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Trois essais sur le travail et l'éducation

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Résumé

L'Afrique fait face au défi de créer des emplois plus nombreux et de meilleure qualité pour répondre à l'augmentation rapide de sa population en âge de travailler. Cela implique de s'attaquer au problème des jeunes diplômés qui éprouvent des difficultés à trouver un emploi correspondant à leurs qualifications, et d'améliorer les systèmes d'éducation et de formation. Cette thèse se penche sur cette problématique touchant à la fois les sphères de travail et d'éducation, et suggère quelques pistes de solutions.

Le premier chapitre part du constat que les perspectives limitées d'emploi hautement qualifié et la pauvreté poussent de nombreux diplômés de l'enseignement supérieur à occuper des emplois ne nécessitant pas de diplôme universitaire. Afin d'examiner ce problème, nous avons mené une expérience de terrain au Burundi qui a permis de déterminer les préférences des employeurs en ce qui concerne l'expérience professionnelle peu qualifiée des récents diplômés de l'enseignement supérieur. Nous estimons l'impact de signaler différents types d'expériences peu qualifiées, telles que le travail en tant qu'agent de vente de crédit téléphonique, serveur, agent de sécurité et autres postes ne nécessitant pas de diplôme universitaire, sur l'intérêt des employeurs d'embaucher un candidat pour un emploi qualifié. Les résultats indiquent que les employeurs préfèrent les demandeurs d'emploi ayant une expérience peu qualifiée plutôt que ceux qui n'ont aucune expérience, quelle que soit la qualité du postulant.

Le deuxième chapitre aborde également le problème du sous-emploi. Plus précisément, il examine l'impact du sous-emploi sur l'enseignement primaire, en utilisant des données de panel au niveau individuel, dans le contexte Éthiopien. L'étude exploite la variation de l'exposition des enfants au sous-emploi des adultes au sein de leur ménage en utilisant une stratégie d'identification qui prend en compte la nature échelonnée du traitement (*staggered treatment*). L'étude examine l'effet causal du sous-emploi sur l'absentéisme scolaire ainsi que sur les activités extrascolaires. Les résultats suggèrent que le sous-emploi réduit la motivation pour fréquenter l'école en augmentant l'implication des enfants dans des activités extrascolaires, à savoir les activités agricoles, la collecte d'eau et de bois de chauffage et d'autres activités. Ces résultats permettent de comprendre une partie des

raisons derrière l'observation contemporaine selon laquelle davantage d'enfants dans les pays en développement vont à l'école mais apprennent relativement peu.

Le dernier chapitre aborde la problématique de la formation des employés en compétences générales par les employeurs. Nous explorons ce phénomène chez les employeurs agricoles du Burundi. Nous cherchons à savoir si les employeurs ne forment pas les travailleurs occasionnels à des techniques agricoles améliorées, à forte intensité de main-d'œuvre, parce qu'ils ne "s'approprient" pas les bénéfices de cette formation. Tout d'abord, nous apportons des preuves empiriques de la présence d'échecs d'appropriation, en incitant un sous-ensemble d'employeurs à former des travailleurs sur certains marchés du travail locaux (villages) et pas sur d'autres. Deuxièmement, nous montrons qu'en augmentant la probabilité que le travailleur formé travaille pour l'employeur formateur à l'avenir, ceci augmente la volonté des employeurs de former de 50 points de pourcentage. Nos résultats suggèrent qu'un écart important entre les rendements privés et sociaux de la formation peut entraver la formation en cours d'emploi, avec des conséquences significatives pour la productivité et la production des travailleurs, surtout lorsque la formation initiale est lacunaire.

Summary

Africa faces the challenge of generating more and better jobs to keep pace with its rapidly expanding working-age population. This entails tackling the problem of young graduates finding it difficult to secure employment that aligns with their qualifications, along with enhancing education and training systems. This thesis delves into these issues and investigates some potential solutions.

The first chapter starts from the observation that limited prospects for high-skill employment and poverty push numerous college graduates into jobs which do not require a college degree. In order to examine this issue, we conducted a field experiment in Burundi which elicited preferences of employers with respect to low-skill job experience of recent college graduates. We estimate the impact of signaling various types of low-skill experiences, such as working as a phone credit sales agent, a waiter, a security guard and other positions that do not necessitate a college degree, on the hiring interest of employers in a high-skill job. Results indicate employers prefer job seekers with low-skill experience rather than individuals with no experience at all, irrespective of the quality of the job seeker.

