and non-financial incentives that have been offered to community health workers and volunteers by governments in sub-Saharan Africa. A focus group discussion (FGD) topic guide was then developed, with probes exploring the most commonly offered incentives obtained from the literature review, to capture DCE attributes along with the possible levels for these attributes. Two FGDs (n=8 and n=5) were carried out in June 2018 with a total of 13 COMBAT volunteers in the Brong-Ahafo region in Ghana. The discussion in one group was recorded and transcribed. Notes were taken in the second group. The transcription and notes were coded and analysed thematically. Several themes emerged and based on discussions with the study team and being mindful of the cognitive burden a long DCE can put on respondents, five attributes with three levels each, were chosen for inclusion in the DCE. These were: financial remuneration (per diem) offered for each sensitization activity, frequency of sensitization activities undertaken per month, reimbursement of transportation expenses incurred during volunteering, training type offered per year, and the frequency of supervision visits made by the management team per year. These attributes along with their levels are given in Table 1.

The DCE was piloted in September 2018 with 13 COMBAT volunteers who had participated in the FGDs. The pilot had a 12-task fractional factorial design, with attribute levels represented using text alongside pictorial descriptions to account for different levels of literacy. Minor changes were made to attribute levels and to the pictorial representations of attributes following the pilot. Results of the pilot were analysed using a multinomial logit model (MNL) on Stata® to obtain the priors, which were then used to generate a 12-task D-optimal design on NGENE (Choice Metrics, 2012).

Table 1: DCE attributes and levels

Attribute	Levels
Financial remuneration (per diem) per sensitization activity	1. 0 Cedis 2. 10 Cedis 3. 20 Cedis
Frequency of volunteering activities undertaken per month	1.1 2. 4 3. 8
Reimbursement of transportation expenses incurred during volunteering	1. No reimbursement 2. Half reimbursement (50%) 3. Full reimbursement (100%)
Trainings offered per year	1.No training offered 2.Training on volunteering offered 3. Professional training offered
Frequency of supervision visits per year	1. No supervision offered 2. Supervision every 3 months 3. Supervision every 6 months

Note: 1 Ghanaian Cedi = USD 0.16

In each task, respondents were presented with four, unlabelled voluntary positions, each representing a generic COMBAT role. The first three options included different levels of the five attributes listed above. The fourth position was a generic opt-out representing the choice of choosing none of the presented voluntary positions (labelled as “I would stop volunteering”), added to ensure the experiment reflected ‘real world’ choices and to allow for the estimation of unconditional demand, modelled simply as a constant with no attribute levels. An example choice task is given in Figure 1.

After looking at hypothetical voluntary positions A, B, and C, and imagining all else between these positions is equal, which position do you prefer?

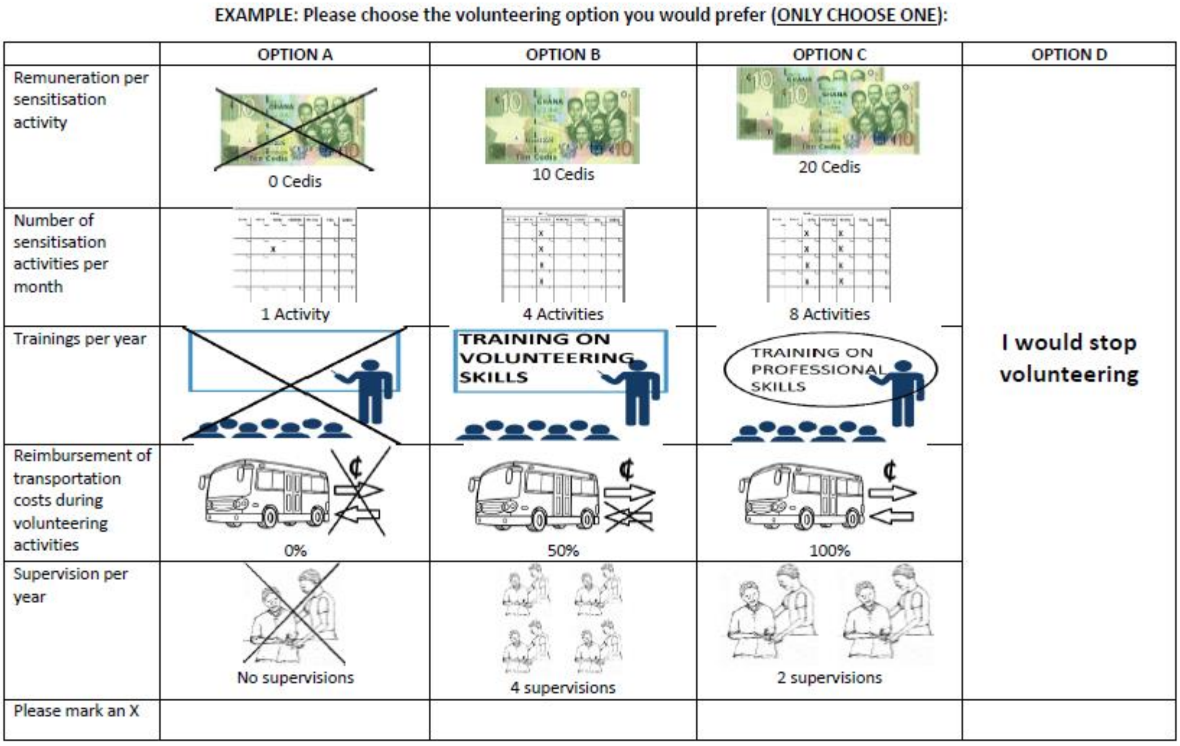

Figure 1: Example DCE choice task

3. MODELLING METHODOLOGY

DCE data were analysed using the random utility framework which assumes that respondents compare all options presented to them in the choice task and pick the one that maximises their utility (McFadden, 1986). For respondent n, alternative i, and choice situation t, their utility, U, can be given by:

$$U_{i,n,t} = V_{i,n,t} + \epsilon_{i,n,t} \quad [1]$$

Where, U, has a deterministic component $V_{i,n,t}$, and a random component $\epsilon_{i,n,t}$ which is assumed to be an independently and identically distributed Extreme Value Type I function (Hensher et al., 2005; Manski, 2001). For each alternative, the deterministic part of the utility can be re-written as:

$$V_{i,n,t} = f(\beta_n, x_{i,n,t}, z_n) \quad [2]$$

Where β_n is the vector of sensitivities for respondent n, $x_{i,n,t}$ is a vector of attributes for alternative i and z_n is a vector of socio-demographic characteristics of respondent n.

In this DCE application, the deterministic part of the utility for a voluntary role i, for individual n was characterised by the selected set of five attributes, and given by:

$$\boldsymbol{\beta_n} X_{n,i} = \beta_{ASC_i} + \beta_1 Perdiem_i + \beta_2 Frequency_i + \beta_3 Vol\_training_i + \beta_4 Pro\_training_i + \beta_5 Half\_transport_i + \beta_6 Full\_transport_i + \beta_7 three\_month\_supervision_i + \beta_8 six\_month\_supervision_i \quad [3]$$

Where β_{ASCi} corresponds to the alternative-specific constant (ASC) for alternative i. We introduced three ASCs, one each for job choices A, B, and C, while the opt-out was coded simply as 0 (zero). The preference weights of attribute levels used to characterise the voluntary roles included in the DCE are represented by β_1 to β_8. Per diem and frequency of visits were specified as continuous variables after being tested against a specification where they were treated as categorical variables. Type of training, number of supervisions, and amount of transport reimbursement were categorical variables, where each category was dummy coded. No training, no transport per diem and no supervision visits were selected as bases for the three categorical attributes.

We conducted an initial exploratory analysis using a multinomial logit model (MNL), where the probability of an individual n choosing alternative i in choice situation t can be given as below.

$$P_{int} = \frac{\exp\left(X_{i,n,t}\beta\right)}{\sum_i \exp\left(X_{i,n,t}\beta\right)} \qquad [4]$$

Since the MNL assumes independence from irrelevant alternatives (IIA) and homogeneity in respondent preferences (Hensher et al., 2005), we estimated a mixed multinomial logit model (MMNL) to relax this assumption and allow for a continuous distribution of coefficients over respondents. This allowed us to examine if heterogeneity in respondent preferences can be captured by random parameters such that $\beta \sim f(\theta_n|\Omega)$ where θ_n was a vector of random parameters and Ω the parameter of distributions (Quaife et al., 2018). The unconditional probability of the sequence of choices, Y_n for respondent n was thus given by:

$$\Pr(Y_n|x_n,\Omega) = \int \prod_{t\in T_n} \frac{\exp\left(\beta' x_{i,n,t}\right)}{\sum_{j\in J} \exp\left(\beta' x_{j,n,t}\right)} f(\theta_n|\Omega) d(\theta_n) \qquad [5]$$

Another way of relaxing the IIA assumption is through estimating latent class models (LCM) which do not require parametric distributional assumptions, like those needed for an MMNL, to be made by the analyst and can help in identifying subgroups of people with different taste heterogeneity. These subgroups are important to identify in research to inform policy as targeted strategies can then be identified to fit people with different preferences. LCMs posit that individual behaviour depends on observable attributes as well as on unobserved (latent) heterogeneity, that varies with factors that can be observed by the analyst (Greene & Hensher, 2003). In LCMs, this latent heterogeneity is accommodated across discrete classes, assuming that there are sub-groups of respondents who will differ in their preferences across classes (i.e. they are defined by different parameter vectors) but have the same preferences (and parameters) within a class. Allocation of individuals to a certain class is probabilistic, and which class contains any particular individual is unknown to the analyst. The central behavioural model generating choice probabilities within each class is normally an MNL, though it is also possible to account for random heterogeneity in preferences within each class, which would give rise to a LC-MMNL model. The analyst stipulates a number of classes and which observed variable to include in the model which can affect the class allocation probability of respondents (Lagarde et al., 2015) (Kate L Mandeville et al., 2016). The optimal number of classes to be included in the LCM are identified based on goodness of fit measures such as an information criteria that penalise improvements in fit as the number of included parameters rise (Greene & Hensher, 2003; Heidenreich et al., 2018). In an LCM, the unconditional probability of respondent n choosing alternative i in choice situation t, can thus be given by

$$P_{it}(i|\beta_k) = \sum_{k=1}^{K} \pi_{nk} \frac{\exp(X_{i,n,t}\beta_k)}{\sum_i \exp\,(X_{i,n,t}\beta_k)} \quad [6]$$

where the probability of respondent n belonging to class k is given by π_{nk} (Quaife et al., 2018). Further, the posterior expected values (conditionals) of class allocation probabilities for each respondent can be produced by the LCM, to allocate each respondent to a class based on their highest probability of falling in a class, and then respondent characteristics can be compared between classes (Lagarde et al., 2015). LCMs are thus well suited for policy-facing research as specific policy recommendations can be made for distinct classes, for targeted policy action.

We estimated LCMs with two to five classes, a panel specification (with multiple responses per individual) and observed variables that influence the probability of class membership and are known to be correlated with incentive preferences, including age, gender, marital status and education. We compared model fit measures including log likelihood, Akaike and Bayesian Information Criteria and McFadden's adjusted Pseudo R^2.

3.1. Model Estimation

We used Apollo version 0.2.6 (Hess & Palma, 2019) in R (version 4.0.2) to estimate our models, using the maximum likelihood approach. The MMNL model was estimated using 2000 Sobol draws, with starting values obtained from the corresponding MNL. The choice of draws was driven by recent literature that favours Sobol draws over Halton or MLHS draws due to correlation concerns in the latter (Czajkowski & Budziński, 2019). All attributes in the MMNL were specified as randomly distributed. All parameters except per diem were set to follow a normal distribution to acknowledge our uncertainty in the nature and direction of heterogeneity around those coefficients. Per diem was set to follow a positive μ-shifted log-normal distribution as the coefficient of per diem was expected to be positive. Recent literature has shown that μ-shifted log-normal distributions can be more desirable in mixed multinomial models for the monetary parameter, in comparison to standard log-normal distributions, when computing welfare estimates. They contribute to mitigating the chances of 'exploding' coefficients as their point mass is further away from zero (Crastes dit Sourd, 2021).

4. RESULTS

4.1. Respondent Characteristics

The final DCE sample comprised 107 out of the 120 COMBAT volunteers contacted. Thirteen COMBATs (11%) were either unavailable during data collection or had relocated outside of the study area and were not traceable. The sample was evenly split between men (50.5%) and women (49.5%), reflecting the composition of COMBATs. The mean age of participants was 46 years (SD 12.2) and the majority of them (77%) were married with 4 children on average (SD 2.5). Less than a third of the respondents had completed secondary school (31%). Table 2 provides key sociodemographic characteristics of the respondents.

Table 2: Participant socio-demographic characteristics

Socio-demographic characteristics		
Gender (N, %)	Female	54 (50.5%)
	Male	53 (49.5%)
Age (Mean, SD)		46 years (12.2)
Marital Status (N, %)	Single	11 (10.3%)
	Married	77 (71.9%)
	Separated	1 (0.9%)
	Divorced	12 (11.2 %)
	Widowed	6 (5.6%)
Number of children (Mean, SD)		4.26 (2.5)
Level of education (N, %)	None	10 (9%)
	Primary	10 (9%)
	Middle school/ Junior Secondary school	54 (50%)
	Secondary school	18 (17%)
	Tertiary education	15 (14%)

4.2. Population level preferences

Most of the 107 respondents answered all 12 choice tasks, except two respondents who answered only 11, making the total number of observations analysed 1282. The opt-out was selected only 4 times (0.3% of choices).

Results from the MNL are given in the supplementary file, Table 6 . MMNL results are given in Table 3, where we report the log likelihood, Akaike and Bayesian Information Criteria (AIC/BIC) as measures of model goodness of fit, as well as the coefficients of each attribute level parameter along with its standard deviation. We see that all three measures are better for the MMNL in comparison to the MNL, suggesting that the MMNL fits our data better, perhaps because there is random heterogeneity in respondent preferences which the MMNL is better able to capture. The non-monetary parameters for which the coefficients are positive can be interpreted as having a positive impact on the utility of COMBATs for the majority of participants (bearing in mind that the parameters are normally distributed) while those with negative coefficients can be seen as contributing to disutility for a majority of the respondents. The coefficient and standard deviation of the per diem attribute correspond to the mean and standard deviation of the underlying normal distribution. Given that this attribute is assumed to be positive μ-shifted, the respondents are assumed to always derive positive utility from a marginal increase in compensation. As expected and in line with results from the MNL, we see that the coefficients for all the non-monetary attributes were positive and highly significant. COMBATs gained most utility from training in voluntary skills (compared to no training), followed by supervision visits held every three months (compared to no supervision offered). However, the standard deviation for both these parameters was large and significant indicating heterogeneity in the sample around preferences for these parameters. COMBATs gained utility from other attributes as well, but to varying magnitudes, as shown in Table 3. Given that all three ASCs were statistically significant, we also conclude that the respondents had baseline preferences for choosing one of the three unlabelled alternatives, compared to choosing the opt-out. However, they preferred choosing one of three alternatives more or less equally across the sample.

Table 3: MMNL results

AIC	2239.91			
BIC	2353.34			
Log likelihood	-1097.95			
Category	**Parameter**	**Estimate**	**SE.**	**T ratio**
Mean (μ)	ASC_a	1.68*	0.83610	2.0037
	ASC_b	1.78 *	0.83032	2.1416
	ASC_c	1.82*	0.82811	2.1984
	Per diem	-3.48**	0.10774	-32.2536
	Frequency of visits	0.07 **	0.01789	3.6981
	Half transport reimbursement	0.73**	0.11080	6.6472
	Full transport reimbursement	0.58*	0.21741	2.6611
	Volunteering training	1.30**	0.19648	6.6071
	Professional training	0.84**	0.20711	4.0716
	3 monthly supervision	1.08**	0.13528	7.8392
	6 monthly supervision	0.90**	0.12275	7.9886
Standard Deviation (σ)	ASC_a	-0.57**	0.14061	-4.0318
	ASC_b	-0.05	0.05557	-0.8704
	ASC_c	0.00	0.04469	0.1534
	Per diem	0.049**	0.11168	8.9209
	Frequency of visits	-0.10**	0.02603	-3.7017
	Half transport per diem	-0.15	0.27649	-0.5289
	Full transport per diem	-0.70*	0.32022	-2.2028
	Volunteering training	1.06**	0.15953	6.6575
	Professional training	-1.11**	0.24125	-4.6143
	3-monthly supervision	-0.678**	0.11269	-5.9434
	6-monthly supervision	0.03	0.07728	0.3453

Note: ** significant at 1% level, * significant at 5% level. AIC = Akaike Information Criterion, BIC= Bayesian Information Criterion.

4.3. Sub-group preferences

Below we present results of the LCMs. Table 4 reports model goodness of fit results for LCMs with 2 to 5 classes. Since none of the interaction parameters for the five socio-demographics included in the LCMs (and mentioned in Table 2) were statistically significant, we decided to analyse main effects models only. A comparison of model fit measures including the log-likelihood, pseudo R^2 and the Akaike Information Criterion (AIC) suggests that the LCM with 5 classes fitted our data best. However, an assessment of the Bayesian Information Criterion (BIC), which incorporates a more stringent penalty term for the number of parameters included in the model, suggests that the model with 2 classes fitted our data better. Further, an assessment of the class allocation probability for each of the classes for the LCM with 5 classes showed that the mean probability of belonging to classes 4 and 5 was <10%, with parameters in these classes being statistically insignificant at the 5% level. An assessment of fit measures for the three-class LCM, however, shows all fit measures except

BIC to be better than those of the LCM with 2 classes and the mean class probability for each of the three classes was >15%, with most parameters being significant at the 5% level. We therefore used the three-class LCM as our main model because we thought it was a better behavioural fit for our data than the other estimated LCMs.

Table 4: Model goodness of fit results

Number of classes	**2**	**3**	**4**	**5**
Log Likelihood	-1134.44	-1096.13	-1058.51	-1045.22
Adjusted Pseudo R^2	0.35	0.37	0.38	0.39
AIC	2308.87	2250.26	2193.01	2184.44
BIC	2433.97	2439.99	2450.1	2510.99
Number of parameters estimated	20	29	38	47

Notes: AIC = Akaike information criterion; BIC = Bayesian information criterion

Results of the three-class LCM (Table 5) show the differing preferences of population sub-groups for different role attributes. On the basis of posterior possibilities, every participant was further assigned to the class where their choice patterns best fitted, and data on respondent characteristics was compared for each class to highlight broad descriptions of each subgroup. The three subgroups were given qualitative titles based on their preferences: ‘the go getters’, ‘the veterans’, and ‘the balanced bunch’.

Table 5: Estimation results for the three-class LCM

Class	**1**			**2**			**3**		
	The go-getters			**The veterans**			**The balanced bunch**		
Mean class allocation probability	33.4%			15.4%			51.2%		
DCE parameters	**Coefficient**	**SE**	**T ratio**	**Coefficient**	**SE**	**T ratio**	**Coefficient**	**SE**	**T ratio**
Per diem	0.03**	0.009409	3.3955	0.33**	0.07	4.8686	0.057**	0.006009	9.5302
Frequency of visits	0.05*	0.022153	2.2481	0.84**	0.22	3.6948	0.04	0.023911	1.7315
Half transport reimbursement	0.52**	0.12516	4.1401	-0.28	0.58	-0.4827	0.61**	0.138168	4.3837
Full transport reimbursement	0.63*	0.294856	2.1487	-3.58**	1.16	-3.0783	0.54*	0.250512	2.1723
Volunteering training	3.24**	0.507692	6.3802	-1.92*	0.81	-2.3793	0.59**	0.175091	3.3558
Professional training	2.97**	0.621929	4.7798	-2.94*	0.75	-3.9436	0.23	0.189661	1.2122
3-monthly supervision	1.18**	0.315823	3.737	-0.86	0.48	-1.7792	0.94**	0.210056	4.4705
6-monthly supervision	0.82**	0.214514	3.829	-0.43	0.48	-0.9043	0.95**	0.139618	6.8367
Participant characteristics	**Class 1**			**Class 2**			**Class 3**		
Female (N,%)	16, 44%			11, 61%			27, 51%		
Median Age in years (SD)	45.7 (11.9)			49.9 (10.4)			45.9 (12.9)		
Married (N,%)	24, 67%			14, 78%			39, 74%		
Secondary school or above (N, %)	14, 39%			3, 17%			16, 30%		
Number of children	4(2)			5 (2.5)			4 (2.6)		
Desired duration to continue volunteering - Mean years (SD)	12 (11.4)			11 (5)			9 (7.6)		
Mean sensitization activities carried out in the past month (SD)	3 (2.3)			4 (2.3)			3 (3.2)		

Mean of individual counselling sessions undertaken in the past month (SD)	6 (5.5)	4 (2.3)	3 (3.1)
Mean referrals carried out in the past month (SD)	0 (1)	1 (0.8)	1 (1.5)

The ‘go getters’, comprising Class 1 and a third of the participants, were the most educated group of the sample with close to 40% having passed secondary school. They were majority men and gained most utility from being trained in voluntary skills, followed by professional skills. They wanted their work to be supervised every 3 months. Some of the COMBATS in this group showed most inclination to stay in their jobs for the longest, though there was large variation in the group. They reported to have undertaken the most counselling sessions in the past month.

The ‘veterans’, Class 2 and the smallest percentage of participants (15%), were the oldest of the respondents, mostly married women, with higher number of children on average in comparison to the other two sub-groups. They were least educated of the classes but self reported to have carried out the most number of sensitization activities in their communities in the past month. They disliked being trained and supervised, however did value the frequency of sensitization visits and the value of their per-diems. They surprisingly also disliked receiving reimbursement for the travel cost incurred during volunteering.

The “balanced bunch”, in Class 3 and comprising the majority of COMBATS (51%) were largely women, married and showed that their utility gained from all the attributes was more or less the same. They reported wanting to stay in their volunteering roles for the least number of years in comparison to the other sub-groups.

5. DISCUSSION

Using DCE data on COMBAT volunteers in Ghana, we estimated the work characteristics with potential to be influenced by program design, that were most highly valued by VAWG-prevention volunteers who are crucial to the delivery of interventions proven to be effective and cost-effective. We used MMNL and LCMs to account for random and discrete heterogeneity in preferences within the population. While the MMNL showed better model fit in comparison to the 3-class LCM, the LCM was considered to be a better behavioural fit for the data as the focus of the paper was to understand the discrete preferences of respondent sub-groups. Since the LCM did not severely underperform in comparison to the MMNL, it was acceptable to present the 3-class LCM as the preferred specification.

Overall, we found that volunteer preferences were in line with previous literature supporting pro-sociality in the behaviour of community volunteers (Kasteng et al., 2016). We found that while per-diems were important to them, COMBAT volunteers gained most utility from getting trained in voluntary and professional skills, followed by having supervision visits every 3 to 6 months. Studies on community level health workers have shown that community recognition, supportive supervision and training and development are key drivers of retention for these cadres (Alem Getie, 2015; Arora et al., 2020; Strachan et al., 2015). It was interesting to note that respondents from all three population sub-groups gained low levels of utility attached to the per diem attribute, in comparison to other role characteristics. There is some literature on the labour market of volunteers that suggests that the motivation behind volunteering is different than that of paid workers and often driven by the perception of being closer to social participation. While no conclusions can be made without further data collection, we believe that their desire to make a social contribution in the community could be driving their low utility for per diem (Kasteng et al., 2016).

We also found variation in incentive preferences of respondents and identified three different sub-groups through the first use, to our knowledge, of a latent class model in this area of application. Results showed that COMBAT volunteers with higher education cared most about receiving further training in voluntary skills, followed by three monthly supervision visits from Gender Centre staff. These findings were in line with literature from labour economics, where the human capital model suggests that individuals invest in building longer term human capital (through studies and training) leading to the accumulation of different skills, which can in turn determine labour productivity and higher salaries in the future (Mincer, 1958). This could also explain why educated COMBATs chose roles with lower per-diem but better training opportunities.

In contrast, older, more experienced but less educated COMBATs disliked these attributes of their jobs and preferred a higher frequency of sensitization visits and higher per-diems. This was not surprising because the expected returns from training are likely to decrease as one grows older, which could be why more experienced COMBAT volunteers were less likely to invest in training, or care too much for supervision visits and simply preferred higher per-diems. One unusual finding was that the ‘veterans’ also seemed to gain disutility from reimbursement for transportation expenses incurred during their work. This could be because in contrast to per diems which are fungible, transport reimbursements were not as reimbursements were only against expenditure and respondents could have had other ways of securing transport. Since the respondents in this sub-group were mostly older women with more children in comparison to other groups, they may have found it to be an inconvenience to have to recoup part of the public transport fare, especially if a cheaper way to commute is available.

The majority of COMBATs comprised the balanced bunch who gained more or less the same amount of utility from all the attributes included in the DCE. This was an interesting finding as it could mean that perhaps the RSS/COMBAT program runs at an optimal level and COMBATs are in general happy with the way the program is currently set up. However, since the DCE only provides insights into the preferences of these volunteers at one point in time, it is not clear for how long the program will remain optimal and what the duration of such interventions should be for them to be successful. It is normally not well understood in VAWG prevention literature what the longevity of prevention programs should be, and for how long these volunteers should be retained for these programs to have the desired impact on the community. Additional research is thus needed in this area so that policy makers can understand how preferences for incentives evolve and resources can be adequately leveraged for the retention of these cadres for the duration needed to make these interventions a success.

The broad conclusions from our results are likely to be important for many other sub-Saharan African countries, especially as the *RRS/COMBAT*, much like other VAWG prevention interventions, relies heavily on volunteers to deliver services. However, there are often methodological challenges and limited evidence on how to best value the time of such, unpaid volunteers. More than the financial costing perspective, where the main cost of unpaid labour includes training cost, it is important to understand the total economic costs of a programme (i.e. the total value of the resources that go into an intervention), in order to determine feasibility and sustainability across settings. Approaches that measure opportunity costs (i.e. the benefits foregone of the next best possible alternative, be it work or leisure) have been used to calculate economic costs of volunteer labour (Drummond et al., 2015). However, in settings with high levels of informal employment, the opportunity cost of volunteering is not easily determined and the replacement cost method presents a more viable way to value volunteer time (Kasteng et al., 2016). For the majority of prevention interventions, the evidence shows that funding should be provided by the health sector in LMICs for them to be cost-effective (Ferrari, 2022). Our findings therefore suggest consideration for further investment in the RRS/COMBAT by the Ghanaian government, leading to full-funding or co-funding with the Gender Centre, for its sustainability.

6. CONCLUSION

Preventing VAWG is imperative in mitigating physical and emotional harm on women and girls. In sub-Saharan Africa, where the burden of VAWG is the highest, the majority of violence prevention programs are delivered by unpaid volunteers whose labour market preferences for role attributes are not known. How these volunteers value different role characteristics is important to retain them in their positions for the sustained delivery of VAWG interventions deemed effective and cost-effective. Our study is the first to generate a key body of evidence on the incentive preferences of VAWG-prevention volunteers in Ghana, which can also be reflective of similar cadres in other African countries.

Our findings were in line with other literature supporting pro-sociality in volunteer preferences which suggests that policy levers such as community appreciation, training and human development, supervision and mentorship are often preferred more than remuneration within these cadres. We also provide robust findings capturing the heterogeneity in respondent preferences and demonstrate the first application of latent class models to identify three sub-groups with distinct incentive preferences within the sample.

Our findings present a step forward towards justifying the scale-up and sustained response of VAWG-prevention through volunteers. We present key evidence on how policy makers can leverage the use of non-financial incentives for the retention of these volunteers who are important in the response needed to meet sustainable development goals and effectively address VAWG in Sub-Saharan Africa.

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SUPPLEMENTARY FILE

The MNL performed well showing statistically significant attribute parameters, all at the 1% level. Table 6 gives the estimation results.

Table 6: MNL results

AIC	2377.71		
BIC	2434.43		
Loglikelihood	-1177.857		
	Estimate	**SE**	**T ratio**
ASC_a	2.12709*	0.817388	2.602
ASC_b	2.15987*	0.812719	2.658
ASC_c	2.19952*	0.810056	2.715
Per diem	0.05786**	0.004668	12.396
Frequency of visits	0.04321**	0.013033	3.316
Half transport per diem	0.55348**	0.079575	6.955
Full transport per diem	0.65078**	0.157391	4.135
Volunteering training	1.06893**	0.133156	8.028
Professional training	0.78824**	0.147366	5.349
3 monthly supervision	0.86294**	0.103352	8.349
6 monthly supervision	0.72955**	0.094088	7.754

Note: ** significant at 1% level, * significant at 5% level.
AIC = Akaike Information Criterion, BIC= Bayesian Information Criterion

CHAPTER 7

Research Paper 3: Linking health worker motivation with their stated job preferences: a hybrid choice analysis in Ethiopia

Overview

Within DCEs, the exploration of heterogeneity in the job preferences of health workers is rapidly growing. However, perhaps surprisingly, one aspect of health worker's behaviour which can be an important source of variation in preferences but hasn't yet been incorporated into choice models, is their motivation to do their jobs. Choosing the correct analysis framework is critical when incorporating unobservable psychological constructs like motivation in the estimation of choice using DCE methods. Over the last decade, hybrid choice models have gained support for being capable of measuring and incorporating these constructs appropriately.

This paper is the first known application of the hybrid choice framework to demonstrate that health worker motivation can be an important source of heterogeneity in their job preferences. In particular, no such research exists on the preferences of lower-skilled community health workers who are key in delivering primary healthcare in many LMICs. Using survey data on HEWs in Ethiopia, this paper demonstrates that multidimensional motivation is an important driver of their job preferences. Intrinsically motivated HEWs show strong disutility towards a higher than average salary, but prefer good facility quality and good health outcomes. However, HEWs that were assessed to be extrinsically motivated had disutility attached to a heavy workload and preferred higher than average salaries.

I expect these findings to be useful to health economists studying preferences and behaviour, choice modelers interested in the more methodological aspects of choice analysis, as well as policy makers considering ways to improve the retention of community-based workers in low-income settings as well as develop ways to get them to exert more effort in their jobs.

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Primary Supervisor	Professor Kara Hanson		

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Linking health worker motivation with their stated job preferences: A hybrid choice analysis in Ethiopia

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ABSTRACT

Understanding health worker job preferences can help policymakers better align incentives to retain a motivated workforce in the public sector. However, in stated preference choice modelling, health worker motivation to do their jobs has not been incorporated, perhaps surprisingly, as an important antecedent to health worker job choices. This paper is the first application of a hybrid choice model to measure the extent to which variations in the job preferences of community health workers (CHWs) can be explained by multidimensional motivation. We interviewed 202 CHWs in Ethiopia in 2019. Motivation was assessed quantitatively using a series of thirty questions, on a five-point Likert scale. Stated preferences for hypothetical jobs were captured using an unlabelled discrete choice experiment. We estimated three models and explored which best fitted choice data. We found that the hybrid choice model fitted better than simpler choice models and provides additional behavioural insight into the preferences of CHWs. Intrinsically motivated CHWs had strong disutility towards a higher than average salary, but preferred good facility quality and good health outcomes. On the contrary, CHWs who were assessed to be extrinsically motivated had disutility attached to a heavy workload and preferred higher than average salaries. We show a link between heterogeneity in the job preferences of CHWs and their motivation, demonstrating that its important for policy makers and managers to understand this link in order to get health workers to exert more effort in return for the right incentives and to retain a motivated workforce in the long run.

1. Introduction

Skilled, knowledgeable, and productive health workers are important for a well-functioning health system (World Health Organization, 2010), equitable access to which is crucial to meet the Sustainable Development Goals (Lassi et al., 2016). Understanding the job preferences of health workers can help policymakers better align incentives and retain a motivated workforce in the public sector, improving the quality and sustainability of healthcare delivery (Lagarde, 2013; Lagarde and Blaauw, 2009; Lindelow and Serneels, 2006).

Discrete choice experiments (DCEs) are a popular method in health economics used to determine the driving factors behind the relative preferences of health workers for different job attributes, that either can't be observed in real life or service characteristics that haven't yet been introduced. The aim of such DCEs is that findings can be leveraged by policy makers to improve health worker retention and productivity in exchange for the right incentives (Lagarde and Cairns, 2012; Mandeville et al., 2016; Mangham and Hanson, 2008; Saran et al., 2020). For example, one study evaluated the relative importance of material and non-material policy incentives in the motivation and retention of community health workers in Western Kenya, using a DCE (Saran et al., 2020). The study showed that community health workers did not just care about salary, but non-material job aspects like appreciation from the community and health facility staff. The DCE, however, did not report whether the health workers most preferring salary had different motivations in comparison to those valuing community appreciation more.

When designing DCEs that can be policy relevant and appeal to the decisions of health workers, a key consideration should also be to incorporate elements of the respondents' cognitive process which have

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been identified as important in decision making (McFadden, 1986). Based on a behavioural approach to choice, McFadden illustrated that the process of making a choice, and choice itself, can be better understood if models can combine '*hard information*' such as well measured socio-economic characteristics of respondents' with *'soft information'* such as indicators of their psychological processes such as attitudes, motivation and affect (McFadden, 2001). The motivation intensity approach defines motivation as a "set of energetic forces that originate both within as well as beyond an individual's being, to initiate work-related behaviour and to determine its form, direction, intensity, and duration" (Pinder, 2014). Further, self-determination theory (Deci and Ryan, 1985; Lohmann et al., 2017) distinguishes between two key dimensions of motivation - extrinsic and intrinsic – both of which are important determinants of what invigorates people to work and refer to motivation driven by external recognition and internal enjoyment for doing the activity, respectively. While improving health worker motivation is known to be a key mechanism for achieving health impact, by encouraging health providers to exert more effort in return for the right incentives (Borghi et al., 2018b; Quaife et al., 2021), in DCEs motivation has never been incorporated as an antecedent to study health worker's job choices.

This paper argues that the overall motivation of health workers, alongside the extent to which they may be extrinsically or intrinsically motivated, influences the job attributes they value, and therefore the utility a given job would provide to them. Motivation is therefore considered a source of variation in preferences among health workers. Including motivation directly into the specification of the utility function of the choice model, such as in the form of an interaction term, is theoretically flawed because of the risk of endogeneity bias and measurement error (Bahamonde-Birke and Ortúzar, 2014; Ben-Akiva and Bierlaire, 1999; Bolduc and Alvarez-Daziano, 2010; Kløjgaard and Hess, 2014; McFadden, 1986; Raveau et al., 2010). Studies that include attitudes and perceptions in the analysis of choice thus tend to use hybrid choice models which allow psychological constructs to be included as latent variables (Kløjgaard and Hess, 2014; Santos et al., 2011).

In this study, we demonstrate the application of a hybrid choice model in understanding the job preferences of community health workers in Ethiopia, also known as health extension workers (HEWs), using motivation as a latent variable. HEWs are responsible for the delivery of 16 primary healthcare interventions, predominantly in rural areas, ranging from preventive services in family planning and immunizations to basic curative services for communicable and some non-communicable diseases (Arora et al., 2020). They account for the second largest health workforce in Ethiopia with close to 21% of the recurrent government health expenditure invested in their salaries (Wang et al., 2016). We believe that a better understanding of how HEWs make trade-offs between attributes of their jobs can inform policy decisions aimed at overcoming the gradual rise in the rate of attrition within this cadre (MERQ Consultancy Plc, 2019).

This study fills two key gaps in the literature on health worker behaviour and preferences. First, to our knowledge, no DCE to date has looked into how motivation of health workers could be a source of preference heterogeneity within stated preferences methods, the knowledge of which can be leveraged by managers to get these health workers to exert more effort in return for the right incentives. Further, previous studies analysing health workers' preferences have been limited by focussing only on highly skilled health workers, such as doctors and nurses, while not including lower skilled health workers such as community health workers who deliver the majority of primary health care services in countries like Ethiopia.

2. Data and DCE design

2.1. Data

We used data from a survey designed to quantitatively assess the job preferences of different cadres of health workers based in four regions of Ethiopia: Tigray, Amhara, Oromia and Southern Nations Nationalities and People (SNNP). The DCE was embedded within an endline survey collecting information for the process evaluation of a quality improvement programme implemented by the Ministry of Health in Ethiopia, conducted in June 2019. More details about the study can be found in Quaife et al. (2021) and Lamba et al. (2021). The sample consisted of a cadre-stratified random sample of 404 middle and lower-skilled health workers in the Ethiopian health system, including data on three cadres – HEWs, non patient-facing staff like health facility administrators, and mid-level maternal and new-born healthcare providers including nurses and midwives. In this paper, since our aim was to focus on understanding the preferences of lower-skilled health workers, and since Lamba et al. (2021) had reported heterogeneity in preferences between the three health worker cadres being studied, we only used data on HEWs (n = 202) who comprised half the survey sample. In addition to the DCE, the survey also collected information on various respondent sociodemographic characteristics. Table 1 provides descriptive statistics for selected sociodemographic characteristics.

Table 1
Respondent characteristics.

Variable description	Results
Respondent age (years)	Mean age (SD): 28 years (4.38)
Current monthly gross salary (ETB)	Mean (SD): ETB 3450 (24.72)
Months spent in the health system	Mean time spent in months (SD): 43 (.27)
Region of work	Tigray: 11.01%, Oromia: 24.95%, Amhara: 26.02%, SNNPR: 38.03%
Highest qualification attained	Level 1,2 or 3: 48.46%, Level4: 47.03%, degree or above: 4.5%
No of times the opt-out was chosen by respondents*	140 out of 1392 choice situations (10.06%)

ETB = Ethiopian Birr * There were no serial non-respondents in the dataset who chose the opt-out for all 7 choice tasks.

2.1.1. Motivation instrument

The survey also collected information about the respondent's motivation to do their jobs. To measure motivation, the survey adapted a quantitative tool which was developed and validated among community health workers in Uganda (Eichler and Levine, 2009), with small changes to wording made to suit the Ethiopian context. This tool consisted of 17 questions, with eight further questions added from a health worker motivation evaluation conducted in Tanzania (Borghi et al., 2018a) to explore extrinsically motivating factors in further depth. Finally, with input from senior staff implementing the QI programme five more questions were added around activities which were part of the programme, relating to training and recognition for doing a good job, taking the total number of questions to 30. All statements had Likert scale response options where 1 = strongly agree, 2 = agree, 3 = neutral, 4 = disagree, 5 = strongly disagree.

A team of seven, trained research assistants from School of Public Health, Addis Ababa University administered the survey face-to-face with the respondents, in Amharic, Tigrigna, and Oromifa languages using Open Data Kit (https://opendatakit.org) software on tablet computers. Informed consent was obtained from all participants before data were collected, and the study was undertaken with ethical approval from the Observational Research Ethics Committee of the London School of Hygiene and Tropical Medicine and a program evaluation waiver from the Ethics Committee of the Ethiopian Public Health Association.

2.2. DCE development and design

The DCE had six job attributes, identified after a thorough review of literature on health workforce discrete choice experiments conducted in the East African context (Blaauw et al., 2013; Mandeville et al., 2017; Mangham and Hanson, 2008; Rockers et al., 2012). Further details on

Table 2
DCE attributes and their levels.

Attribute	Attribute levels
Salary	1. 20% below average 2. Average earnings 3. 20% above average
Training	1. No training available 2. 5 days per year dedicated training time (improving work-related and transferable skills) 3. 10 days per year dedicated training time (improving work-related and transferable skills)
Workload	1. Light: more than enough time to complete duties 2. Medium: enough time to complete duties 3. Heavy: barely enough time to complete duties
Management style	1. Management is supportive, and makes work easier 2. Management is not supportive, and makes work more difficult
Health facility quality	1. Your workplace is good: it has reliable electricity and other services, supplies are always available 2. Your workplace is basic: it has unreliable electricity, whilst supplies you need are not always available
Opportunities to improve health outcomes	1. Your work will have a large impact on improving health in the local community 2. Your work will have a small impact on improving health in the local community

the process of selection of attributes are reported in Lamba et al. (2021); Table 2 provides the list of attributes and levels. The DCE was piloted among 19 district health office staff in December 2017, before the baseline survey for the main study was conducted. The pilot had a ten-task fractional factorial design while the final was a seven-task, D-optimal design based on priors from the pilot, conducted in NGENE (Choice Metrics, 2012). The design was main effects only, and because it was a subsection of a survey which took a relatively long time to complete, design diagnostics indicated that we were able to reduce respondent burden through reducing the number of tasks from 10 to seven. In each task the participants were presented with two job alternatives representing a generic health worker's job.

To increase realism and allow for the estimation of unconditional demand, a generic opt-out alternative was included, modelled simply as a constant with no attribute levels, representing the choice of picking neither of the presented job profiles and staying in their current job. Fig. 1 shows an example of how choice tasks were presented to respondents. We used Apollo version 0.2.5 (Hess and Palma, 2019) in R (version 4.0.2) to analyse our data.

3. Methods

3.1. Modelling framework

Standard random utility models estimated on DCE data are based on the notion that respondent choice is determined by the utilities that they perceive for the given alternatives. For respondent n, alternative i, and choice situation t, this utility, U, can be given by

$$U_{i,n,t} = V_{i,n,t} + \varepsilon_{i,n,t} \tag{1}$$

It is made up of a modelled component $V_{i,n,t}$ and a random component $\varepsilon_{i,n,t}$ which follows a type 1 extreme value distribution. Further, we have:

$$V_{i,n,t} = \beta_n' x_{i,n,t} \tag{2}$$

where β_n is a vector of taste coefficients and $x_{i,n,t}$ is a vector of attributes for alternative i, which can include alternative specific constants (ASCs) for all but one of the alternatives. Given the assumptions about the error term, the probability that respondent n chooses a given alternative i conditional on β_n and the ASCs in choice situation t corresponds to the well-known multinomial logit model structure:

$$P_{i,n,t} = \frac{e^{V_{i,n,t}}}{\sum_{j=1}^{J} V_{j,n,t}} \tag{3}$$

The elements in β_n can be allowed to vary across respondents, either based on their observed characteristics (by adding interaction variables) or randomly by using a joint distribution $f(\beta_n|\Omega)$ where Ω is a vector of parameters to be estimated, relating to the means and covariance structures of the elements in β_n. This leads the model to capture random heterogeneity in preferences.

A share of the variance of random taste heterogeneity for job characteristics can be linked to random variations in *motivation* by the means of a hybrid choice model structure. Data on psychological constructs such as motivation come from answers to psychometric tools comprising of attitudinal statements which cannot be treated as direct measures of the attitude itself and are prone to measurement error. As such, these constructs can't be included directly in the utility function of choice models as interaction variables and need to be treated differently.

The hybrid choice framework provides a way to accommodate such psychological constructs by jointly modelling the responses to the stated choice component as well as to attitudinal questions, as illustrated by Fig. 2.

In other words, this modelling framework suggests that answers to attitudinal questions should be treated as dependent rather than explanatory variables (Ben-Akiva et al., 2002), and in addition to the attributes of job alternatives, motivation can be used as a latent variable (or a series of latent variables related to different aspects of motivation) to explain the relationship between the observed job choices of community health workers and the answers to a series of questions related to respondent motivation.

In the context of this paper, this modelling framework allows us to disentangle the share of unobserved heterogeneity in respondent preferences for job attributes which is related to random variations in taste, from the share which is related to random variations in motivation across respondents. This gives richer behavioural insights. We conducted exploratory factor analysis to identify the correlation between statements included in the motivation tool and to assess the number of latent variables that can be included in our hybrid choice model. This is explained in further detail in the following section.

3.2. Factor analysis of motivation measure

For our factor analysis, we used the covariance between variables to identify distinct underlying groups of variables which are correlated with one another. This made it possible for us to understand the dimensionality of the motivation measure and the main statements explaining each dimension. Each individual factor was incorporated as a separate latent variable in the hybrid choice model.

Overall, three factors were revealed to be statistically significant and for each of them, the representative statements were also identified. Only 24 out of 30 statements passed our criteria of inclusion[1] and the

[1] As recommended in the literature, we used a threshold of 0.35 to reflect a strong relationship with a factor and dropped variables from the list of 30 questions with factor loadings less than 0.35 (Ferguson and Cox, 1993; Tabachnick et al., 2007). From among these, we used a Scree plot and multiple runs to come up with the optimal number of factors (Chandler et al., 2009). To reduce the number of variables with high loadings and to allow factors to be correlated, we used maximum likelihood ProMax oblique rotation. We assumed that construct validity was indicated by loading at least two variables per factor and absence of substantive cross-loading (Costello and Osborne, 2005). We ran models with between two and five factors, removing variables which did not load on any factor to 0.35, and used eigenvalues >1 as selection criterion alongside identifying models with substantial cross-loading of variables to factors.

	Job A	Job B	
Salary	Average earnings	20% below average	**Neither of these - I prefer my current job**
Opportunities to improve health	Your work will have a small impact on improving health in the local community	Your work will have a large impact on improving health in the local community	
Management style	Management is not supportive, and makes work more difficult	Management is supportive, and makes work easier	
Facility quality	Your workplace is basic: it has unreliable electricity and other services, whilst supplies you need are not always available	Your workplace is good: it has reliable electricity and other services, supplies are always available	
Training	5 days per year dedicated training time (improving work-related and transferable skills)	10 days per year dedicated training time (improving work-related and transferable skills)	
Workload	Light: more than enough time to complete duties	Heavy: barely enough time to complete duties	

Fig. 1. Example choice task.

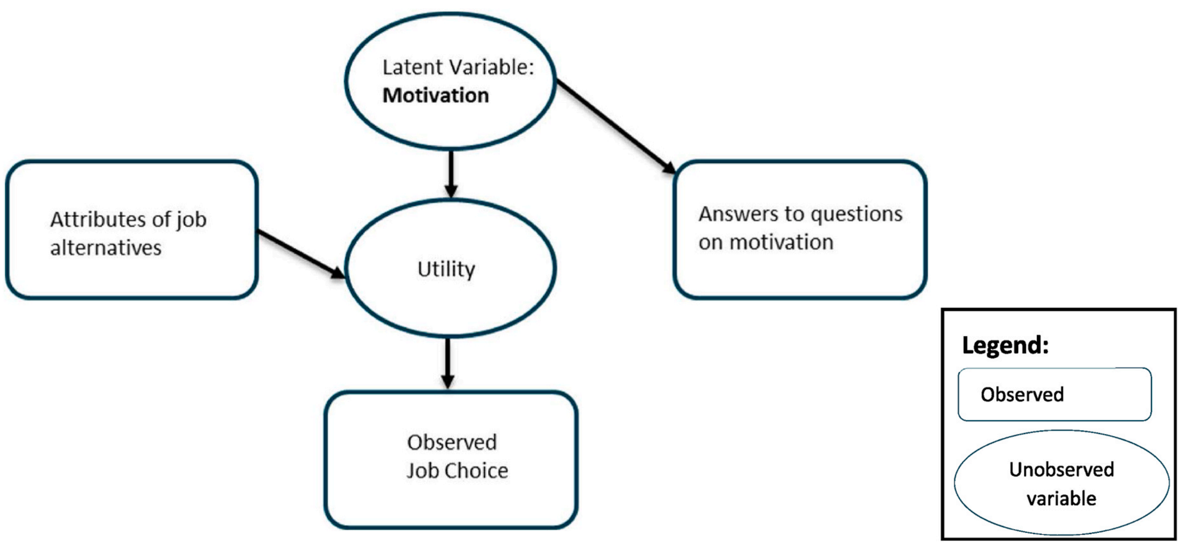

Fig. 2. Study hybrid choice model structure.

rest were dropped. The factors along with their statements and factor loadings are given in the supplementary file. We assigned qualitative titles to the identified factors based on the statements that characterised each one. These three factors corresponded to the latent variables (α_{1-3}) included in the model and are described below:

α_1: Intrinsic motivation (driven by reaching personal and professional goals)
α_2: General contentment with the job
α_3: Extrinsic motivation (driven by external recognition)

3.3. Model specifications

We estimated three main models to demonstrate a gradual build-up of model complexity. We started with a main effects Multinomial Logit (MNL) model, followed by allowing for random heterogeneity in preferences by estimating a main effects Mixed Multinomial Logit (MMNL) model. Finally, to measure the relationships between motivation and respondent preferences, we estimated a Hybrid Choice Model (HCM), where motivation enters our model as a series of latent variables.

To get around the issues with local optima, we ran all models with different sets of starting values, obtained through the analysis of appropriate base models (Kløjgaard and Hess, 2014). As we have more than five attributes in our DCE, we used 2000 MLHS draws (Czajkowski and Budziński, 2019).

3.3.1. MNL and MMNL

We used the specification below to parameterise the MNL:

$$\begin{aligned} V_{n,j,t} = {} & \beta_{asc} + \beta_{salary\ \ avg} \cdot x_{salary\ \ avg,j} + \beta_{salary\ \ plus} \cdot x_{salary\ \ plus,j} \\ & + \beta_{good\ \ mgmt} \cdot x_{good\ \ mgmt,j} + \beta_{good\ \ facility} \cdot x_{good\ \ facility,j} + \beta_{training\ \ 5} \cdot x_{training\ \ 5,j} \\ & + \beta_{training\ \ 10} \cdot x_{training\ \ 10,j} + \beta_{medium\ \ workload} \cdot x_{medium\ \ workload,j} \\ & + \beta_{heavy\ \ workload} \cdot x_{heavy\ \ workload,j} + \beta_{good\ \ impact} \cdot x_{good\ \ impact,j} \end{aligned} \tag{4}$$

where $j = A, B$ for the two job alternatives at choice situation t, β_{asc} is the alternative specific constant (ASC) for the job, and different βs represent the parameters for each attribute level used to characterise job alternatives included in the DCE. We dummy coded all attributes where the base level was fixed to zero. Our choice for which alternative should be used as a base for the ASC, as well as the base selection for other attributes followed choice modelling literature in the choice of normalization for alternative-specific constants and categorical variables by deliberately over-specifying the model (attempting to estimate all parameters) and then omitting those with the lowest variance (Walker, 2001). On the basis of this, we normalized to zero the constant for job A, less than average salary, no days of training and low workload. The opt-out was parametrised with just an ASC.

Further, to allow for random heterogeneity in respondent preferences, we estimated an MMNL, such that the utility derived from a given attribute level (taking *salary average* as an example) was now given by:

$$\beta_{salary\ \ average} = \mu_{salary\ \ average} + \sigma_{salary\ \ average} \cdot \eta_{salary\ \ average,n} \tag{5}$$

where $\eta_{salary\ average,\ n}$ indicates a vector of draws coming from a standard normal distribution $N \sim (0,1)$. All attributes were assumed to be randomly distributed, and except *heavy workload*, they were all specified to follow a normal distribution. *Heavy workload* was set as a negative μ-shifted log-normal distribution (Crastes dit Sourd, 2021) to acknowledge literature on the negative effects of long term heavy workload and to recognise that the majority of respondents in our dataset were either neutral to a heavy workload or showed disutility towards it (Kc et al., 2020; Trivellas et al., 2013). It's worth noting that the assumption of independence of random parameters comes at the cost of not being able to account for scale effects; a necessity given the computational concerns around a heavily parameterized specification.

3.3.2. The hybrid choice model

The specification of the HCM can broadly be broken down in three components: the specification of the structural equation of the latent variable, specification of the measurement model, and specification of the utility function in the choice model component.

3.3.2.1. Structural equation of the latent variable. We used three latent variables in our model, relating to the three dimensions of motivation. The structural equation for each latent variable l can simply be written as $\alpha_{l,n}$, which indicates a vector of draws coming from a standard normal distribution $N \sim (0,1)$.

3.3.2.2. The measurement model. As explained above, by using an exploratory factor analysis on the 30 indicators in the motivation tool we were able to identify 24 indicators with factor loadings >0.35, followed by identifying three factors indicating different dimensions of motivation. The results of the factor analysis are given in the supplementary file. Thirteen indicator statements loaded to the first factor, eleven loaded to the second factor and two statements loaded to the third factor. Further, in an attempt to reduce issues during model estimation, while ensuring that all the latent variables were identified, we only used the indicators featuring the highest factor loadings for each one of the three factors. The k statements on motivation used in the final models are reported in Table 3. A total number of 7 statements were used in the modelling work.

We used an ordered logit specification for all 7 indicator questions (with s levels each), in line with the approach advocated by Daly et al. for ordinal indicators (Daly et al., 2012). The likelihood for observing a given value s for indicator I linked to latent variable l corresponds to:

$$P_{I_{k,n}} = \sum_{s=1}^{S} (I_{k,n} = = s) \left[\frac{e^{\tau_{k,s} - \zeta_k\ \alpha_{l,n}}}{1 + e^{\tau_{k,s} - \zeta_k\ \alpha_{l,n}}} - \frac{e^{\tau_{k,s-1} - \zeta_k\ \alpha_{l,n}}}{1 + e^{\tau_{k,s-1} - \zeta_k\ \alpha_{l,n}}} \right] \tag{6}$$

where ζ_k measures the impact of a given latent variable on indicator I and where $\tau_{k,s}$ with $s = 0, \ldots, 5$ are a set of estimated threshold parameters where $\tau_{k,0} = -\infty$ and $\tau_{k,5} = +\infty$ for normalization purposes. The selected indicator statements within each latent variable, along with the expected relationship between I_{kn} and $\alpha_{n,k}$ are given in Table 3.

Table 3
Motivation statements included.

Motivation statements	α	ζ	τ	Direction of association b/w for I_{kn} and $\alpha_{n,k}$
I am respected in my community for the work I do (positively framed)	1	1	1	opposite
My work is important because I help people (positively framed)	1	2	2	opposite
I can solve most problems I have at work if I work hard (positively framed)	1	3	3	opposite
I am proud of the work I do (positively framed)	2	4	4	opposite
In general I am satisfied with my role (positively framed)	2	5	5	opposite
At the moment I don't feel like working as hard as I can (negatively framed)	3	6	6	same
I am strongly motivated by the recognition I get from other people (positively framed)	3	7	7	opposite

Since some indicator statements were positively framed while others were negatively framed, a positive value for ζ_k in the above equation would mean that as $\alpha_{n,k}$ increases, the likelihood of a higher value for I_{kn} decreases for positively framed statements and opposite for negatively framed statements (Kløjgaard and Hess, 2014).

Specification of utility in the choice model component of the hybrid choice model.

The utility derived from a given attribute β (taking *salary average* as an example and omitting subscripts for clarity) now becomes the following for the HCM:

$$\beta_{salary\ \ average} = \mu_{salary\ \ average} + \sigma_{salary\ \ average}\eta_{salary\ \ average} + \theta 1_{salary\ \ average}\alpha_1 + \theta 2_{salary\ \ average}\alpha_2 + \theta 3_{salary\ \ average}\alpha_3 \tag{7}$$

The parameters labelled as θ capture the effect of the latent variables α_1, α_2 and α_3 on preferences. Interpreting the results requires the reader to look jointly at the sign and magnitude of the θ parameters as well as the ζ parameters introduced in Equation (6) and Table 3. This is further detailed in the results section where we show how the variations in α_1, α_2 and α_3 (which again, are normally distributed with a mean of 0) jointly affect the choice model and the indicator, giving rise to a hybrid model. This model now jointly maximises the likelihood of observing the choices made by each respondent (*choice model component*) and the likelihood of observing each of the seven statements on motivation (*measurement models component*). Given the many distributional assumptions made, simulation methods are used for estimating the parameters and all models were estimated using 2000 MLHS draws. The likelihood function of the hybrid choice model corresponds to:

$$LL(\Omega_\beta, \theta, \zeta, \tau) = \sum_{n=1}^{N} ln \int_\beta \int_\alpha \prod_{t=1}^{T} P_{nt} \cdot \prod_{k=1}^{K} P_{I_{k,n}} f(\beta_n|\Omega) g(\alpha) \delta\beta\delta\alpha \tag{8}$$

This is different than the likelihood for a corresponding MMNL, where the three latent variables α_1, α_2 and α_3 do not influence taste heterogeneity and where there is no measurement model:

Table 4
Goodness of fit, MNL and MMNL models.

Model	MNL	MMNL
Log likelihood	−1289.822	−1150.178
AIC	2601.64	2344.36
BIC	2659.32	2459.6
Number of parameters	11	22

Table 5
Estimation results of the HCM.

Choice component log-likelihood	−1113.802		
Number of parameters	81		
Category	**Parameter**	**Estimate**	**Rob.t ratio**
Attribute mean (μ)	ASC 2	0.12955	1.43
	ASC 3	−4.75157**	−5.07
	Average salary	−0.41659**	−2.53
	20% more than average salary	0.26213	1.06
	5 days training	0.14988	0.46
	10 days training	−0.94624**	−3.13
	Medium workload	−0.39988	−1.23
	Heavy workload	−1.61824**	−2.81
	Good facility quality	0.44614**	2.12
	Good management	1.03045**	4.30
	Good outcome	−0.22582	−0.82
Attribute standard deviation (σ)	ASC 2	0.2136	−0.74
	ASC 3	4.00681**	4.96
	Average salary	0.0209	−0.15
	20% more than average salary	1.14456**	−3.49
	5 days training	0.99024**	−3.01
	10 days training	0.25803	0.50
	Medium workload	1.7077**	4.02
	Heavy workload	0.1402	0.85
	Good facility quality	0.64544**	−2.28
	Good management	0.41344*	1.87
	Good outcome	0.74496*	−1.90
Latent Variable 1 - intrinsic motivation			
<u>Measurement Equations</u>			
Interactions between α1 and choice model attributes (θ1)	ASC	−1.5222**	−2.78
	Average salary	0	NA
	20% more than average salary	0.67199*	1.86
	5 days training	−1.02352**	−2.27
	10 days training	−0.27666	−0.98
	Medium workload	0.42258	1.22
	Heavy workload	0.95491**	3.62
	Good facility quality	−0.74191**	−3.29
	Good management	−0.3876*	−1.66
	Good outcome	−0.51671**	−2.23
Impact of latent variables on motivation questions (ζ)	ζ_{m5}	3.70489**	2.88
	ζ_{m22}	1.83052**	4.85
	ζ_{m24}	1.82158**	4.58
Latent variable 2 –General contentment with job			
<u>Measurement Equations</u>			
Interactions between LV2 and choice model attributes (θ2)	ASC	0.37246	1.07
	Average salary	0.08053	0.59
	20% more than average salary	0	NA
	5 days training	−0.53012**	−2.28
	10 days training	0.14651	0.59
	Medium workload	−0.14496	−0.46
	Heavy workload	0.66867**	2.15
	Good facility quality	−0.28935	−1.47
	Good management	−0.17999	−1.12
	Good outcome	−0.1224	−0.51
Impact of latent variables on motivation questions (ζ)	ζ_{m2}	−1.49849**	−4.40
	ζ_{m1}	−5.71517	−1.50
Latent variable 3 – Extrinsic motivation			
<u>Measurement equations</u>			
Interactions between LV3 and choice model attributes (θ3)			
	ASC	1.61086**	3.02
	Average salary	−0.434	−1.54
	20% more than average salary	0.09582	0.28
	5 days training	0	NA
	10 days training	−0.77831*	−1.87
	Medium workload	−0.88214**	−2.21
	Heavy workload	−1.76243**	−3.72
	Good facility quality	1.10404**	4.14
	Good management	0.31079	1.30
	Good outcome	0.95504**	2.78
Impact of latent variables on motivation questions (ζ)	ζ_m6	0.67385**	2.73
	ζ_m3	0.65095**	3.74
τ_{m51}	–	−1.77883	−2.89
τ_{m52}	–	7.70711	3.27
τ_{m53}	–	10.46417	2.98
τ_{m221}	–	−1.65646	−5.55
τ_{m222}	–	4.43378	6.42

(*continued on next page*)

Table 5 (*continued*)

Choice component log-likelihood	−1113.802		
Number of parameters	81		
Category	**Parameter**	**Estimate**	**Rob.t ratio**
τ_{m223}	–	4.57458	6.69
τ_{m224}	–	6.86627	5.80
τ_{m241}	–	−1.50778	−5.17
τ_{m242}	–	6.85885	5.68
τ_{m11}	–	−1.87618	−6.39
τ_{m12}	–	1.89631	5.97
τ_{m13}	–	1.9793	6.17
τ_{m14}	–	4.3585	6.99
τ_{m21}	–	−4.54287	−1.64
τ_{m22}	–	7.41804	1.70
τ_{m23}	–	8.01774	1.68
τ_{m24}	–	16.377	1.67
τ_{m61}	–	−4.11719	−7.81
τ_{m62}	–	0.12542	0.79
τ_{m63}	–	0.23654	1.51
τ_{m64}	–	3.8526	8.24
τ_{m31}	–	−1.98732	−8.40
τ_{m32}	–	1.11754	6.59
τ_{m33}	–	1.29559	7.27
τ_{m34}	–	5.48945	5.40

** significant at 5% level, * significant at 10% level. *Note:* The effects of certain latent variables on attributes were set to zero because they were very small and insignificant. These include the effect of LV1 on average salary, the effect of LV2 on 20% more than average salary, and the effect of LV3 on 5 days of training. As visible in this table, one tau per indicator variable for motivation was normalized.

$$LL(\Omega_\beta) = \sum_{n=1}^{N} ln \int_{\beta} \prod_{t=1}^{T} P_{nt} f(\beta_n|\Omega)\delta\beta \tag{9}$$

4. Results

Results from the three main models show that as random heterogeneity in respondent preferences is incorporated in the MMNL, model fit improves in comparison to the MNL. This was as expected because the MNL is quite restrictive and does not allow for the heterogenous preferences of respondents. Table 4 gives the model goodness of fit.

We also see that the signs of all attributes were consistent between the three models, which was reassuring in establishing the general fit of our data with the models. The results of the MNL and MMNL are given in the supplementary file. Further, a reduced form hybrid choice model was also estimated in order to assess if he log-likelihood at convergence for such a model was different than the log-likelihood of the choice model component of the HCM at convergence.

4.1. Estimation results

Table 5 shows the estimation results of the HCM. These are informative in understanding how the three dimensions of HEW motivation, given by the three latent variables, affect their preferences for different job attributes.

We start with $\alpha1$ (representing *intrinsic motivation*) and focus on the parameters labelled as θ and ζ, which we interpret based on the direction of association between indicator questions and the latent variables given in Table 3. We find that HEWs who agreed to the three motivational statements informing $\alpha1$, indicating intrinsic motivation, were also more likely to prefer jobs that offered less days of training, good facility quality, and good health outcomes. They show dislike towards 20% more than average salaries. Looking at parameters related to $\alpha2$ (representing *general contentment with job*), we find that the respondents who are more likely to agree with *"I am proud of the work I do"* and *"In general I am satisfied with my role"* have lower preferences for less days of training and care less about heavy workloads. Finally, results about $\alpha3$

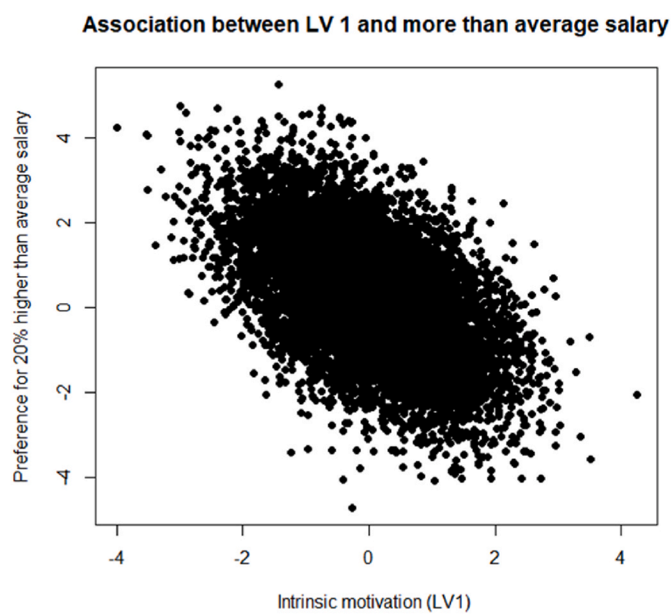

Fig. 3. Association between intrinsic motivation and a higher than average salary.

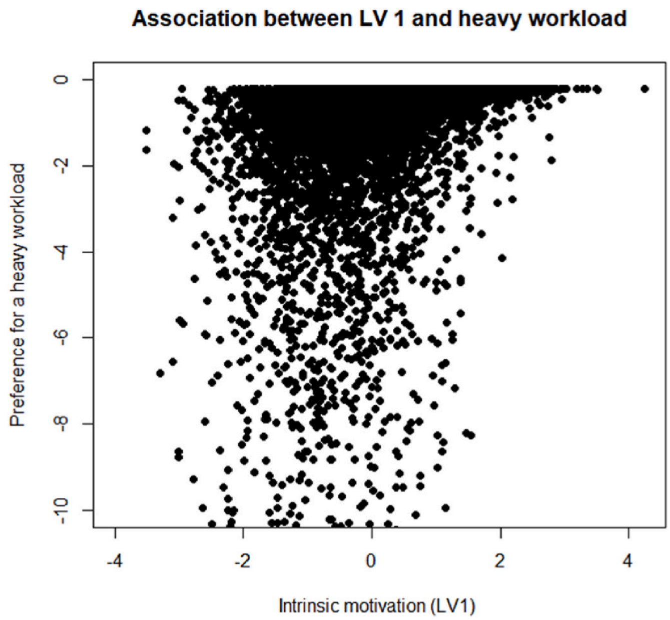

Fig. 4. Association between extrinsic motivation and a heavy workload.

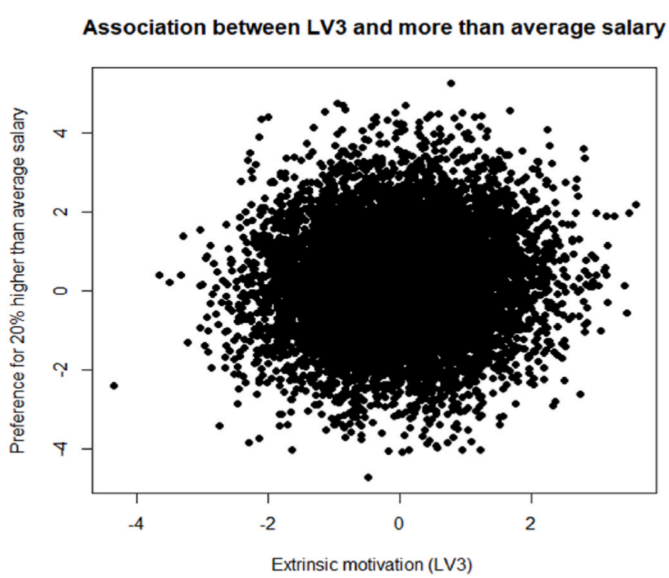

Fig. 5. Association between extrinsic motivation and a higher than average salary.

(representing *extrinsic motivation*) show that HEWs who are more likely to agree with "*at the moment I don't feel like working as hard as I can*" have stronger disutility for a heavy workload and preferences for good facility quality. At the same time, respondents who are more likely to agree with "*I am strongly motivated by the recognition I get from other people*" have opposite preferences, that is they experience less disutility from heavy workload and less utility from good facility quality.

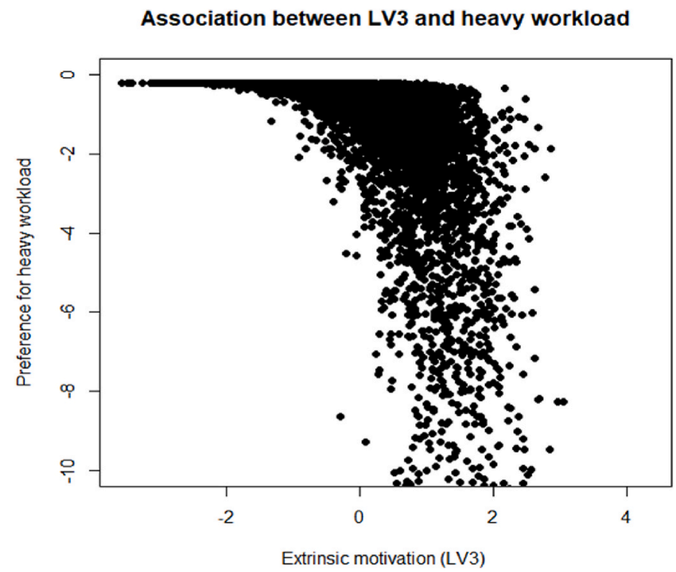

Fig. 6. Association between extrinsic motivation and a heavy workload.

We further demonstrate the association between multidimensional motivation and HEW preferences, by plotting the correlation between respondent preferences for 20% more than average salary and the θ parameters which capture the effect of the latent variables α_1 (intrinsic motivation), α_3 (extrinsic motivation) on their preferences for the attribute level. We also plot the correlation between preferences for a heavy workload and the θ parameters for the two latent variables. In line with the literature, we hypothesise that extrinsically motivated people will prefer a higher than average salary and dislike a heavier workload, while people with intrinsic motivation will not care too much about a heavy workload and not prefer a higher salary (Deci and Ryan, 1985). Most of the results for latent variable 2, depicting general contentment with HEW jobs were found to be statistically insignificant.

Fig. 3 shows the direction in which intrinsic motivation affects HEW's preferences for a higher than average salary. We see that as HEWs become more intrinsically motivated, their preferences for a higher average salary decrease. Fig. 4 shows the same association but for a heavy workload. We see that as intrinsic motivation diminishes (goes from 0 to −4), preferences for a heavy workload also reduce, however, with a rise in intrinsic motivation, HEWs become more neutral to a heavy workload.

Contrary to the above, extrinsically motivated HEWs show some preferences towards a higher than average salary (Fig. 5), and strong dislike towards a heavy workload (Fig. 6).

Lastly, Fig. 7 shows the extent to which the variance in each attribute can be explained by all three latent variables. It can be seen that while a large proportion of variance for most of the attributes can be explained by latent variables 1 and 3 (intrinsic and extrinsic motivation, respectively), average salary and 10 days of training are especially worth noting as LV3 accounts for 96% and 80% variance, respectively. LV2 or general contentment with job contributes to a much lower proportion of preference variation contributed by motivation as a whole. It is important to note that the remaining heterogeneity in Fig. 7 is random, and not linked to any of the latent variables in particular.

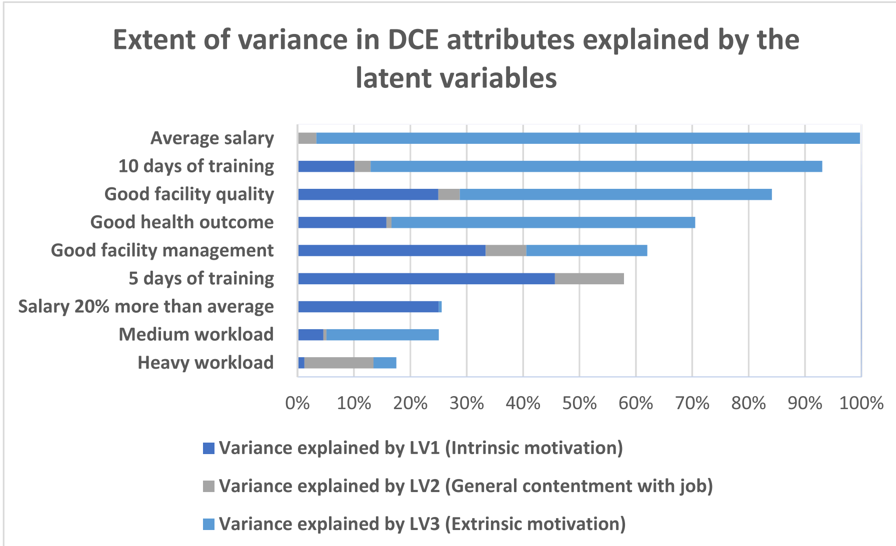

Fig. 7. Extent of variation in preferences explained by the three latent variables.

5. Discussion and conclusions

Using data on CHWs in Ethiopia, we showed that health worker motivation is linked to their preferences for job attributes. We showed that for this analysis, when using motivation to explain heterogeneity in preferences, hybrid choice models outperform the models more traditionally used and allow us to overcome empirical concerns with endogeneity bias and measurement error (Buckell et al., 2021).

One of the key strengths of this study, in comparison to others on this topic, is that it explores the preferences and motivations of a group of lower-skilled frontline health workers who are central to the delivery of primary health care in Ethiopia and on whom there is little research. Our results show that HEWs that agreed to statements representing intrinsic motivation, also preferred jobs that offered lesser number of training days, opportunities to improve the health outcomes of people, and had supportive managers. They were neutral to a heavy workload, and disliked jobs with higher than average salaries. This is in line with theories on motivation which describe intrinsic motivation to be about a person's desire to expend efforts based on their interest in and enjoyment of the activity itself (Gagné and Deci, 2005; Grant, 2008) rather than external rewards like salary. Further, substantiated by findings from our qualitative research with HEWs (Arora et al., 2020), we believe that a preference to spend lesser number of days on training is driven by their desire to not miss work for an extended period of time which can put them behind in the delivery of their tasks. We also found that HEWs with higher degrees were less likely to be intrinsically motivated. This was expected as better educated people in the labour market often tend to be driven by external rewards like higher remuneration for their work (Schweri and Hartog, 2015). Extrinsic motivation on the other hand refers to a person's desire to make effort to obtain outcomes that are external to the activity itself and separable from it (Amabile, 1993; Brief and Aldag, 1977) so, people who tend to be extrinsically motivated are likely to be driven by things like their salary, praise from supervisors. Majority of our findings from the latent variable representing extrinsic motivation were not significant, however we did find that HEWs who were more likely to agree with statements representing extrinsic motivation also showed stronger disutility for a heavy workload and stronger preferences for a higher than average salary, which was in line with our expectations.

Our methods are subject to some limitations. First, we recognise that the quantitative tool on motivation was adapted from studies conducted in other countries which may have reduced its internal and external validity because Ethiopia has its distinct cultural, political, and health system landscape. To overcome this, we used expert opinion to ensure that the tool was tailored to the context, and then piloted it with health workers prior to rolling it out to make sure it is comprehendible. Second, while we have estimated a very detailed specification of the hybrid choice model with three latent variables, there are always opportunities for further developments. Our specification of the hybrid choice model focussed solely on motivation as the latent construct but there is clearly scope to also explore other latent components that could be present in the underlying structure of the model. Further, the reported association between the latent variables on choice behaviour should be interpreted with caution. Since motivation was not observed over time and the data was cross-sectional in nature, it is not clear if e.g. extrinsically motivated people preferred higher than average salaries or people who preferred higher salaries tended to be extrinsically motivated. Our intension was thus never to measure causality between motivation and job preferences, but to develop a model to estimate the extent of random variation that can be explained by motivation. Moreover, it was not clear which indicators from the tool on motivation should have been used to measure motivation in the hybrid choice model or whether to use the full set of available indicators. Using only some of the indicators risks overlooking key information, but on the other hand, using all indicators increases computational burden and can pose significant problems for modelling, because many indicators could be highly correlated which can leads to a proliferation of parameters and technical issues such as collinearity (Buckell et al., 2021). We, thus, included only statements with the highest factor loadings for each of the three latent variables, which we believed captured the key aspects of each dimension of motivation sufficiently. Third, due to correlation concerns, we had to reject Halton draws in favour of using 2000 MLHS draws (Bhat, 2003; Hess et al., 2006). We recognise that some recent literature does favour Sobol draws (Czajkowski and Budziński, 2019), however we thought the key point was to avoid Halton draws in this instance. Finally, due to our decision to include salary as a qualitative attribute, we were unable to include willingness-to-pay estimates in the study which could have provided useful information about how HEWs trade-off between individual attributes. It was not completely clear to us, why the *average salary* attribute in our models was not of the expected sign. Respondents may have read quickly and when they saw "20%" they assumed it was "20% higher than average", not distinguishing between 20% higher and 20% lower. This would even be suggested by the results as there is no statistical difference between above-average and below-average (the omitted category) salaries. Without additional research and in the absence of qualitative evidence, however, it is not possible to know whether the validity of these parameter estimates is undermined.

Our approach to measure the labour market choices of community health workers using a hybrid choice approach provides promising results for choice modelers as well as managers and policy makers. These results are important from a behavioural and policy perspective as now we have more insight into the decision making processes, linking multidimensional motivation with job choices of health workers. These findings could be leveraged by managers and policy makers as psychometric tests, to assess the drivers of an individual in the labour workforce, are more commonly available and can be conducted ex ante to reveal their internal cognitive processes that make them expend effort towards a job. Future research linking other psychological processes like the knowledge and attitude of health workers, to the heterogeneity in their job preferences, is encouraged to further understand the factors that drive the decision making of frontline health workers.

Author statement

Nikita Arora: Conceptualization, Methodology, Data Formal analysis, Writing-from original draft preparation to final editing. **Romain Crastes dit Sourd:** Conceptualization, Data Formal analysis, Writing – original draft preparation. **Matthew Quaife:** Conceptualization, Data collection, Writing-reviewing and editing. **Kara Hanson:** Conceptualization, Writing-reviewing and editing, Supervision. **Dorka Woldesenbet:** Data collection, Writing-reviewing and editing. **Abiy Seifu:** Data collection, Writing-reviewing and editing.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2022.115151.

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Supplementary file

Table 6 gives the results of the factor analysis, including all 30 statements on motivation.

Table 6: Results of the factor analysis

Statements	Factor 1 loadings	Factor 2 loadings	Factor 3 loadings
I am respected in my community for the work I do	0.72	-0.08	-0.12
My work is important because I help people	0.70	-0.13	-0.02
I can solve most problems I have at work if I work hard	0.69	-0.12	0.13
I am keenly aware of the career goals I have set for myself	0.67	0.04	-0.10
If I do well at work, I will achieve my goals	0.65	-0.01	0.04
It is important that I do a good job so that the health system works well	0.62	-0.07	0.20
Training sessions that I attend are worthwhile and add benefit to my career path	0.54	-0.11	0.23
I gain knowledge from being in this role	0.51	0.08	0.19
To be motivating, hard work must be rewarded with more status and money	0.51	-0.23	0.17
I can complete all of the work I am expected to do	0.50	0.12	-0.38
I feel committed to my role	0.48	0.10	-0.24
I feel like performing the duties required of me	0.48	0.20	-0.27
I am willing to do more than is asked of me in my role	0.39	0.23	0.16
I am proud to be working in my role	0.03	0.81	-0.06
In general I am satisfied with my role	0.02	0.67	0.00
I am proud of the work I do	0.24	0.64	0.12
The system of choosing who attends training sessions is fair	-0.06	0.44	0.03
My supervisors and managers are supportive of me	0.08	0.42	-0.03
My job makes me feel good about myself.	0.37	0.40	0.20
My work place provides everything I need to do my job properly	-0.13	0.39	-0.03
I am strongly motivated by the income I can earn at work	0.12	0.38	0.04
My salary accurately reflects my skills and workload	-0.15	0.36	0.22
At the moment I don't feel like working as hard as I can	-0.01	-0.18	0.36
I am strongly motivated by the recognition I get from other people	0.22	0.18	0.42

Figure notes: the statements in grey loaded to factor 1, statements in blue loaded to factor 2, and the statements in green loaded to factor3

Table 7 presents estimation results of the main effect MNL model.

Table 7: Estimation results of MNL

Parameter	Estimate	Rob.s.e.	Rob.t.ratio
ASC 2	0.06721	0.04716	1.4251
ASC 3	-1.32642	0.22736	-5.8341
Average salary	-0.14423	0.08335	-1.7305
20% more than average salary	0.22427	0.11645	1.9258
5 days training	0.1348	0.14404	0.9358
10 days training	-0.39102	0.14498	-2.6971
Medium workload	-0.18338	0.1442	-1.2717

Heavy workload	-0.49583	0.10057	-4.9303
Good facility quality	0.23313	0.08588	2.7147
Good management	0.56187	0.10043	5.5948
Good outcome	-0.10102	0.13062	-0.7734

Table 8 gives the estimation results of the main effects MMNL model.

Table 8: Estimation results of the MMNL

Category	**Parameter**	**Estimate**	**Rob.s.e.**	**Rob.t.ratio**
	ASC 2	0.102081	0.0703	1.45216
	ASC 3	-4.279222	0.67666	-6.32403
	Average salary	-0.412419	0.14759	-2.79434
	20% more than average salary	0.372877	0.21013	1.77454
	5 days training	0.110371	0.28292	0.39011
	10 days training	-1.087717	0.27811	-3.9111
	Medium workload	-0.235479	0.28526	-0.8255
	Heavy workload	-1.314493	0.37711	-3.48574
	Good facility quality	0.267694	0.12764	2.09729
	Good management	0.962115	0.17775	5.41281
Attribute mean (μ)	Good outcome	-0.336504	0.24027	-1.40054
	ASC 2	-0.002088	0.03239	-0.06446
	ASC 3	3.365752	0.3891	8.65011
	Average salary	-0.009091	0.03241	-0.28051
	20% more than average salary	-0.782301	0.22273	-3.5123
	5 days training	-0.350515	0.41888	-0.83679
	10 days training	-0.636157	0.43043	-1.47796
	Medium workload	2.091217	0.32716	6.39211
	Heavy workload	1.589823	0.40046	3.97001
	Good facility quality	-0.849086	0.1693	-5.01541
	Good management	0.020835	0.05456	0.38187
Attribute standard deviation (σ)	Good outcome	0.441759	0.42974	1.02796

CHAPTER 8

Research paper 4: Discrete choice analysis of health worker job preferences in Ethiopia: separating attribute non-attendance from taste heterogeneity

Overview

As identified in Chapter 2, a growing body of literature in health economics has started to recognise that respondents in DCEs do not always attend to all the attributes presented to them - an information processing strategy called attribute non-attendance (ANA). Choice models that don't account for ANA could end up estimating the wrong coefficient estimates and misunderstanding respondent preferences. However, assuming that the respondent's choice to not consider all attributes is always non-attendance, when it could reflect preference heterogeneity, can also result in the wrong cost-benefit ratios. Using DCE data on Ethiopian community health workers, this paper uses semi-parametric mixtures of latent class models to disentangle successfully inferred non-attendance from respondent's heterogenous preferences for job attributes. It is the first application of these models in the context of human resources for health in a low-income country context.

This paper demonstrates that such models are better able to probabilistically determine all possible ANA strategies while accounting for respondent's low taste sensitivities for certain attributes, in comparison to the latent class models normally used in health economics. It also reports that preferences for attributes and the extent of ANA can vary by the cadre of health workers, highlighting the need for choosing well-defined and relevant attributes in a DCE to ensure that ANA does not result from an inadequate experimental design.

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Primary Supervisor	Professor Kara Hanson		

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SECTION E

Student Signature	[redacted]
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RESEARCH ARTICLE

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Discrete choice analysis of health worker job preferences in Ethiopia: Separating attribute non-attendance from taste heterogeneity

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Abstract

When measuring preferences, discrete choice experiments (DCEs) typically assume that respondents consider all available information before making decisions. However, many respondents often only consider a subset of the choice characteristics, a heuristic called attribute non-attendance (ANA). Failure to account for ANA can bias DCE results, potentially leading to flawed policy recommendations. While conventional latent class logit models have most commonly been used to assess ANA in choices, these models are often not flexible enough to separate non-attendance from respondents' low valuation of certain attributes, resulting in inflated rates of ANA. In this paper, we show that semi-parametric mixtures of latent class models can be used to disentangle successfully inferred non-attendance from respondent's "weaker" taste sensitivities for certain attributes. In a DCE on the job preferences of health workers in Ethiopia, we demonstrate that such models provide more reliable estimates of inferred non-attendance than the alternative methods currently used. Moreover, since we find statistically significant variation in the rates of ANA exhibited by different health worker cadres, we highlight the need for well-defined attributes in a DCE, to ensure that ANA does not result from a weak experimental design.

KEYWORDS
attribute non-attendance, discrete choice experiment, health workers, preference heterogeneity

JEL CLASSIFICATION
C01, C35, D01, D80

1 | INTRODUCTION

Grounded in the economic theory of consumer behavior (Lancaster, 1966; McFadden, 1974), discrete choice experiments (DCEs) are popularly used by health economists for the valuation of health products and services (Soekhai et al., 2019). It is believed that DCE results can inform the allocation of healthcare resources, and support recommendations about welfare polices (de Bekker-Grob et al., 2012; Lagarde et al., 2012; Mandeville et al., 2014; Rockers et al., 2012; Ryan, 2004; Saran et al., 2020).

Discrete choice experiments require respondents to process sizable amounts of information and it is typically assumed that respondents consider all available information before making their choices. However, a growing body of evidence now shows that respondents don't always behave this way, instead consciously or subconsciously use simple rules or heuristics to process information before making their decisions (Heidenreich et al., 2018; Hensher et al., 2005; Hess et al., 2013; Lagarde, 2013). One of these information processing strategies, attribute non-attendance (ANA), relates to respondents only trading-off a subset of the available attributes before choosing their preferred alternative. This violates the axiom of continuous preferences - a key tenet of consumer theory and implies that respondents make trade-offs between all attributes across each of the alternatives before making their decision (Campbell et al., 2008; Hensher et al., 2005; Hensher & Rose, 2009; Scarpa et al., 2009). Over the last decade, researchers have also increasingly acknowledged that failing to account for ANA may lead to biased coefficient estimates and a skewed understanding of respondent preferences (Heidenreich et al., 2018; Hole et al., 2013; Nguyen et al., 2015; Scarpa et al., 2009). However, accounting for ANA while assuming responder's choice to not consider all characteristics is always non-attendance, when it could reflect preferences, can also result in the wrong cost-benefit ratios and consequently distorted welfare estimates (Heidenreich et al., 2018).

In the DCE literature, a range of approaches have been used to account for ANA. These can broadly be classified into stated and inferred ANA. In stated ANA, analysts use respondent's self-reported answers to indicate the extent to which they have ignored attributes (Collins, 2012; Hensher & Rose, 2009; Scarpa et al., 2009) while inferred ANA uses econometric modeling to estimate the probability with which respondents could have used different non-attendance strategies (Campbell et al., 2008; Carlsson & Martinsson, 2003; Hensher et al., 2005; Hess et al., 2007; Hole et al., 2013; Lagarde, 2013). Both approaches restrict individual parameters of attributes that are considered to have been ignored, to zero. While the jury is still out about which is the most reliable method, the inference of ANA using an analytical approach has stronger appeal, especially when working with the understanding that non-attendance in the dataset may partially reflect preferences. Previous studies have cautioned that respondnets' ability to reflect on their own decision making could be biased by their sub-consicous preferences, questioning stated ANA methods to accurately capture non-attendance (Heidenreich et al., 2018; Hensher & Rose, 2009; Hole et al., 2013). Although, econometric models used in inferring ANA can also produce results that are confounded with preference heterogeneity, if they are not flexible enough to separate respondent's genuinely low valuation of attributes, from ANA (Hensher et al., 2005; Hess et al., 2013; Hole et al., 2013). Our paper contributes to this literature by demonstrating the use of semi-parametric models in the probabilistic determination of all possible ANA strategies used by a sample of frontline health workers in Ethiopia, while accounting for preference heterogeneity. We find that non-attendance levels fall and model goodness-of-fit substantially improves when heterogeneity in respondent preferences is accounted for using discrete-continuous latent class models (LCM). We also report that preferences for attributes and the extent of ANA varies with the cadre of health workers.

Not enough research has been done in health economics to assess if inferred ANA is a heuristic or genuine preference, especially using econometric models that are flexible enough to separate the two without relying on supplementary information from respondents. To our knowledge, one other study in the health context has used a similar econometric approach to ours where a mixed endogenous attribute attendance model was estimated to tease out preference heterogeneity from ANA using DCE data on the prescription behavior of Norwegian doctors (Hole et al., 2013). Ours will be the first application of this approach in a low-and middle-income country setting. Two factors underlie the importance of study context, and the value of applying an improved approach to the econometric inference of ANA in LMICs. First, there is some literature that suggests that ANA maybe a greater threat to the validity of DCE results in LMICs, than in higher-income settings. Nguyen et al. (2015) reviewed relevant DCEs conducted in developed and developing counties and used their results on ANA from a DCE conducted in Vietnam to demonstrate that rates of ANA are on average higher in developing countries than in developed ones. Second, the application of advanced econometric modeling techniques to identify ANA in health workers' employment preferences in Ethiopia is important because ANA potentially undermines the validity of marginal valuations. Generating valid estimates is important if research is to inform policy.

2 | DATA

We used data from a DCE designed to quantitatively assess the job preferences of health workers based in four regions in Ethiopia: Tigray, Amhara, Oromia and Southern Nations, Nationalities, and People's Region, which altogether make up for more than 80% of the country's total population. Many DCEs have been conducted to understand the job incentives that align best with the preferences of doctors and nurses in LMICs (Mandeville et al., 2014, 2016, 2017; Smitz et al., 2016; Song et al., 2015), which is relevant in improving their retention in the workforce. However, only limited quantitative research is available on the job preferences of medium and low-skilled health workers like midwives and community health workers, who are often the backbone of primary healthcare delivery in countries like Ethiopia. In our study, we focus on understanding the job preferences of three frontline health worker cadres: community health workers called *health extension workers (HEW); mid-level healthcare providers* including midwives; and *non-patient facing staff* such as health facility administrators. More details about the three cadres and the health labor market in Ethiopia can be found in our previously published work with these health workers in Lamba et al. (2021). This DCE was embedded within a survey collecting endline information for a process evaluation of a quality improvement (QI) program targeted to improve the knowledge and motivation of these health worker cadres, implemented by the Ministry of Health in Ethiopia. The study found that the QI program had almost no impact on health worker motivation, but some impact on health worker knowledge. The DCE was added to this data collection as a standalone module to investigate job preferences of different cadres (Lamba et al., 2021).

The endline survey was conducted in June 2019, with a cadre-stratified random sample of 404 health workers in the Ethiopian health system, where 68% (275) of the original sample was re-interviewed along with 129 newly recruited respondents. The sample comprised 202 HEWs (50%); 40 non-patient facing staff (10%); and 162 mid-level healthcare providers (40%). A target sample size of 50 respondents per region was chosen, based on the primary research question of assessing changes in motivation as measured by Likert scale questions. After piloting, the largest S-estimate for any level of the final design was checked for consistency with this sample size – this was 184, so the design was deemed to give a good chance of giving significant parameters at the 5% level. Since one of our key findings in Lamba et al. (2021) was that health worker preferences differed by their cadre type, we hypothesized that cadre will also impact the rates of ANA for different job attributes. To make the estimation of these complex models computationally possible in a reasonable time frame, we split the dataset into two and present results among HEWs and other cadres separately.

A team of seven trained research assistants from Addis Ababa University administered the DCE, face-to-face with the respondents, using Tigringya, Amharic, and Oromifa languages and Open Data Kit (https://opendatakit.org) software on tablet computers. To reduce social desirability bias in responses, we allowed research assistants to explain the experiment to respondents, after which they were told to make a decision about their preferred job on their own.

Informed consent was obtained from all participants before data were collected, and the study was undertaken with ethical approval from the Observational Research Ethics Committee of the London School of Hygiene and Tropical Medicine and a program evaluation waiver from the Ethics Committee of the Ethiopian Public Health Association.

2.1 | Discrete choice experiment development and design

The DCE had six attributes, identified after a thorough review of literature on health workforce choice experiments conducted in the East African context (Blaauw et al., 2013; Mandeville et al., 2017; Mangham & Hanson, 2008; Rockers et al., 2012). Ten potential attributes were initially shortlisted and eventually reduced to six, guided by the findings of a qualitative study conducted in Ethiopia, a year previously to data collection (Wang et al., 2016). The selected attributes described pecuniary and non-pecuniary workplace incentives, facility and management structures characterizing the key features of the jobs of all three sampled cadres. Table 1 provides the final list of attributes included in the DCE along with their levels; each attribute level was dummy coded as 0 or 1. From these attributes, 216 ($3^3 \times 2^3$) possible combinations of jobs could have been formed.

The DCE was piloted among 19 district health office staff in December 2017, before the baseline survey for the main study was conducted. The pilot had a ten-task fractional factorial design while the final was a seven-task, D-optimal design based on priors from the pilot, conducted in NGENE (Choice Metrics, 2012). The design was main effects only, and because it was a subsection of a survey which took a relatively long time to complete, no additional quality check tasks were included for example, dominance checks or repeat tasks.

TABLE 1 DCE attributes and their levels

Attributes	Attribute levels
Salary	20% below average Average earnings 20% above average
Training	No training available 5 days per year dedicated training time (improving work-related and transferable skills) 10 days per year dedicated training time (improving work-related and transferable skills)
Workload	Light: More than enough time to complete duties Medium: Enough time to complete duties Heavy: Barely enough time to complete duties
Management style	Management is supportive, and makes work easier Management is not supportive, and makes work more difficult
Health facility quality	Your workplace is good: It has reliable electricity and other services, supplies are always available Your workplace is basic: It has unreliable electricity, whilst supplies you need are not always available
Opportunities to improve health outcomes	Your work will have a large impact on improving health in the local community Your work will have a small impact on improving health in the local community

Abbreviation: DCE, discrete choice experiments.

	Job A	Job B	
Salary	Average earnings	20% below average	**Neither of these - I prefer my current job**
Opportunities to improve health	Your work will have a small impact on improving health in the local community	Your work will have a large impact on improving health in the local community	
Management style	Management is not supportive, and makes work more difficult	Management is supportive, and makes work easier	
Office quality	Your workplace is basic: it has unreliable electricity and other services, whilst supplies you need are not always available	Your workplace is good: it has reliable electricity and other services, supplies are always available	
Training	5 days per year dedicated training time (improving work-related and transferable skills)	10 days per year dedicated training time (improving work-related and transferable skills)	
Workload	Light: more than enough time to complete duties	Heavy: barely enough time to complete duties	

FIGURE 1 Example choice task

Each task displayed two, unlabeled job alternatives described by six attributes, where each alternative represented a generic health worker's job in Ethiopia. Participants were asked the following question: "*Here are two jobs described by some of their characteristics. Compared to your current job, please choose which you would prefer*". Respondents were also explained that barring the given attributes, all other characteristics in the jobs were identical. Figure 1 shows an example choice task, as presented to the respondents.

To increase realism and allow for the estimation of unconditional demand, a generic opt-out alternative, modeled simply as a constant with no attribute levels, was included to represent the choice of picking neither of the presented job profiles and staying in their current jobs. We used Apollo version 0.2.4 (Hess & Palma, 2019) in R (version 4.0.2) to analyze our data.

3 | METHODOLOGICAL APPROACH

3.1 | The mixed multinomial logit model

Standard random utility models in DCEs are based on the framework by McFadden (1974), and believe that respondent choice is determined by the utilities that they perceive for given alternatives. For respondent n, alternative i, and choice situation t, utility, U, can be given by

$$U_{i,n,t} = V_{i,n,t} + \epsilon_{i,n,t} \tag{1}$$

where, U, is made up of a deterministic component $V_{i,n,t}$, and a random component $\epsilon_{i,n,t}$ which is assumed to be an independently and identically distributed Extreme Value Type I function (Hensher et al., 2005; Manski, 2001). Further, the deterministic part of the utility can be re-written as:

$$V_{i,n,t} = f(\beta_n, x_{i,n,t}, z_n) \tag{2}$$

where β_n is the vector of sensitivities for the respondent, $x_{i,n,t}$ is a vector of attributes for alternative i and z_n is a vector of socio-demographic characteristics of respondent n.

In this DCE application, the deterministic utility for a job alternative i, for individual n, characterized by a selected set of six attributes, can be given by:

$$\begin{aligned}\beta_n x_{n,i,t} = \beta_{asci} + \beta_1 Salary_i + \beta_2 Impact_i + \beta_3 Management_i + \beta_4 Facility_i \\ + \beta_5 Training_i + \beta_6 Workload_i\end{aligned} \tag{3}$$

where β_{asci} corresponds to an alternative-specific constant for alternative i. Two ASCs were featured in the models given that there were three alternatives in each choice task. β_1 to β_6 represent the preference weights of attributes used to characterize job alternatives included in the DCE.

Typically, a multinomial logit model (MNL) is used to estimate the probability with which each respondent makes a sequence of choices. However, since the model is restrictive and assumes all respondents to have the same preferences for a given attribute, we start our estimation with a mixed multinomial logit model (MMNL) which allows us to relax this assumption and for the coefficients to follow a distribution.

If $f(\theta_n|\Omega)$ is the joint density over taste parameters, where θ_n is a vector of random parameters and Ω the parameter of the distributions, using an MMNL the probability of the sequence of choices, Y_n, made by respondent n can be given by:

$$\Pr(Y_n|x_n, \Omega) = \int \prod_{t \in T_n} \frac{\exp(\beta' x_{nit})}{\sum_{j \in J} \beta' x_{njt}} f(\theta_n|\Omega)\, d(\theta_n) \tag{4}$$

Even though the MMNL does not capture ANA in the dataset, we estimate it as a base model to gradually build up model complexity as well as to include it in the comparison of goodness of fit between different models.

3.2 | Latent class model for attribute non-attendance

Using discrete distributions to model the underlying preferences of respondents, LCMs are popular semi-parametric specifications that accommodate response heterogeneity in choice models (Hensher et al., 2005). LCMs assume that the behavior of respondents depends on observable attributes and on latent heterogeneity that varies with factors observed by the analyst. In an LCM, the population of respondents can be divided into a set number of Q classes that differ in their preferences. While preferences are assumed to be different between classes, within each class all members are assumed to share the same preferences (Hensher et al., 2005). The model assumes that class allocation is probabilistic and which class contains any particular individual is unknown to the analyst. In a conventional LCM that is modeling heterogeneity in preferences, the optimal number of classes to be included is normally determined by noticing the change in model goodness of fit as the number of classes go up one-by-one. This can be done by monitoring an information criterion like Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) which penalizes model fit as the number of parameters increase (Heidenreich et al., 2018). In contrast, a latent class model for attribute non-attendance (ANA-LC) estimates a behavioral model which assumes that respondents use heuristics in processing information in a DCE, and only attend to a subset of the given K attributes. This results in 2^K different combinations of ANA and each combination can be given by a class in the ANA-LC (Collins, 2012; Hensher et al., 2005; Lagarde, 2013). With six attributes in our sample, we estimated sixty four (2^6) latent classes in our ANA-LC. Estimating an LCM with 64 classes using the standard practice of estimating a constant for each of the 64 classes (minus one), could have proved to be burdensome and reduced model parsimony substantially due to a spike in the number of estimated parameters. So, following the approach by Hole et al. (2013), we estimated a constant for each of the six attributes instead, and generated the probability of an attribute being attended to (or not) over all 64 combinations, by introducing a binary logit model for each of the attributes. This increased the number of estimated parameters in the model by six, not 63. A drawback of the specification, however, is that it is important to assume that the non-attendance probabilities are independent. A detailed description of this specification is provided in the Supporting Information S1 accompanying this article, but as an illustration, we show that the probability ω that all the attributes were attended to, corresponds to:

$$\omega_{Complete\ attendance} = \frac{\exp\left(\delta_{salary}\right)}{1+\exp\left(\delta_{salary}\right)} \cdot \frac{\exp\left(\delta_{training}\right)}{1+\exp\left(\delta_{training}\right)} \cdot \frac{\exp\left(\delta_{workload}\right)}{1+\exp\left(\delta_{workload}\right)} \cdot \frac{\exp\left(\delta_{quality}\right)}{1+\exp\left(\delta_{quality}\right)} \cdot \frac{\exp\left(\delta_{management}\right)}{1+\exp\left(\delta_{management}\right)} \cdot \frac{\exp\left(\delta_{opportunities}\right)}{1+\exp\left(\delta_{opportunities}\right)} \tag{5}$$

While the probability of a combination where all attributes were attended to except for *salary* and *workload,* corresponds to:

$$\omega_{salary\ and\ workload\ non\text{-}attendance} = \frac{1}{1+\exp\left(\delta_{salary}\right)} \cdot \frac{\exp\left(\delta_{training}\right)}{1+\exp\left(\delta_{training}\right)} \cdot \frac{1}{1+\exp\left(\delta_{Workload}\right)} \cdot \frac{\exp\left(\delta_{quality}\right)}{1+\exp\left(\delta_{quality}\right)} \cdot \frac{\exp\left(\delta_{management}\right)}{1+\exp\left(\delta_{management}\right)} \cdot \frac{\exp\left(\delta_{opportunities}\right)}{1+\exp\left(\delta_{opportunities}\right)} \tag{6}$$

Equations (5) and (6) are adaptions of the equations used for similar analysis by Hole et al. (2013). The extent to which a single attribute, say salary, was ignored could also be calculated by simply imputing the value of δ_{salary}, calculated using the ANA-LC, in the salary component of Equation (6).

3.3 | Assessing patterns of ANA using discrete-continuous mixture models

In health economics literature, LCMs that simply account for all or a reduced version of the possible 2^k strategies have been considered to be sufficient for estimating the patterns of ANA in a dataset (Heidenreich et al., 2018; Lagarde, 2013). However, if substantial preference heterogeneity unrelated to ANA exists, such LCMs are likely to give results that are confounded by respondent's taste heterogeneity (Hess et al., 2013; Hole et al., 2013). As a result, the share of respondents that get allocated to a non-attendance class don't necessarily have zero sensitivity toward the attribute but a relatively low sensitivity, and that real non-attendance is rarer than imagined thereby generating misleading model estimates (Campbell et al., 2008; Collins, 2012; Hess et al., 2013).

In order to distinguish preference heterogeneity from ANA in our dataset, we estimated a logit model that combined discrete and random parameters (Hess et al., 2013; Hole et al., 2013). The resultant model, which we called "ANA-MMNL", accounted for continuous taste heterogeneity in respondent preferences while inferring all 64 permutations of ANA. The probability of observing a sequence of choices made by a given respondent n according to the ANA-MMNL model, thus correspondeds to:

$$\Pr\left(Y_n | x_n, \Omega\right) = \sum_{q \in Q} \omega_{nq} \int \prod_{t \in T_n} \frac{\exp\left(\beta' x_{nit}\right)}{\sum_{j \in J} \beta' x_{njt}} f\left(\theta_n | \Omega\right) d\left(\theta_n\right) \tag{7}$$

We compare ANA models without and with mixing in the paper, so the within-class probabilities of the former corresponds to MNL, not MMNL. All MMNL and ANA-MMNL models, which accounted for random heterogeneity in respondent preferences, were estimated using 5000 Sobol draws where all attribute levels followed a normal distribution except higher than average salary, which we constrained to positive lognormal based on the expectation that all respondents will gain utility from this level. During the initial estimation of some ANA-MMNL models we found that certain attributes were always attended to, resulting in very large values of their delta parameters. In such cases, we re-estimated the final models after excluding the corresponding ANA classes for these parameters, to ensure model parsimony and convergence (Hess et al., 2013).

4 | RESULTS

We start by presenting our goodness of fit results, followed by estimation results from the models that perform best, for each of the two sub-samples. Finally, we compare the rates of ANA between ANA-LC and ANA-MMNL models, disaggregated by cadre type.

4.1 | Model fit

Table 2 reports the BIC, AIC and log-likelihood of the three main models - MMNL, ANA-LC and ANA-MMNL for both sub-samples. For the dataset with HEWs, we see that the ANA-MMNL outperforms the other models on all three measures of fit. This was expected as the ANA-MMNL provides gains in efficiency by allowing further flexibility in the distribution of preferences across respondents, while maintaining model parsimony by including only 6 additional parameters to the model. For Other cadres, we see that while ANA-MMNL outperforms the other models on AIC and log-likelihood, it gets penalized for the number of parameters by the BIC where MMNL outperforms it. This was not surprising as the penalty term for the number of parameters included in the model is larger in BIC than in AIC, and we believed that all parameters entering the model at this stage were necessary for successfully inferring ANA.

To confirm our results and to assess if the ANA-MMNL statistically supersedes the other models, we present results from Likelihood Ratio tests between MMNL and ANA-MMNL; and ANA-LC and ANA-MMNL in Table 3. These results were consistent with our expectations. We show strong statistical evidence in favor of ANA-MMNL outperforming the other models for both the sub-samples.

4.2 | Estimation results

Since the ANA-MMNL models fitted our data best for both the sub-samples, below we only present results from these models. Class membership for non-attendance was calculated using Equation (5), which provided estimates for the extent of non-attendance (δ) of each attribute. As the values of δ parameters decreased, ANA increased. Rates of non-attendance are presented in Table 6 and discussed in detail in the following section. Table 4 gives ANA-MMNL results for HEWs. We report that HEWs preferred good management, lower number of training days, and good facility quality. They showed disutility toward a heavy workload, higher number of training days and average salary. Its worth noting that while the

TABLE 2 Goodness of fit results

		MMNL	ANA-LC	ANA-MMNL
HEW	AIC	2397.13	2531.22	2386.16
	BIC	2512.7	2620.53	2506.99
	Log-likelihood	−1176.56	−1248.61	−1170.08
Other cadres	AIC	2555.01	2697.31	2550.21
	BIC	2670.60	2818.15	2707.83
	Log-likelihood	−1255.51	−1325.65	−1245.10

Abbreviations: AIC, Akaike information criterion; ANA-LC, latent class model for attribute non-attendance; ANA-MMNL, discrete-continuous mixture model; BIC, Bayesian information criterion; HEW, health extension workers; MMNL, mixed multinomial logit model.

TABLE 3 Likelihood Ratio test results: ANA-MMNL outperforms ANA-LC and MMNL

Models	Parameters	Models	Parameters
HEW			
ANA-LC	17	MMNL	22
ANA-MMNL	23	ANA-MMNL	23
Difference	6	Difference	1
LR test *p*-value	<0.001	LR test *p*-value	<0.001
Other cadres			
ANA-LC	23	MMNL	22
ANA-MMNL	30	ANA-MMNL	30
Difference	7	Difference	8
LR test *p*-value	<0.001	LR test *p*-value	0.008

Note: The MMNL and ANA-LC are restricted versions of the ANA-MMNL. ANA-MMNL is the urestricted model in these Likelihood ratio tests.

Abbreviations: ANA-LC, latent class model for attribute non-attendance; ANA-MMNL, discrete-continuous mixture model; HEW, health extension workers; LR, likelihood ratio; MMNL, mixed multinomial logit model.

mean preferences of HEWs for *medium workload* were insignificant, there was statistically significant heterogeneity in the sample for preferences toward that attribute level.

Further, Table 5 gives the mean preferences for the pooled sample comprising Other cadres. We find that respondents from Other cadres preferred a medium workload, good facility quality, good management and a higher than average salary. They disliked a higher number of training days and receiving an average salary. They were also more likely to choose to stay in their current job, that is, choose the opt-out rather than either of the two hypothetical jobs.

4.3 | Rates of ANA across models

Table 6 gives the rates of ANA across ANA-LC and ANA-MMNL models for all three cadres. Starting with rates of non-attendance for ANA-LC models, we see that the most ignored attribute by HEWs was *salary*, followed by *workload*. There was substantial non-attendance for *opportunities to improve health outcomes* and *facility quality* with over 70% of HEWs ignoring them. *Training* and *management* were the only attributes where non-attendance was less than 50%. For the same model, we see that the rates of ANA exhibited by Other cadres were quite different from HEWs but similar between mid-level healthcare providers and non-patient facing staff. Mid-level healthcare providers show very high rates of ANA for all attributes except *opportunities to improve health outcomes,* similarly to non-patient facing staff with the only difference that non-patient facing staff attend to salary a lot more than any other cadres with only 35% not attending to it.

On the contrary to the above, we note that ANA-MMNL models report drastically lower rates of ANA in comparison to ANA-LC models, in line with our hypothesis that these models allow respondents' low preferences to be separated from non-attendance. HEWs seem to completely attend to all attributes except workload, similarly to mid-level healthcare providers, while non-patient facing staff show complete attendance only for *management* and *opportunities to improve health outcomes.* This cadre shows complete and substantial non-attendance for *facility quality* and *workload,* respectively, while lower rates for *salary* and *training*.

5 | DISCUSSION AND CONCLUSIONS

Overall, our findings support the growing evidence that a significant proportion of participants ignore attributes in choice experiments. There are still only a few studies that have accounted for ANA in the health economics literature, though this number is slowly increasing (Erdem et al., 2015; Heidenreich et al., 2018; Hole et al., 2013; Lagarde, 2013; Ryan et al., 2009; Scott, 2002).

Using data on the job preferences of health workers in Ethiopia, our findings add to this nascent body of literature and show that respondents don't always comply with the axiom of continuous preferences in DCEs. Moreover, our analysis also underlines that ANA may sometimes be confused with the low valuation of attributes, although the latter provides

TABLE 4 Estimation results of ANA-MMNL, for HEWs

No. of observations	**1413**		
No. of respondents	**202**		
McFadden's pseudo R^2	**0.2462**		
Category	**Parameter**	**Coefficient**	**Robust T ratio**
Attribute mean (μ)	*Asc for job 1*	−0.090	−1.32
	Asc for opt out	−3.427***	−4.70
	Avg. Salary	−0.434***	−3.30
	20% more than avg. salary	0.022[a]	−1.15
	5 days training	0.556**	2.49
	10 days training	−0.835**	−2.79
	Medium workload	3.037	0.64
	Heavy workload	−1.922**	−2.45
	Good facility quality	0.260**	2.31
	Good management	0.929***	5.50
	Good opportunities to improve health	−0.105	−0.39
Attribute standard deviation (σ)	*Asc for job 1*	0.032	0.36
	Asc for opt out	2.985***	7.07
	Avg. Salary	−0.003	−0.33
	20% more than avg. salary	2.304	1.47
	5 days training	−0.649*	−1.92
	10 days training	0.490	1.10
	Medium workload	−4.540**	−2.26
	Heavy workload	−0.579	−0.50
	Good facility quality	−0.819***	−5.50
	Good management	−0.005	−0.31
	Good opportunities to improve health	−0.423	−0.75
Extent of non-attendance (δ) for HEWs	*Workload*	−0.775	−0.77

Note: As stated above, in our estimation of the ANA-MMNL for HEWs, all attributes except *Workload* were always attended to (had 0% non-attendance). They were thus excluded from final model estimation. The opt-out was selected 11.5% of the times.

[a]Since more than average salary had a positive log normal distribution, the coefficient presented in Table 4 is the exponent of the actual value: −3.822.

***Significant at 1% level, **significant at 5% level, *significant at 10% level.

valid information about respondents' preferences. We demonstrate that the ANA-MMNL, which accounts for preference heterogeneity, outperforms the ANA-LC in terms of goodness of fit. The estimated ANA probabilities are substantially lower in the ANA-MMNL than in the ANA-LC, which may imply that health workers with weaker preferences were wrongly classified as non-attenders in the simpler model. Non-attendance is noticeable in the more flexible ANA-MMNL models as well, so its' not the case that accounting for random heterogeneity in preferences will get rid of non-attendance all together. Rather, allowing for both ANA and preference heterogeneity simultaneously, provides a better picture of respondents' decision-making behavior than either the ANA-LC or the MMNL. We also find substantial variation in the rates of ANA exhibited by different health worker cadres. It was noticeable that non-patient facing staff showed statistically significant ANA for more number of attributes, in comparison to HEWs and mid-level providers. This was not surprising as HEWs and mid-level healthcare providers are more used to making choices similar to those in the experiment (such as choosing between different medical treatments) on a regular basis and so the prevalence of simplifying shortcuts was less common in these groups in comparison to health facility administrators (comprising non-patient facing staff). Our findings were in line with those from Hole et al. (2013), who also demonstrated the use of these models on data from a DCE on doctors' choice of medication, using similar specifications.

The methods in our paper were subject to a number of limitations. Firstly, there has been an ongoing debate about how many draws one should use to make the results of simulation based models of "satisfying" quality. While the debate

TABLE 5 Estimation results of ANA-MMNL, for Other cadres

No. of observations	1414		
No. of respondents	202		
McFadden's pseudo R^2	0.1985		
Category	**Parameter**	**Coefficient**	**Robust T ratio**
Attribute mean (μ)	*Asc for job 1*	−0.142**	−2.45
	Asc for opt out	−2.336***	−6.24
	Avg. Salary	−0.597***	−3.92
	20% more than avg. salary	0.171[a],**	−1.87
	5 days training	0.222	1.02
	10 days training	−0.889***	−4.19
	Medium workload	2.710***	3.10
	Heavy workload	−3.344	−0.88
	Good facility quality	0.210**	2.04
	Good management	0.574***	3.96
	Good opportunities to improve health	0.244	1.40
Attribute standard deviation (σ)	*Asc for job 1*	0.001	0.38
	Asc for opt out	2.322***	8.08
	Avg. Salary	0.001	0.10
	20% more than avg. salary	1.257**	2.42
	5 days training	−0.670**	−2.93
	10 days training	−0.444	−1.08
	Medium workload	0.052	0.53
	Heavy workload	2.066	1.19
	Good facility quality	−0.439**	−2.29
	Good management	−0.001	−0.15
	Good opportunities to improve health	−0.004	−0.21
Extent of non-attendance (δ) for mid-level healthcare providers	*Salary*	10.977	0.94
	Training	14.630***	8.29
	Workload	−2.030**	−2.76
	Opportunities to improve health	9.125***	5.66
Extent of non-attendance (δ) for non-patient facing staff	*Salary*	−0.552	−0.29
	Training	1.689	0.49
	Workload	−0.880*	−1.71
	Opportunities to improve health	−14.754***	−7.42

Note: As stated above, in our estimation of the ANA-MMNL for Other cadres, workload and management were always attended to. They were thus excluded from final model estimation. The opt-out was selected 11.5% of the times.

[a]Since more than average salary had a positive log normal distribution, the coefficient presented is the exponent of the actual value, −1.765.

***Significant at 1% level, **significant at 5% level, *significant at 10% level.

continues, for the MMNL and ANA-MMNL models in our paper, we decided to use 5000 Sobol draws which was substantially higher than those used in previous studies in similar contexts (Hess et al., 2013; Hole et al., 2013). Using more draws is always better then using fewer because not only do the estimates become more precise due to reduced simulation error (Czajkowski & Budziński, 2019), a higher number of draws also helps in uncovering any identification problems (Chiou & Walker, 2007). Our choice and number of draws was further guided by the results of Czajkowski et al., who showed that using over 2000 Sobol draws in the case of a DCE with five attributes could be enough to reach sufficient simulation precision. Further, we believe that the lack of a qualitative approach for the selection of attributes in our paper could have been a limitation. Its' crucial to make sure that the chosen attributes and levels are salient to respondents, as no

TABLE 6 Rates of ANA captured in different ANA models

	ANA-LC						ANA-MMNL					
			Other cadres						*Other cadres*			
Attribute	***HEW***	***T-ratio***	***Non-patient facing***	***T-ratio***	***Mid-level provider***	***T-ratio***	***HEW***	***T-ratio***	***Non-patient facing***	***T-ratio***	***Mid-level provider***	***T-ratio***
Salary	100%	>10**	91%	2.2*	35%	0.4	0%	-	63%	1.5	0%	0.0
Training	48%	8.8**	95%	7.7**	84%	5.7*	0%	-	16%	0.4	0%	0.6
Workload	83%	>10**	71%	3.3**	74%	0.4	68%	3.2**	71%	6.6**	88%	>10**
Facility quality	70%	>10**	80%	3.8**	82%	0.8	0%	-	0%	-	0%	-
Management	22%	1.9*	99%	0.0	67%	0.0	0%	-	0%	-	0%	-
Health outcomes	72%	8.1**	34%	0.1	40%	0.2	0%	-	100%	>10**	0%	0.6

Note: Standard errors and robust T ratios were estimated using the Delta method (Oehlert, 1992).

Abbreviations: ANA-LC, latent class model for attribute non-attendance; ANA-MMNL, discrete-continuous mixture model; HEW, health extension workers.

*Significant at the 5% level, **significant at the 1% level.

experimental design or econometric analysis can compensate for wrongly defined attributes (Coast et al., 2012). We do strongly believe that our method for selecting attributes was reasonable and the results from our pilot confirmed that respondents had a good understanding of the choice tasks. The format of the choice tasks and the way they are administered can also urge respondents to adopt heuristics in DCEs. To mitigate the possibility of respondents ignoring attributes due to the format of our choice tasks, we chose a design that was similar to and well grounded in recent literature on health workforce DCEs (Mandeville et al., 2016; Saran et al., 2020; Takemura et al., 2016). As a token of our appreciation for the respondent's time, we provided to them a small amount of mobile credit. Since the DCE was administered using a tablet, hand held by the respondent themselves and not overseen by research assistants, we think the chances of social desirability bias or "strategic answering" were also minimal. There is some debate on the use of text versus images to represent the attributes and levels. We opted to display choice tasks only as text since pictures can convey their own meanings, sometimes different from the text, which can misrepresent the attribute levels (Veldwijk et al., 2015). Due to our decision to include salary as a qualitative attribute, we were unable to include willingness-to-pay estimates in the study which could have provided useful welfare estimates.

A surprising result was that the coefficient associated with the average salary level was negative, implying that both HEWs and Other cadres preferred a lower-than-average salary over an average one. We believe that this result might be due to some misunderstanding of what "average earnings" meant and their corresponding actual value might have been better to include. Respondents may have read quickly and when they saw "20%" they assumed it was "20% higher than average", not distinguishing between 20% higher and 20% lower. This would even be suggested by the results as there is no statistical difference between above-average and below-average (the omitted category) salaries. These results were similar to those of Lamba et al. (2021) who showed that HEWs and non-patient facing staff did not significantly value higher than average salaries. Without additional research and in the absence of qualitative evidence, however, it is not possible to know whether the validity of these parameter estimates is undermined. Despite the unusual results around the salary attribute, we believe that our study and analysis reflect adequately the preferences expressed by health workers. Our findings were in line with previous health workforce DCEs which report that community level workers often have higher preferences for non-financial attributes, in comparison to financial remuneration (Abdel-All et al., 2019; Mandeville et al., 2016; Saran et al., 2020). A study on community health workers from India, for example, demonstrated that more than 85% of the respondents were willing to sacrifice a large proportion of their monthly salary for a job that offered them career progression (Abdel-All et al., 2019).

Finally, our findings show that while health workers preferred 5 days of training, they had disutility attached to undertaking 10 days of training, compared to no training. We believe that this is a plausible finding as our qualitative research with the sample showed that they did in fact prefer a short training regime, compared to a longer one, as that is less disruptive to their work and doesn't require as much time to catch up with their tasks on their return.

The quantitative analysis of information processing strategies such as ANA is a growing field of research in health economics. In particular, studies comparing willingness to pay estimates under the assumption that ANA is a heuristic and ANA is a preference show that its important to disentangle the two to improve policy advice coming from DCEs. For example, wrong assumptions about ANA can effect the estimated benefits and consequently the cost-benefit ratio in economic evaluations (Heidenreich et al., 2018).

This paper suggests avenues of future research for health economists involved in the study of heuristics in DCEs. First, studying attribute level non-attendance, instead of just ANA, could lead to further gains in model fit and improve choice predictions. Erdem et al. (2015) demonstrate that in cases where attribute levels are "nominal" (i.e., with no natural sense of ordering), which is common practice in health-related DCEs, it is possible to study whether respondents, while attending to the attribute as a whole, tend to ignore a subset of attribute levels. We do not explore this in this paper as none of the attributes in our dataset were nominal. Further, in the transport literature for example, it has been reported that respondents sometimes employ a heuristic called "aggregation of common-metric attributes" where they treat two or more attributes as being identical and simply add them up (Hole et al., 2013). While this was less relevant in this application, since our attributes were qualitative and less amenable to aggregation, it would be useful to study the affects of such heuristics on welfare measures. Finally, it would also be valuable to better understand the motives of respondents for ignoring attributes. For example, in one study respondents ignored the cost attribute to signify their refusal to trade between money and other valued goods such as the environment (Carlsson et al., 2010). Further qualitative research on this topic may be valuable to tease out reasons for non-attendance in DCEs.

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CONFLICT OF INTEREST

Nikita Arora, Kara Hanson, Mylene Lagarde, Dorka Woldesenbet, Abiy Seifu, Romain Crastes dit Sourd have no conflict of interest to declare. Matthew Quaife holds grants from Bill and Melinda Gates Foundation, outside the submitted work.

DATA AVAILABILITY STATEMENT

Data are available on reasonable request made to the corresponding author.

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SUPPORTING INFORMATION

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ONLINE SUPPLEMENTARY INFORMATION

THE ATTRIBUTE NON-ATTENDANCE LATENT CLASS MODEL (ANA-LC)

First we start by providing information on how an attribute non-attendance latent class model (ANA-LC) differs from a standard LCM which is specified to estimate heterogeneity in respondent preferences. We also provide details on the specification of the 64 class ANA-LC used in our analysis, focusing on the issue around identification of parameters for each one of the classes, which can affect model parsimony. Finally, we provide average class attendance for each class/ANA combination in the Results section.

Latent class models for preference heterogeneity and ANA-LC

In a latent class model (LCM) modelling preference heterogeneity, marginal utilities are estimated for each group or class in the population. For example, in a two class LCM with two attributes, the utility function for individual n, alternative j at time t of each of the two classes can be written as follows:

$$u_{njt}^{class1} = \beta_1^{class1} attribute1_{njt} + \beta_2^{class1} attribute1_{njt} + \varepsilon_{njt}$$

$$u_{njt}^{class2} = \beta_1^{class2} attribute2_{njt} + \beta_2^{class2} attribute2_{njt} + \varepsilon_{njt}$$

When specifying the above model, four different marginal utilities and thus four different parameters would need to be identified (β_1^{class1},β_2^{class1},β_1^{class2},β_2^{class2}). With a rise in the number of classes in a model, the number of parameters that need to be identified also quickly rise. The way an LCM that’s modelling heterogeneity in respondent preferences is specified, is often different from an ANA-LC. In the former, the number of latent classes in which respondents could be allocated to is unknown to the analyst a priori. The optimal number of classes is normally determined by noticing the change in model goodness of fit as the number of classes go up one-by-one. This can be done by monitoring an information criterion like AIC or BIC which penalizes model fit as the number of parameters increase.

In contrast, an ANA-LC estimates a behavioral model which assumes that respondents use heuristics in processing information in a DCE, and only attend to a subset of the given K attributes. This results in 2^K different combinations of ANA. In this model, the number of classes in which the respondents could be allocated to coincides with the combinations with which ANA could occur and is known to the analyst beforehand (Heidenreich et al., 2018). Scarpa et al (Scarpa et al., 2009) and Collins et al (Collins, 2012) have demonstrated that researchers can end up with misleading estimates of ANA shares if a reduced version of the ANA model with less classes is estimated. This could be because the classes may not be independent.

Therefore, we estimated an ANA model with all 2^K classes. Researchers in Health Economics have previously used a step-wise approach to modeling all possible combinations of ANA (Lagarde, 2013), including only those classes in their ANA-LCs, that that are nonempty. Whether a class ends up being empty or not is dependent on the value of the corresponding constant in a class allocation model. Researchers generally estimate a multinomial logit model with one constant per class, one of which is the base and is thus constrained to be zero.

An alternative to this approach is to estimate a model with 2^K classes but use a different parameterization for the LCM where class allocation probabilities are not captured by a (large) set of constants, but by a product of logit probabilities corresponding to the probability of each attribute being attended to or not (Hole et al., 2013). This allows to reduce the number of parameters estimated, maintaining model parsimony. In the context of this paper, this means that we consider 64 classes corresponding to different patterns of ANA, but this only requires the estimation of 6 additional parameters instead of 63 (64 minus 1).

METHOD

As explained above, we estimated a constant for each of the six attributes and generated the probability of an attribute being attended to, over all 64 combinations, by introducing a binary logit model for each of the attributes, which was specified as:

$$P_{attribute} = \delta_{attribute} + HEW_{attribute} * HEW + patientfacing_{attribute} * patientfacing \; [1]$$

Where $\delta_{attribute}$ was the constant for a given attribute; $HEW_{attribute}$ and $patientfacing_{attribute}$ were constants for that attribute, each for the corresponding covariate of two cadres – HEWs (health extension workers) and patient-facing staff.

For example, the way we specified the probability of respondents attending to Salary was given by

$$P_{salary} = \delta_{salary} + HEW_{salary} * HEW + patientfacing_{salary} * patientfacing \; [2]$$

Each of the 64 combinations of ANA were then specified as a separate class using equation 1, where when an attribute was considered to have been ignored, it was restricted to zero. For example, the probability of a combination where all attributes were attended to except for *salary* and *workload,* corresponded to:

$\omega_{salary\ and\ workload\ non-attendance} =$

$$\frac{1}{1+\exp(\delta_{salary})} \cdot \frac{\exp(\delta_{training})}{1+\exp(\delta_{training})} \cdot \frac{1}{1+\exp(\delta_{Workload})} \cdot \frac{\exp(\delta_{quality})}{1+\exp(\delta_{quality})} \cdot \frac{\exp(\delta_{management})}{1+\exp(\delta_{management})} \cdot \frac{\exp\ (\delta_{opportunities})}{1+\exp\ (\delta_{opportunities})} [$$

And was specified as,

$$P\ (class_1) = \ 0 + P_{training} + 0 + P_{quality} + P_{management} + P_{opportunities}$$

RESULTS

Table 1 describes the patterns of non-attendance represented in each class and the proportion of HEWs who adopted those strategies. Table 2 describes the same but for Other cadres. Where an attribute was considered to be ignored, the parameter weight was restricted to '0' in the model.

Table 1: Average class membership of HEWs in the ANA-LC

		ANA patterns tested								
Class number	**Average class membership**	**Salary offered**		**Training offered**		**Workload**		**Good facility quality**	**Good management**	**Good outcome**
Class_1	0.53%	0	0	0	0	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_2	2.84%	0	0	β_train5	β_train10	0	0	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_3	1.38%	0	0	β_train5	β_train10	β_workmed	β_workheav	0	β_gdmgmt	β_gdoutcome
Class_4	0.16%	0	0	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	0	β_gdoutcome
Class_5	1.53%	0	0	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	0
Class_6	0.00%	β_salavg	β_salplus	0	0	0	0	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_7	0.00%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	0	β_gdmgmt	β_gdoutcome
Class_8	0.00%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	β_gdfacqual	0	β_gdoutcome
Class_9	0.00%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	0
Class_10	0.00%	β_salavg	β_salplus	β_train5	β_train10	0	0	0	β_gdmgmt	β_gdoutcome
Class_11	0.00%	β_salavg	β_salplus	β_train5	β_train10	0	0	β_gdfacqual	0	β_gdoutcome
Class_12	0.00%	β_salavg	β_salplus	β_train5	β_train10	0	0	β_gdfacqual	β_gdmgmt	0
Class_13	0.00%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	0	0	β_gdoutcome
Class_14	0.00%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	0	β_gdmgmt	0
Class_15	0.00%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	0	0
Class_16	2.57%	0	0	0	0	0	0	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_17	1.25%	0	0	0	0	β_workmed	β_workheav	0	β_gdmgmt	β_gdoutcome
Class_18	0.15%	0	0	0	0	β_workmed	β_workheav	β_gdfacqual	0	β_gdoutcome
Class_19	1.38%	0	0	0	0	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	0
Class_20	6.64%	0	0	β_train5	β_train10	0	0	0	β_gdmgmt	β_gdoutcome
Class_21	0.78%	0	0	β_train5	β_train10	0	0	β_gdfacqual	0	β_gdoutcome
Class_22	7.36%	0	0	β_train5	β_train10	0	0	β_gdfacqual	β_gdmgmt	0

Class_23	0.38%	0	0	β_train5	β_train10	β_workmed	β_workheav	0	0	β_gdoutcome
Class_24	3.58%	0	0	β_train5	β_train10	β_workmed	β_workheav	0	β_gdmgmt	0
Class_25	0.42%	0	0	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	0	0
Class_26	0.00%	β_salavg	β_salplus	0	0	0	0	0	β_gdmgmt	β_gdoutcome
Class_27	0.00%	β_salavg	β_salplus	0	0	0	0	β_gdfacqual	0	β_gdoutcome
Class_28	0.00%	β_salavg	β_salplus	0	0	0	0	β_gdfacqual	β_gdmgmt	0
Class_29	0.00%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	0	0	β_gdoutcome
Class_30	0.00%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	0	β_gdmgmt	0
Class_31	0.00%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	β_gdfacqual	0	0
Class_32	0.00%	β_salavg	β_salplus	β_train5	β_train10	0	0	0	0	β_gdoutcome
Class_33	0.00%	β_salavg	β_salplus	β_train5	β_train10	0	0	0	β_gdmgmt	0
Class_34	0.00%	β_salavg	β_salplus	β_train5	β_train10	0	0	β_gdfacqual	0	0
Class_35	0.00%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	0	0	0
Class_36	6.02%	0	0	0	0	0	0	0	β_gdmgmt	β_gdoutcome
Class_37	0.71%	0	0	0	0	0	0	β_gdfacqual	0	β_gdoutcome
Class_38	6.66%	0	0	0	0	0	0	β_gdfacqual	β_gdmgmt	0
Class_39	0.34%	0	0	0	0	β_workmed	β_workheav	0	0	β_gdoutcome
Class_40	3.24%	0	0	0	0	β_workmed	β_workheav	0	β_gdmgmt	0
Class_41	0.38%	0	0	0	0	β_workmed	β_workheav	β_gdfacqual	0	0
Class_42	1.83%	0	0	β_train5	β_train10	0	0	0	0	β_gdoutcome
Class_43	17.23%	0	0	β_train5	β_train10	0	0	0	β_gdmgmt	0
Class_44	2.03%	0	0	β_train5	β_train10	0	0	β_gdfacqual	0	0
Class_45	0.99%	0	0	β_train5	β_train10	β_workmed	β_workheav	0	0	0
Class_46	0.00%	β_salavg	β_salplus	0	0	0	0	0	0	β_gdoutcome
Class_47	0.00%	β_salavg	β_salplus	0	0	0	0	0	β_gdmgmt	0
Class_48	0.00%	β_salavg	β_salplus	0	0	0	0	β_gdfacqual	0	0
Class_49	0.00%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	0	0	0
Class_50	0.00%	β_salavg	β_salplus	β_train5	β_train10	0	0	0	0	0

Class_51	1.66%	0	0	0	0	0	0	0	0	β_gdoutcome
Class_52	15.60%	0	0	0	0	0	0	0	β_gdmgmt	0
Class_53	1.84%	0	0	0	0	0	0	β_gdfacqual	0	0
Class_54	0.89%	0	0	0	0	β_workmed	β_workheav	0	0	0
Class_55	4.75%	0	0	β_train5	β_train10	0	0	0	0	0
Class_56	0.00%	β_salavg	β_salplus	0	0	0	0	0	0	0
Class_57	0.59%	0	0	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_58	0.00%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_59	0.00%	β_salavg	β_salplus	β_train5	β_train10	0	0	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_60	0.00%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	0	β_gdmgmt	β_gdoutcome
Class_61	0.00%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	0	β_gdoutcome
Class_62	0.00%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	0
Class_63	4.30%	0	0	0	0	0	0	0	0	0
Class_64	0.00%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	β_gdoutcome

Table 2: Average class membership of Other cadres in the ANA-LC

		ANA patterns tested								
Class number	**Average class membership**	**Salary offered**		**Training offered**		**Workload**		**Good facility quality**	**Good management**	**Good outcome**
Class_1	0.22%	0	0	0	0	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_2	0.12%	0	0	β_train5	β_train10	0	0	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_3	0.19%	0	0	β_train5	β_train10	β_workmed	β_workheav	0	β_gdmgmt	β_gdoutcome
Class_4	0.12%	0	0	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	0	β_gdoutcome

Class_5	0.03%	0	0	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	0
Class_6	1.16%	β_salavg	β_salplus	0	0	0	0	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_7	1.87%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	0	β_gdmgmt	β_gdoutcome
Class_8	0.89%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	β_gdfacqual	0	β_gdoutcome
Class_9	0.28%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	0
Class_10	1.00%	β_salavg	β_salplus	β_train5	β_train10	0	0	0	β_gdmgmt	β_gdoutcome
Class_11	0.45%	β_salavg	β_salplus	β_train5	β_train10	0	0	β_gdfacqual	0	β_gdoutcome
Class_12	0.15%	β_salavg	β_salplus	β_train5	β_train10	0	0	β_gdfacqual	β_gdmgmt	0
Class_13	0.73%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	0	0	β_gdoutcome
Class_14	0.24%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	0	β_gdmgmt	0
Class_15	0.11%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	0	0
Class_16	0.63%	0	0	0	0	0	0	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_17	1.02%	0	0	0	0	β_workmed	β_workheav	0	β_gdmgmt	β_gdoutcome
Class_18	1.08%	0	0	0	0	β_workmed	β_workheav	β_gdfacqual	0	β_gdoutcome
Class_19	0.15%	0	0	0	0	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	0
Class_20	0.53%	0	0	β_train5	β_train10	0	0	0	β_gdmgmt	β_gdoutcome
Class_21	0.32%	0	0	β_train5	β_train10	0	0	β_gdfacqual	0	β_gdoutcome

Class_22	0.08%	0	0	β_train5	β_train10	0	0	β_gdfacqual	β_gdmgmt	0
Class_23	0.53%	0	0	β_train5	β_train10	β_workmed	β_workheav	0	0	β_gdoutcome
Class_24	0.13%	0	0	β_train5	β_train10	β_workmed	β_workheav	0	β_gdmgmt	0
Class_25	0.08%	0	0	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	0	0
Class_26	5.28%	β_salavg	β_salplus	0	0	0	0	0	β_gdmgmt	β_gdoutcome
Class_27	2.48%	β_salavg	β_salplus	0	0	0	0	β_gdfacqual	0	β_gdoutcome
Class_28	0.79%	β_salavg	β_salplus	0	0	0	0	β_gdfacqual	β_gdmgmt	0
Class_29	4.02%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	0	0	β_gdoutcome
Class_30	1.27%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	0	β_gdmgmt	0
Class_31	0.59%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	β_gdfacqual	0	0
Class_32	2.05%	β_salavg	β_salplus	β_train5	β_train10	0	0	0	0	β_gdoutcome
Class_33	0.68%	β_salavg	β_salplus	β_train5	β_train10	0	0	0	β_gdmgmt	0
Class_34	0.30%	β_salavg	β_salplus	β_train5	β_train10	0	0	β_gdfacqual	0	0
Class_35	0.49%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	0	0	0
Class_36	2.86%	0	0	0	0	0	0	0	β_gdmgmt	β_gdoutcome
Class_37	2.78%	0	0	0	0	0	0	β_gdfacqual	0	β_gdoutcome
Class_38	0.42%	0	0	0	0	0	0	β_gdfacqual	β_gdmgmt	0

Class_39	4.65%	0	0	0	0	β_workmed	β_workheav	0	0	β_gdoutcome
Class_40	0.69%	0	0	0	0	β_workmed	β_workheav	0	β_gdmgmt	0
Class_41	0.62%	0	0	0	0	β_workmed	β_workheav	β_gdfacqual	0	0
Class_42	1.43%	0	0	β_train5	β_train10	0	0	0	0	β_gdoutcome
Class_43	0.36%	0	0	β_train5	β_train10	0	0	0	β_gdmgmt	0
Class_44	0.20%	0	0	β_train5	β_train10	0	0	β_gdfacqual	0	0
Class_45	0.33%	0	0	β_train5	β_train10	β_workmed	β_workheav	0	0	0
Class_46	11.23%	β_salavg	β_salplus	0	0	0	0	0	0	β_gdoutcome
Class_47	3.58%	β_salavg	β_salplus	0	0	0	0	0	β_gdmgmt	0
Class_48	1.66%	β_salavg	β_salplus	0	0	0	0	β_gdfacqual	0	0
Class_49	2.68%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	0	0	0
Class_50	1.38%	β_salavg	β_salplus	β_train5	β_train10	0	0	0	0	0
Class_51	12.01%	0	0	0	0	0	0	0	0	β_gdoutcome
Class_52	1.93%	0	0	0	0	0	0	0	β_gdmgmt	0
Class_53	1.62%	0	0	0	0	0	0	β_gdfacqual	0	0
Class_54	2.69%	0	0	0	0	β_workmed	β_workheav	0	0	0
Class_55	0.91%	0	0	β_train5	β_train10	0	0	0	0	0
Class_56	7.51%	β_salavg	β_salplus	0	0	0	0	0	0	0

Class_57	0.04%	0	0	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_58	0.41%	β_salavg	β_salplus	0	0	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_59	0.22%	β_salavg	β_salplus	β_train5	β_train10	0	0	β_gdfacqual	β_gdmgmt	β_gdoutcome
Class_60	0.35%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	0	β_gdmgmt	β_gdoutcome
Class_61	0.16%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	0	β_gdoutcome
Class_62	0.05%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	0
Class_63	7.04%	0	0	0	0	0	0	0	0	0
Class_64	0.08%	β_salavg	β_salplus	β_train5	β_train10	β_workmed	β_workheav	β_gdfacqual	β_gdmgmt	β_gdoutcome

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PART III – DISCUSSION

CHAPTER 9

DISCUSSION AND CONCLUSIONS

This thesis set out to examine heterogeneity in the job-preferences of community-based healthcare workers in Ethiopia and Ghana, with a view to inform policy interventions targeting the retention of lay health workers in LMICs. This chapter brings together the main findings from the results chapters, presented in line with the study objectives stated in Chapter 4. It then describes the methodological and empirical contributions from this work, followed by a critical assessment of the limitations of this research. It finally reviews the implications on research and policy, and then concludes.

9.1. Summary of key findings

9.1.1. Objective 1

<u>To understand the importance of financial and non-financial incentives in retaining community-based healthcare workers in their jobs</u>

The first objective of this thesis was to understand the key incentive preferences of community-based healthcare workers. Using data on HEWs in Ethiopia, I explored the job incentives that HEWs valued the most, focussing on the role of non-financial incentives in influencing their decision to stay in their positions. This was addressed in research paper 1. Semi-structured interviews with HEWs and leavers of HEW positions, described in detail in Chapter 5, showed that the current incentives offered to them in their public health sector jobs were generally inadequate, with complaints about both financial aspects such as salaries and allowances and non-financial aspects including career development, supervision by managers, and demand-side acceptance from their communities. Results also showed that while these health workers valued the monetary incentives offered to them, their retention was largely driven by non-financial factors such as being appreciated by their communities and managers for their work. The absence of these non-wage factors often catalysed exits from their jobs.

Paper 1 applied the social identity approach to explain these empirical findings. The approach suggests that processes within an individual that influence preferences and behaviour can be dependent on interpersonal relationships and group memberships. When a person identifies as a member of a group and when that identity is important to them, their behaviour could become more focused towards what is seen to be in the group's interest rather than their own. We observed this other-regarding behaviour in the context of HEWs in Ethiopia. Their identity as a member of their community often drove their preferences for job attributes, prioritising incentives that reinforced this identity (such as receiving appreciation from the community), more than furthering self-interest, for example, interest in higher salaries. The strong preferences of these community health workers, and other similar community-based healthcare workers, for non-financial job attributes align with qualitative literature in this field in other LMICs. For example, community health workers in rural Malawi described a positive work environment through supportive relationships between them and their supervisors to be crucial and enabling for their work (Ndambo et al., 2022). Similarly, the most preferred job characteristic of community health workers in Kenya was community appreciation for their work (Saran et al., 2020). These findings were also corroborated by quantitative research presented in Papers 2 and 3.

9.1.2. Objective 2

To explore sources of heterogeneity in the stated preferences for job characteristics of community-based healthcare workers

The second objective, which was to examine the stated job preferences and sources of heterogeneity in the preferences of community-based healthcare workers, was addressed in research papers 2 and 3. The importance of investigating the preferences of sub-groups of the study population and carefully examining the possible sources of heterogeneity has been described in detail in the literature review in Chapter 2. In the context of this thesis, the existence of heterogeneity in the preferences of health workers would suggest that individual characteristics can interact with job characteristics to produce different levels of the utility of a job for a worker, which needs to be investigated to recommend tailored compensation packages and could be used to recruit individuals with certain personality traits. Smith et al. (Smith et al., 2013) demonstrated using experimental dictator games that some nursing students in South Africa, Kenya, and Thailand had altruistic or pro-social values. They proposed that these values and motivations can be leveraged by policymakers and managers for improved retention of nurses in rural areas, by identifying and recruiting altruistic individuals who are more likely to stay in the profession (Smith et al., 2013). The presence of pro-social motivation could be an important source of variation in preferences among health workers, and associated with retention in rural areas. Other, observed respondent characteristics, can also be a source of heterogeneity in preferences which could be leveraged for developing tailored compensation packages. For example, a DCE study on health workers in Tanzania found that women tended to care less for pecuniary incentives and were more concerned with working in a well-functioning health facility, in comparison to men who preferred pecuniary incentives (Kolstad and Kowalski, 2012).

In Paper 2, I used DCE data from Ghana to investigate the average preferences for role incentives of a sample of COMBATs, and account for discrete heterogeneity in their preferences by using latent class models, identifying three population sub-groups with distinct job preferences. The younger 'go-getters', a third of the sample, were more educated on average and showed very strong preferences for on-the-job training and supervision visits. The 'veterans', 15% of the sample, were older, more experienced at their jobs, and preferred to receive higher per diems, and undertake more sensitisation visits while gaining disutility from other attribute levels. Lastly, the 'balanced bunch' encompassing the majority of the sample (51%), valued all aspects of their roles roughly equally. Understanding preferences and how they vary among sub-groups can be used by programme managers to develop tailored compensation packages targeted to improve volunteer motivation and retention.

Paper 3 examines multidimensional motivation and the stated job preferences of HEWs in Ethiopia to measure the share of random variation in preferences which can be linked to random variations in motivation. Findings aligned with my *a priori* hypotheses based on the literature presented in Chapter 2. I show that HEWs who were intrinsically motivated preferred better health outcomes for the community and disliked higher than average salaries whereas extrinsically motivated HEWs had disutility attached to a heavy workload and preferred higher than average salaries. In line with the work by Smith et al., these findings could also be used to inform the recruitment of HEWs who are intrinsically motivated and thus more likely to exert more effort in their jobs to improve heath outcomes and stay in their positions for longer (Banuri et al., 2018).

9.1.3. Objective 3

<u>To extend the existing methods of choice modelling for distinguishing the heterogeneous preferences of community-based healthcare workers from decision-making heuristics</u>

The third objective was addressed by research paper 4. It builds on the empirical evidence suggesting that individuals don't always consider all attributes of a good or service when choosing between alternatives presented to them in a DCE, an occurrence known as ANA. There is value in disentangling ANA from preference heterogeneity as assuming the respondent's choice to not consider all attributes is always ANA, when it could reflect preference heterogeneity, can result in the wrong coefficient estimates. Paper 4 uses data on three community healthcare workers in Ethiopia, from the same survey as Paper 3. It uses semi-parametric mixtures of latent class models to disentangle successfully inferred ANA from the weaker preferences for some attributes. It shows that such models provide more reliable estimates of ANA in a dataset, in comparison to other, simpler, models used in health economics literature so far. The paper also finds statistically significant variation in the rates of ANA exhibited by different health provider cadres, highlighting the need to have well-defined attributes in a DCE to ensure that ANA does not result from an inadequate experimental design.

9.2. Overall contribution of the Thesis

The contributions to knowledge of this thesis are both empirical and methodological.

9.2.1. Contribution to empirical findings

The use of DCEs to study the job preferences of health workers with a view to inform policy, in itself is also an important empirical contribution. While studies applying DCEs to similar contexts are increasing in number (Mandeville et al., 2016, Lagarde et al., 2011, Saran et al., 2020, Gopalan et al., 2012) locally generated information is always needed as preferences always vary by context. Most studies on the preferences of different job incentives use qualitative methods which often creates a 'laundry list' of preferred incentives, without any means of weighting their importance rather than measuring how different incentives influence the decision of choosing a job alternative. DCEs allow policy makers to understand the trade-offs made by health workers, which in the context of limited and competing health system resources can be useful to inform policies to enhance retention and sustained healthcare delivery.

A second contribution has been to generate evidence about the determinants of the short-term labour supply of community-based healthcare workers in Sub-Saharan Africa. This cadre play a key role in healthcare delivery but there is little literature around their labour market preferences. The majority of evidence in this context has so far been focussed on professional health worker cadres such as doctors (Mandeville et al., 2014, Mandeville et al., 2016, Blaauw et al., 2010). A systematic review of health workforce DCEs showed that doctors and medical students have been the most studied cadres (Mandeville et al., 2014). A comparison of results from these studies broadly showed the importance of bonus payments, post graduate training, and the unpopularity of time commitments for the uptake of rural posts. For example a DCE performed with doctors in Peru showed that they were 5 times more likely to choose a job in the city than in a rural area and that salary increases for specialization acted as incentives for jobs in rural areas (Miranda et al., 2012). Given the distinct employment and remuneration structures of community-based healthcare workers globally, it is important to explore whether their job preferences are systematically different distinct from professional cadres like doctors.

Research papers 1 to 3 represent a body of work that examines the heterogenous job preferences of two cadres of community-based healthcare workers – community health workers (CHWs) in Ethiopia and community health volunteers in Ghana. These papers highlight two things. First, while monetary compensation is important, non-monetary incentives are crucial motivators for community-based healthcare workers and should be considered as part of the compensation package to facilitate improved performance and retention. These findings were similar to other similar studies on CHWs. For example, a recent study on CHWs in Uganda identified non-monetary job attributes such as reliable transportation, consistent training, identity badges and branded uniform to be more valuable than salaries for CHW retention and performance and was linked to retention (Agarwal et al., 2021). Secondly, these papers demonstrate that estimating the average preferences of health workers is not sufficient and heterogeneity in their job preferences needs to be accounted for to use results from such DCEs to inform human resource policies. A systematic review of health workforce DCEs showed that studies frequently pooled results from heterogenous subgroups or extrapolated these results to the general population which was not ideal to inform policy (Mandeville et al., 2014). Health worker DCEs have increasingly started to acknowledge this, and are now accounting for discrete and continuous heterogeneity in their modelling of preferences for job roles and incentives (Mandeville et al., 2016, Agarwal et al., 2021, Saran et al., 2020, Miners et al., 2017, Soekhai et al., 2019). As mentioned above, Papers 2 and 3 use discrete choice modelling methods to explore multiple sources of preference heterogeneity in the datasets, ranging from deterministic characteristics like age and gender to latent constructs like motivation.

9.2.2. Contribution to methods

This thesis has also sought to make several contributions to methods in the field of choice modelling using stated preference data from healthcare settings. In the analysis of job choices, a large number of stated preference surveys using DCEs only account for deterministic heterogeneity between respondents (Lamba et al., 2021, Saran et al., 2020, Beam et al., 2018) or discrete random heterogeneity using standard latent class models (Mandeville et al., 2016, Blaauw et al., 2010, Lagarde et al., 2015, Miners et al., 2017). However, when health workers are trading off between different job incentives, different health workers will have different preferences and some of this heterogeneity in preferences can be attributed to unobservable constructs such as past experiences, attitudes, and motivations – all of which are idiosyncratic in nature. Modelling respondent choices that have the potential to be substantially influenced by these unobservable attitudinal constructs can show remarkable variation in individual preferences driven by these constructs. While it is common to collect answers to attitudinal questions during stated choice surveys (e.g. responses on Likert scales), there is now a large body of work that argues that such questions are not direct measures, but rather indicators of underlying attitudes and motivations and should thus not be included in choice models as explanatory variables (Hess et al., 2021, Buckell et al., 2021, Beck and Hess, 2018, Hensher et al., 2005). Instead, they should be treated as latent constructs that explain the answers to these questions and at the same time influence choice behaviour. This approach, called the hybrid choice approach, seeks to bypass concerns around endogeneity bias and measurement error as the responses to these questions are no longer treated as explanatory, but dependent variables (Ben-Akiva et al., 2002). In this thesis, I demonstrate the importance of including psychological constructs like motivation as a source of variation in the job preferences of health workers as it could account for a large share of the random heterogeneity in preferences between respondents. Research paper 3 is the first application of a hybrid choice approach to explore the link between multidimensional motivation and job preferences between respondents.

Furthermore, this thesis also makes use of semi-parametric mixtures of latent class methods to account for heuristics in decision analysis. Not enough research has been done in health economics to assess whether inferred ANA is a heuristic or genuine preference, especially using econometric models that are flexible enough to separate the two without relying on supplementary information from respondents. To my knowledge, one other study (Hole et al., 2013) in the health context has used a similar econometric approach to that used in Paper 4 , however, mine will be the first application of this approach in an LMIC setting. Two factors underlie the importance of study context and the value of applying an improved approach to the econometric inference of ANA in LMICs. First, there is some literature that suggests that ANA may be a greater threat to the validity of DCE results in LMICs, than in higher-income settings. Nguyen et al (Nguyen et al., 2015) reviewed relevant DCEs conducted in high and low income countries and used their results on ANA from a DCE conducted in Vietnam to demonstrate that rates of ANA were on average higher in LMICs than in higher income countries. Second, the application of advanced econometric modelling techniques to identify ANA in health workers’ employment preferences in Ethiopia is important because ANA potentially undermines the validity of marginal valuations. Generating valid estimates is important if research is to inform policy.

9.3. Strengths and limitations of the thesis

The strengths and limitations of the applied methods and approaches have already been discussed in detail in each of the four empirical papers in Part 2 of this thesis. This section brings together the key elements discussed earlier and reflects on the limitations of the overall thesis.

9.3.1. Reflections on the use of DCEs

As the thesis makes extensive use of DCEs, the limitations of stated choice research need to be acknowledged. Whether DCEs can reliably predict behaviour outside of the experimental context has been a matter of concern due to their hypothetical nature, even before the widespread application of DCEs to health workforce issues (McPake et al., 2014). Although research has shown that DCEs can produce reasonable predictions of health-related behaviours (Quaife et al., 2018) there is still a need for more research assessing their external validity, particularly using empirical work examining predicted and revealed preferences of a representative sample of respondents (Lancsar and Swait, 2014).

Both the DCEs analysed in this thesis constructed unlabelled choice experiments to replicate the main labour market decisions faced by community-based healthcare workers in Ethiopia and Ghana. Choice tasks from the DCE in Ethiopia were represented only as text, not images, as it was believed that images could convey their own meanings, different from text, which could have confused the respondents. While this DCE did not undertake formative qualitative work for the development of attributes, adequate measures in line with recommendations from the literature were taken to ensure that the design of the DCE was suitable, mitigating the risk of hypothetical bias. The results from the pilot also confirmed that respondents had a good understanding of the choice tasks. As salary was included as a qualitative attribute, I was unable to include willingness-to-pay estimates in the study which could have provided useful welfare estimates.

One surprising result was that the coefficient associated with the average salary level was negative in both papers using this DCE data from Ethiopia, implying that community health workers preferred a lower-than-average salary over an average one. This result might have been due to some misunderstanding of what “average earnings” meant and it might have been better to include their corresponding actual value. Respondents may have read quickly and when they saw “20%” they assumed it was “20% higher than average”, not distinguishing between 20% higher and 20% lower. This explanation is consistent with the results which showed no statistical difference between above-average and below-average (the omitted category) salaries. These results were similar to those of Lamba et al. (2021) using the baseline survey of the same project who showed that community health workers and non-patient facing staff did not significantly value higher than average salaries. Without additional research and in the absence of qualitative evidence, however, it is not possible to know whether the validity of these parameter estimates is undermined. Despite the unusual results around the salary attribute, my findings from this analysis were in line with previous health workforce DCEs which report that community-based healthcare workers often have higher preferences for non-financial attributes, in comparison to financial remuneration (Abdel-All et al., 2019, Mandeville et al., 2016, Saran et al., 2020). A study on community health workers from India, for example, demonstrated that more than 85% of the respondents were willing to sacrifice a large proportion of their monthly salary for a job that offered them career progression (Abdel-All et al., 2019).

Despite the widespread use of hybrid choice models over the last decade, some recent work argues that the potential to derive policy implications from these latent class models is limited, mainly because of their cross-sectional nature (Chorus and Kroesen, 2014, Beck and Hess, 2018). The data from DCEs is cross-sectional and any policy designed to influence the latent construct, motivation in this case, would require longitudinal data with information about how a respondent's own behaviour may change based on a change in the underlying latent variable. Though the concerns raised by Chorus and Kroesen (2014) are legitimate, these limitations are not unique to hybrid choice models and can be argued are a limitation for the use of DCEs to inform policy (Vij and Walker, 2016).

While the majority of findings from the DCE in Ghana were in line with previous literature in this context, one unusual finding was that community-based volunteers from one of the population subgroups seemed to gain disutility from reimbursement for transportation expenses incurred during their work. This could be because in contrast to per-diems which are fungible, transport per-diems were not, as reimbursements were only against expenditure and respondents could have had other ways of securing transport. Since the respondents in this sub-group were mostly women with more children in comparison to other groups and married, they may have found it to be an inconvenience to have to recoup part of the public transport fare, especially if a cheaper way to commute is available.

9.3.2. Reflections on the change in empirical approach due to fieldwork disruptions

While the main strengths and weaknesses of the empirical approach of the thesis were driven by the use of the methods chosen, comments can be made about the changes to the empirical approach due to disruptions in fieldwork caused by the COVID-19 pandemic, followed by a civil war in northern Ethiopia. Details about the changes made are included in the reflective statement in Chapter 4. Here, I list some of the key changes that could have led to limitations in the work presented in this thesis.

The DCE in Ethiopia was conceived to be embedded in a cross-sectional survey undertaken by me face-to-face with HEWs in four regions: Tigray, Oromia, SNNPR and Amhara in 2020. While the purpose of enquiry of the DCE was the same – to understand the stated job preferences of HEWs – the DCE I had conceptualised was different than the DCE I ended up analysing in the following two ways. First, I had planned to undertake formative qualitative work with the study sample to identify and shortlist attributes and attribute levels for the DCE, in line with best practices mentioned in the literature (Coast et al., 2012). Second, I had planned for the attribute on remuneration to be continuous, to be able to derive marginal rates of substitution/ willingness to pay estimates.

I see the availability of the secondary DCE dataset both as a strength and limitation of this thesis. While it gave me the opportunity to analyse DCE data on community health workers in Ethiopia as planned, my inability to influence the survey and DCE design meant that I had to develop my study questions that could be answered with the data I had, rather than collecting data to answer research questions developed a-priori. However, because I did manage to undertake formative qualitative work with HEWs, now published as research paper 1, I was able to use this first-hand understanding of their job preferences and heterogeneity in their preferences to be able to produce a coherent piece of research.

DCE analysis from Ghana also used a secondary dataset, sourced through colleagues working as part of the Foreign, Commonwealth and Development Office (erstwhile DFID) funded *What Works* project (UK Aid, 2019). One limitation to this piece of research could have been that the lack of familiarity with the context meant that my analytical choices may have been less than fully-informed. However, I had multiple interactions with the study team who conducted focus group discussions with the community volunteers, and the economists who designed the DCE which allowed me to understand the research context well.

9.4. Implications for research

The section below synthesises the broad implications of this research, and suggests scope for future research.

9.4.1. The need for data on lay health workers

Despite the achievements made using stated preference data due to the limited availability of any other form of data in this thesis, there is urgent need to collect labour market information on cadres of community-based healthcare workers in sub-Saharan Africa. Particularly, a thorough documentation of the working conditions, remuneration, and career progression opportunities of such cadres is important. After all, it is difficult to think about appropriate policy incentives for these heath workers when their baseline conditions or *status quo* is not known.

From a labour market perspective, a thorough investigation of the remuneration offered to community based healthcare workers would provide very useful information in support of the effort to retain them (McPake et al., 2014). Health workers in LIMCs, especially lay community workers and volunteers, often have multiple sources of income including official wages, per-diems, transport and other allowances, non-health income such as from farming (Rosen, 1986). This is often referred to as 'complex remuneration' (Bertone and Witter, 2015), and understanding the total financial incentives available to them may have benefits to improving their retention. For example, the community based volunteers in Ghana were found to receive per-diems during training, which was the only official source of documented income from the program, however most of them reported receiving income from other sources by additionally working within and outside of the health sector. Comparison of overall remuneration levels between the community volunteer role and other sources could support the provision of adequate allowances as income forgone in other areas of work.

Furthermore, in contrast to general beliefs about what makes a job lucrative, policymakers should be aware that financial incentives such an increase in salaries and allowances, though certainly valued, may not be most effective in retaining motivated health workers in the longer term. Thus, more longitudinal data following up community healthcare workers over time, tracking their labour market decisions in detail would enable more accurate assessment of retention, particularly the identification of non-pecuniary factors that may lead to their exit. This data would also be useful to identify the time points in which these workers are particularly vulnerable to exit.

9.4.2. Generalisability to other contexts

It is important to consider generalisability of the main findings from this research to other similar settings in sub-Saharan Africa. A review of literature on CHW programs suggests that Ethiopia and Ghana are not exceptional with regard to community based healthcare workers preferring non-financial incentives. For example, a study in Bangladesh reported reasons cited by CHWs for leaving their posts which included lack of time to attend to their own children and other household responsibilities, insufficient profit/salary, and their families' disapproval (Khan et al., 1998). In Nigeria, village health workers were reported to be dissatisfied with the lack of career advancement opportunities, along with poor supervision and low salaries (Gray and Ciroma, 1988). Therefore, the broad conclusions of the DCE – the expansion of certain types of non-pecuniary factors and the focus on understanding heterogeneity in their preferences - are likely to be generalizable beyond Ethiopia and Ghana.

The applicability of these findings could be, however, limited due to contextual factors. For example, Ethiopia has a unique community health worker program where recruitment of community health workers is only targeted towards women and as stated above, the preferences of women maybe different than men (Kolstad and Kowalski, 2012). Further work exploring the generalizability of the findings from this thesis, would thus be a worthwhile investment so that findings are not applied in the wrong settings (McPake et al., 2014).

9.5. Implications for policy and practice

This section provides a summary of the general policy implications of this work, rather than reiterating recommendations made in earlier sections.

9.5.1. Evidence-based policy making on HEWs in Ethiopia

The HEP, described in detail in section 3.1 in Chapter 3, is credited with success, including improvements in community knowledge and health seeking behaviour, child and maternal health, control of communicable diseases, sanitation and hygiene in Ethiopia since its rollout in 2003 (Assefa et al., 2019). To build on these achievements, and to ensure a more equitable implementation of the program, the second generation HEP was launched in 2015 (Harb, 2021). To assess the progress of the program so far and to inform the development of a roadmap for the second generation program, an assessment of the existing HEP was launched in 2019-20 funded by the Bill and Malinda Gates Foundation (BMGF) and implemented by a national consultancy organisation called Monitoring, Evaluation, Research and Quality Improvement (MERQ). This roadmap is currently under development with the aim to use findings from the MERQ evaluation and research evidence from other sources to create detailed strategies to improve HEP in three core areas: provision of adequate training and incentives to HEWs; improving the infrastructure of health posts; and improving the package of health services delivered by HEWs. During the course of research for this thesis, I have co-authored a research paper studying the factors affecting the attrition and intention to leave of HEWs with the MERQ evaluation team (Tekle et al., 2022). Papers 1-3 can add to the body of work referenced in the redesigning of HEP in Ethiopia.

9.5.2. The use of a hybrid choice approach for policy making

While more work still needs to be done to establish the benefits to policy and practice of the hybrid choice framework, such models do offer advantages over choice models without latent variables conducted to inform health policy so far. Unlike the simpler models used, hybrid choice models are able to provide a mathematical framework for lending structure and meaning to the underlying sources of heterogeneity and applying theories of behaviour to explain them (Vij and Walker, 2016). In the context of this thesis, demonstrating that multidimensional motivation in community-based healthcare workers can explain a large part of the random heterogeneity in their preferences for job attributes could enable policy makers to leverage this association for basing their decisions around the recruitment and allocation of health workers.

9.6. Conclusion

There is growing awareness about the importance of community based healthcare workers for the sustainable delivery of primary healthcare in LMICs. This has focussed attention on understanding their preferences for job incentives to improve retention, performance and recruitment. Since no two health workers are alike, it is important to explore sources of heterogeneity in their preferences and investigate how this can be modelled using rigorous methods. In this thesis, I set out to investigate the heterogenous job preferences of community health workers in Ethiopia and community based volunteers in Ghana, with a view to improve their retention. I found that both cadres strongly valued non-pecuniary incentives in their jobs, such as their ability to improve the health outcomes of community members, training opportunities, and good supervision by managers. Random variations in multidimensional motivation accounted for a huge share of heterogeneity in the preferences for most job attributes of community health workers in Ethiopia. This thesis demonstrated using multiple methods, particularly choice modelling, that a greater application of these techniques to data on lay health provider cadres in LMICs would support evidence generation that can support more effective health workforce policies.

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APPENDIX

Appendix 1: LSHTM ethics approval for thesis

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United Kingdom
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www.lshtm.ac.uk

LONDON SCHOOL of HYGIENE &TROPICAL MEDICINE

Observational / Interventions Research Ethics Committee

Ms Nikita Arora
LSHTM

20 March 2019

Dear Nikita,

Study Title: Reform to Retain: Analysis of Factors Affecting Labor Choices of Community Health Workers in Ethiopia

LSHTM Ethics Ref: 16177

Thank you for responding to the Observational Committee's request for further information on the above research and submitting revised documentation.

The further information has been considered on behalf of the Committee by the Chair.

Confirmation of ethical opinion

On behalf of the Committee, I am pleased to confirm a favourable ethical opinion for the above research on the basis described in the application form, protocol and supporting documentation as revised, subject to the conditions specified below.

Conditions of the favourable opinion

Approval is dependent on local ethical approval having been received, where relevant.

Approved documents

The final list of documents reviewed and approved by the Committee is as follows:

Document Type	File Name	Date	Version
Investigator CV	Matt Quaife - CV 3page AP Jan 19	14/01/2019	1
Investigator CV	Hanson short CV_June 2018	14/01/2019	1
Investigator CV	CV_Nikita Arora copy	16/01/2019	1
Investigator CV	CV Josephine Borghi	21/01/2019	1
Investigator CV	Short CV_Abiy Seifu Estifanos_01Nov2018	21/01/2019	1
Information Sheet	information sheet and consent form_HEWs leaver_v2	26/02/2019	2
Information Sheet	information sheet and consent form_HEWs_V2	26/02/2019	2
Information Sheet	information sheet and consent form_KIIs_v2	26/02/2019	2
Information Sheet	Information sheet and consent form_DCE	26/02/2019	2
Advertisements	Recruitment procedures	05/03/2019	1
Covering Letter	Ethics response letter_LSHTM 16177_KH_NA	05/03/2019	1
Protocol / Proposal	Research Proposal_Nikita Arora_V2_01.03.19	05/03/2019	2

After ethical review

The Chief Investigator (CI) or delegate is responsible for informing the ethics committee of any subsequent changes to the application. These must be submitted to the Committee for review using an Amendment form. Amendments must not be initiated before receipt of written favourable opinion from the committee.

The CI or delegate is also required to notify the ethics committee of any protocol violations and/or Suspected Unexpected Serious Adverse Reactions (SUSARs) which occur during the project by submitting a Serious Adverse Event form.

An annual report should be submitted to the committee using an Annual Report form on the anniversary of the approval of the study during the lifetime of the study.

At the end of the study, the CI or delegate must notify the committee using an End of Study form.

All aforementioned forms are available on the ethics online applications website and can only be submitted to the committee via the website at: http://leo.lshtm.ac.uk

Additional information is available at: www.lshtm.ac.uk/ethics

Yours sincerely,

Professor John DH Porter
Chair

ethics@lshtm.ac.uk
http://www.lshtm.ac.uk/ethics/

Improving health worldwide

Appendix 2: Thesis ethics approval from Addis Ababa University, Ethiopia

ADDIS ABABA UNIVERSITY, COLLEGE OF HEALTH SCIENCES (IRB)
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Institutional Review Board

ANNEX 3
Form AAUMF 03-008

IRB's Decision

Meeting No: 03/2019 Date: 20/03/ 2019
Protocol number: 015/19/SPH

Protocol Title: Reform to retain: understanding factors affecting motivation of health extension workers to inform human resource policy interventions in Ethiopia	
Principal Investigator:	Abiy Seifu
Institute:	College of Health Sciences, AAU
Elements Reviewed (AAUMF 01-008) :	☑ Attached ☐ Not attached
Review of Revised Application ☐ Yes ☐ No	Date of Previous review:
Decision of the meeting:	☑ Approved ☐ Approved with Recommendation ☐ Resubmission ☐ Disapproved

I. Elements approved-
1. Protocol Version No: 02
2. Protocol Version Date:
3. Informed consent Version No.02
4. Informed Consent Version Date:

II. Obligations of the PI-
1. Should comply with the standard international & national scientific and ethical guidelines
2. All amendments and changes made in protocol and consent form needs IRB approval
3. The PI should report SAE within 10 days of the event
4. End of the study, including manuscripts and thesis works should be reported to the IRB

III. TO NERC ☐

Institution Review Board (IRB) Approval: Period from: April 09, 2019 to April 08, 2020
Follow up report expected in
3 Months ___ 6 months ____ 9 months _✓___ one year____

Chairperson, IRB
Dr. AdamuAddissie

Signature [redacted]

Date: 09/04/2019

ADDIS ABABA UNIVERSITY Faculty of Medicine

Appendix 3: Ethical approval for DCE data from Ethiopia

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Ethiopian Public Health Association
(EPHA)

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Ref.No. EPHA/06/2830/

ቀን
Date Feb. 18, 2017

Mr. Abiy Seifu
Principal Investigator
School of Public Health College of Health Sciences
Addis Ababa University
Addis Ababa

Dear Abiy,

Subject: "Evaluation of a Quality Improvement Maternal and Newborn Health Intervention in Ethiopia".

On a letter dated February 17, 2017 you have submitted an application to Internal Scientific and Ethical Review Committee (ISERC) for the approval of the project entitled "**Evaluation of a Quality Improvement Maternal and Newborn Health Intervention in Ethiopia**".

Accordingly, the EPHA ISERC has reviewed the proposal and agreed that the project is purely a program evaluation not a research. Therefore, this is to kindly notify you that ISERC approval does not require for this type of project.

With regards,

[redacted]

Semegnew Mengistu
Deputy Executive Director,
Members Affairs & Networking Director

CC: - Project Management Dept.
- Research, Training and Publication Dept.
- ISERC Administrator
EPHA

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Appendix 4: Ethical approval for DCE data from Ghana

Appendix 5: Interview Topic Guides for qualitative data collection

1. **FOR HEWS:**

INTERVIEW TOPIC GUIDE

Understanding the working conditions and job motivation of health extension workers to improve their retention in the health workforce

Warm-Up Questions:

1. Perhaps you could tell me a bit about yourself?
2. What job title do you have?
3. How would you describe your relationship status?
4. Where do you call home? How long have you lived there?
5. What is your age?

Theme 1: Experience of their current jobs:

I'd be very keen to find out more about your work in the health sector.

6. Please could you describe to me what your typical working day looks like?
7. How long have you worked in this facility?

Theme 2: Reasons for choosing healthcare work:

Now perhaps you could tell me in detail about different aspects of your job as a HEW:

8. What lead you to choose the job you do now?
9. What are some of the things that keep you motivated in your work? Are there also things that demotivate you about your current job? Can you think of what you might be doing if you were not a health extension worker?

Theme 3: Relationships at the health facility and availability of supervision

10. We sometimes end up spending more time with our colleagues at work on a daily basis than our families, so these relationships can be important. Whom do you normally work with in accomplishing your tasks and responsibilities– including peers, partners, and supervisors?
11. I am very interested to find out about your experiences regarding supervision and the guidance available at your work. Can you think of an anecdote/story/ incidence where you received memorable oversight?
12. Do you think the management recognises your good performance in any way? If so, How?

Theme 4: Preference around wages

13. Different people like to be remunerated differently for the work they do. How do you feel about the remuneration you receive for your work here?
14. Do you have to supplement your income from other sources?

Theme 5: Access to training

Perhaps you can now tell me a bit about your preparation to become a HEW:

15. Could you please describe to me how and from where you were trained for this position?
16. How was your experience of this training?

17. Do you feel trained enough to thrive in your job as a health extension worker?

Theme 6: knowledge of career progression opportunities

I have learned a great deal from you about your job delivering primary healthcare to the community as a HEW in this area. Now, I would like to better understand what you think about career progression

18. Are you aware of any career progression prospects and opportunities within this job, in your region? [Probe: eg. the RHB In Tigray Is envisaging the training of HEWs in nursing school moving forward and progression of other HEWs to nurses, FHT]
19. Do you think you receive the relevant Information and communication about potential upgrades, on a regular basis, within this role? [probe: rural HEWs often tend to miss out on Information due to their work location]
20. How do you feel about the available opportunities regarding career progression – within the public sector and/or outside?

Theme 7: Other things that keep the staff motivated

21. Can you tell me what your usual work schedule is like (work hours and days per week)?
22. How would you describe your workload?
23. Do you live in the same community where you work? How do you feel about mobilizing the community you work in? Do you find it hard to work where you don't live? (probe - language barrier? Less buy-in from the community)

LASTLY,

Who could I talk to, to learn more about things that motivate health extension workers**?**

IT WAS A PLEASURE TALKING TO YOU, THANK YOU FOR TAKING THE TIME TO HELP US WITH OUR PROJECT!

Interview end time:

2. FOR LEAVERS OF HEW POSITIONS

INTERVIEW TOPIC GUIDE

Understanding the job motivators and perspectives of women who have previously worked as HEWs, but have left their jobs in the public health sector in Ethiopia

Warm-Up Questions:

Perhaps you could tell me a bit about yourself?

- Are you currently employed?
- What job title do you have?
- How would you describe your relationship status? Do you have children?
- Where do you call home? How long have you lived there?
- What is your age?

Theme 1: Experience of your previous job:

I'd be very keen to find out more about your previous work in the health sector.

1.1 Please could you take me through a typical working day for you when you worked as a health extension worker (HEW)?
1.2 How long did you work in the health post as a HEW? How long in the public health sector in Ethiopia?

Theme 2: **Reasons for choosing and then leaving healthcare work:**

Now perhaps you could tell me in detail about different aspects of your job, when you were a HEW:

2.1 What lead you to choose the job of a HEW?
2.2 What are some of the things that kept you motivated in your work? Were there things that demotivated you about your past job? Can you think of anything better you could have done in the time you were employed as a health extension worker?
2.3 What lead to the decision of you leaving your job?

Theme 3: Relationships at the health facility

3.1 Relationship at work can be important as sometimes we tend to spend a significant amount of time with our colleagues, when carrying out our jobs. Whom did you normally work with in accomplishing your tasks and responsibilities– including peers, partners, and supervisors – when you were a HEW?

3.2 Can you tell a short story about your experiences of working with your peers, supervisors?

3.3 How, according to you, could these relationships be made more meaningful?

Theme 4: Preference around wages

4.1 Different people like to be remunerated differently for the work they do. How did you feel about the remuneration you received for your work, as a health extension worker?

4.2 Did you have to supplement your income from other sources?
4.3 If you are employed now, how do you feel about the income you receive form this work?

Theme 5: Access to training

Perhaps you can now tell me a bit about your preparation to become a HEW:

5.1 Could you please describe to me how and from where you were trained for this position?
5.2 How was your experience of this training?
5.3 Do you feel trained enough to thrive in your job as a health extension worker?

Theme 6: Career progression opportunities

I have learned a great deal from you about your experiences while delivering primary healthcare to the community as a HEW. Now, I would like to better understand what you thought about career progression opportunities made available to you in your previous job.

6.1 Were you aware of the possibility of career progression as a HEW in your region? *[Probe: eg. the RHB In Tigray is envisaging the training of HEWs in nursing school moving forward and progression of rural HEWs to nurses, urban HEWs to be part of FHT]*
6.2 Were you happy about the opportunities available? If you could suggest a possible career trajectory of HEWs, how would that look?

Lastly, do you have any final input regarding potential changes that could be made to working conditions of health extension workers, so women like you, could be retained in their jobs?

Thank you.

Interview end time:

FOR EXPERT ELICITATION

INTERVIEW TOPIC GUIDE

Understanding the predictors of motivation, estimates of attrition and the potential policy levers for improving retention of HEWs through expert opinion of woreda health staff

Warm-Up Questions:
Perhaps you could tell me a bit about yourself?

- What job title do you have?
- What is your role in the health sector?
- How long have you worked at this health facility? How long have you worked for the Ethiopian health sector?

Theme 1: health Extension program:
1. Are you aware of the health extension program (HEP)? Could you please describe the program to me briefly?

2. Could you please take me through the mandated distribution of health extension workers in every region/woreda/kebele including numbers posted in each of these geographical areas, under HEP? Do you work in close collaboration with HEWs?

3. What is your role in the management of health extension workers? How many HEWs work under your supervision?

Retention of health extension workers in their work place:
4. What do you think are the top drivers of workplace motivation of health extension workers in your woreda? Probe: healthcare delivery to their community, their position the community, salary

5. Have you received any complaints about things in their jobs that they feel dis-incentivised or de-motivated by?

Attrition in the workforce:
6. How many HEW positions are there in your woreda?

7. Are you aware of the number of health extension workers that graduated from TVET in your woreda, this Ethiopian year?

8. What proportion of this cohort that graduated do you think will join the health workforce as health extension workers?

9. Out of the number of HEW positions that you had mentioned exist in your region, what proportion will be left vacant in the next one year you think?

10. What will be the top reasons why health extension workers will leave their job you think?

Policy levers to improve attrition:
11. If you were to look at their jobs as being made up of a series of attributes or job level characteristics like workload, salary, career progression opportunities – which would you say could be improved for improving their retention in the public health sector in Ethiopia?

Thank you

Appendix 6: Consent forms for qualitative interviews

1. **Information sheet to explain participation in individual interviews to explore job attributes impacting job-satisfaction of health extension workers in Ethiopia**

Introduction

We would like to invite you to take part in a research study. Joining the study is entirely up to you. Before you decide, you need to understand why the research is being done and what it would involve. One of our team will go through this information sheet with you, and answer any questions you may have. Ask questions if anything you read is not clear or you would like more information. Please feel free to talk to others about the study if you wish. Take time to decide whether or not to take part.

Addis Ababa University and the London School of Hygiene and Tropical Medicine would like to invite you to participate in a research study on the motivation and job preferences of health extension workers, being conducted in two regions, Oromia and Tigray, in Ethiopia. This study is being conducted within a PhD project, in collaboration with the IDEAS study, which is funded by the Bill and Melinda Gates Foundation.

We would like to learn about what motivates you in your job, and how you feel about the different aspects of your work as a health extension worker. This information will be used to help us develop a bigger survey to explore what motivates people like you to stay in your jobs. We have randomly selected around 20 HEWs from health posts in the two regions to participate, and you are one of those selected.

If you agree to take part, you will be interviewed by me at a time that is convenient to you. We will find a quiet place for the interview, which will take about an hour. If you agree, in order to remember what we talk about today, I will write down what you say as well as tape record this interview

I will keep everything you say confidential by not writing your name on my notes, storing the notes and recordings under lock and key. If the study team reports your opinions or ideas, your name will not appear, and we will make sure that you cannot be identified. Please note that none of what you share with us will ever be shared with your employers.

Taking part in the study may not benefit you directly but will help us understand what motivates health extension workers to keep working within the Ethiopian health system. Taking part is voluntary. You can refuse to answer any question I ask or stop the interview at any time. You do not have to give a reason to refuse to take part or to stop the interview. Refusing to participate will not cause anything bad to happen to you or to your family.

We do appreciate the time volunteered by our respondents to participate in our study, but we do not pay them in return for being interviewed.

I would now like to formally ask you to participate. If anything was unclear or you would like more information, please ask me. Thank you for taking time to read this information leaflet. I want to be sure you are taking part because you want to, so I am going to ask you to sign a form that says you agree to take part. I will read you the form and then ask you to sign. If you do not want to participate that is OK, just let me know.

Informed consent form

Title of research: Reform to Retain: Analysis of Factors Affecting Labour choices of Community Health Workers in Ethiopia

Lead Investigators: Nikita Arora, Abiy Seifu
For more information contact: Abiy Seifu +251912629135, Nikita Arora +447926991085
Please tick all boxes that apply:

I have read the information sheet and/or have been given a clear explanation of the study	
I understand that I can leave the study at any time without giving a reason	
I am happy for the interview to be audio recorded	
I am happy for you to write about what I have said during our interview in reports, on the understanding that you will not reveal my identify	
I am happy for you to include quotations from this interview in reports, on the understanding that I will not be able to be identified from these quotes	
I am happy for the information I provide may be used by others for future research	
I am happy for the information collected in our interview to be transferred to London, UK	
Any questions I had concerning this research study have been answered.	
I am willing to be interviewed now	

Interviewee **Name (in BLOCK CAPITALS)**	
Signature	Date
Researcher **Name (in BLOCK CAPITALS)**	
Signature	**Date**

2. **Information sheet to explain participation in individual interviews to explore factors affecting the motivation of health extension workers and policy levers that could improve their retention in Ethiopia**

Introduction

We would like to invite you to take part in a research study. Joining the study is entirely up to you. Before you decide, you need to understand why the research is being done and what it would involve. One of our team will go through this information sheet with you and answer any questions you may have. Ask questions if anything you read is not clear or you would like more information. Please feel free to talk to others about the study if you wish. Take time to decide whether or not to take part.

Addis Ababa University and the London School of Hygiene and Tropical Medicine would like to invite you to participate in a research study on the motivation and job preferences of health extension workers, being conducted in two regions in Ethiopia. This study is being conducted in the context of a PhD project, in collaboration with the IDEAS study, which is funded by the Bill and Melinda Gates Foundation.

We would like to learn from you, from your knowledge of or involvement with the health extension program, about factors that you think motivate health extension workers to stay in their job, and changes to which job attributes could lead to improvements in their overall retention in the Ethiopian public health system. This information will be used to help us develop our understanding of policy levers that might reduce turnover in health extension worker positions. have randomly selected around 5 key informants from health centres in two regions in the country to participate, and you are one of those selected.

If you agree to take part, you will be interviewed by me at a time that is convenient to you. We will find a quiet place for the interview, which will take about an hour. If you agree, in order to remember what we talk about today, I will write down what you say as well as tape record this interview

I will keep everything you say confidential by not writing your name on my notes, storing the notes and recordings under lock and key. If the study team reports your opinions or ideas, your name will not appear, and we will make sure that you cannot be identified. Please note that none of what you share with us will ever be shared with your employers.

Taking part in the study may not benefit you directly but will help us understand what motivates health extension workers to keep working within the Ethiopian health system. Taking part is voluntary. You can refuse to answer any question I ask or stop the interview at any time. You do not have to give a reason to refuse to take part or to stop the interview. Refusing to participate will not cause anything bad to happen to you or to your family.

We do appreciate the time volunteered by our respondents to participate in our study, but we do not pay them in return for being interviewed.

I would now like to formally ask you to participate. If anything was unclear or you would like more information, please ask me. Thank you for taking time to read this information leaflet. I want to be sure you are taking part because you want to, so I am going to ask you to sign a form that says you agree to take part. I will read you the form and then ask you to sign. If you do not want to participate that is OK, just let me know.

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I am happy for you to write about what I have said during our interview in reports, on the understanding that you will not reveal my identify	
I am happy for you to include quotations from this interview in reports, on the understanding that I will not be able to be identified from these quotes	
I am happy for the information I provide may be used by others for future research	
I am happy for the information collected in our interview to be transferred to London, UK	
Any questions I had concerning this research study have been answered.	
I am willing to be interviewed now	

Interviewee **Name (in BLOCK CAPITALS)**	
Signature	Date
Researcher **Name (in BLOCK CAPITALS)**	
Signature	**Date**

3. **Information sheet to explain participation in individual interviews to explore motivation for leaving health extension worker positions and the availability of alternative opportunities they might be engaged in, in Ethiopia**

Introduction

We would like to invite you to take part in a research study. Joining the study is entirely up to you. Before you decide, you need to understand why the research is being done and what it would involve. One of our team will go through this information sheet with you, and answer any questions you may have. Ask questions if anything you read is not clear or you would like more information. Please feel free to talk to others about the study if you wish. Take time to decide whether or not to take part.

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We understand that you once worked as a health extension worker but are no longer in that position. We would like to learn about your previous experiences in your job as a health extension worker, what motivated you to leave it and which opportunities you have been engaged in since. This information will be used to help us understand the larger context in which the health extension workers work and *reasons for attrition from their positions. We have randomly selected around 20 women who previously worked as health extension workers, and you are one of those selected.*

If you agree to take part, you will be interviewed by me at a time that is convenient to you. We will find a quiet place for the interview, which will take about an hour. If you agree, in order to remember what we talk about today, I will write down what you say as well as tape record this interview

I will keep everything you say confidential by not writing your name on my notes, storing the notes and recordings under lock and key. If the study team reports your opinions or ideas, your name will not appear, and we will make sure that you cannot be identified. Please note that none of what you share with us will ever be shared with your employers.

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Any questions I had concerning this research study have been answered.	
I am willing to be interviewed now	

Interviewee **Name (in BLOCK CAPITALS)**
Signature Date
Researcher **Name (in BLOCK CAPITALS)** **Signature** **Date**