The second chapter also speaks to the problem of underemployment. More specifically, it examines the impact of underemployment on primary schooling, using individual level panel data from Ethiopia. The study exploits the variation in children's exposure to underemployment of adults within their households using an identification strategy that takes into account the staggered nature of the treatment. The study investigates the causal effect of underemployment on school absenteeism as well as out of school activities. The empirical evidence suggests that underemployment reduces the motivation for schooling by increasing the involvement of children in out-of-school activities, namely household agricultural activities, collecting water and firewood, and other activities. These findings contribute to understanding some of the reasons behind the contemporary observation that more children in developing countries are attending school but are learning relatively less.

The final chapter shifts the focus on the problem of under-training by employers in general skills. We explore this phenomenon among agricultural employers in Burundi. We investigate whether employers do not train casual laborers in improved, labor-intensive, agricultural techniques because they do not "appropriate" the returns. First, we provide empirical evidence for appropriability failures by inducing a subset of employers to train workers in some local labor markets (villages) and not others. Second, we show that by increasing the likelihood that the trained worker will work for the training employer in the future, employers' willingness to train increases by 50 percentage points. Our findings suggest that a sizable wedge between private and social returns to training may impede on-the-job training, with meaningful consequences for worker productivity and output, especially if the education system is weak.

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Introduction Générale

Nombreux sont ceux qui considèrent l'éducation comme un moyen d'obtenir un bon emploi. Ainsi, lorsque l'éducation acquise ne correspond pas aux attentes en termes d'emploi, débouchant sur le chômage ou le sous-emploi, cela peut donner lieu à des sentiments de frustration et de découragement. Dans un premier temps, cette thèse se penche sur la question du sous-emploi lié au niveau d'instruction qui, comme nous l'expliquons ci-dessous, est un indicateur plus instructif que le chômage en ce qui concerne l'état du marché du travail en Afrique subsaharienne (ci-après l'Afrique), région qui est le focus de cette étude. Nous examinons d'abord si l'expérience acquise pendant une période de sous-emploi post-universitaire peut servir de tremplin pour obtenir des emplois correspondant au niveau d'instruction. Nous étudions ensuite l'impact du sous-emploi sur l'éducation primaire. Considérant l'entreprise comme un lieu de formation particulièrement important lorsque le système d'éducation traditionnel fait face à des défis majeurs, cette thèse se concentre par la suite sur la question de la formation par les employeurs en compétences générales, également appelées compétences transversales, qui peut s'avérer sous-optimale, en raison du risque qu'un employé, une fois formé, quitte trop tôt l'entreprise pour un autre employeur.

Avant d'aborder ces différentes thématiques, nous introduisons divers aspects du travail et de l'éducation en Afrique afin de contextualiser les analyses des différents chapitres et de clarifier certaines terminologies fréquemment utilisées dans cette thèse. Dans un premier temps, nous présentons une vue d'ensemble du marché du travail africain, en soulignant la disparité entre l'afflux croissant de jeunes sur le marché du travail et la rareté des opportunités d'emploi formel. Notre discussion porte ensuite sur le passage de l'éducation à l'emploi, en examinant de près les obstacles que rencontrent les jeunes diplômés pour obtenir des emplois correspondant à leurs qualifications scolaires. Nous approfondissons ensuite la question du sous-emploi en Afrique, en distinguant ce phénomène de concepts étroitement liés. Nous abordons ensuite les défis inhérents au système éducatif africain et confrontons les perspectives utilitaires et idéalistes de l'enseignement supérieur. Nous terminons cette introduction en attirant l'attention sur l'importance des compétences générales. Dans l'ensemble, cette introduction aborde les défis complexes associés au travail et à l'éducation dans le contexte africain, préparant le terrain pour un examen plus détaillé de certaines questions précises dans les parties subséquentes de la thèse. Bien que ces dernières soient centrées sur le Burundi et l'Éthiopie, nous soutenons qu'à bien des égards, ces pays sont similaires à plusieurs autres pays africains sans pour autant minimiser les idiosyncrasies nationales.

i Aperçu du marché du travail africain

Le taux de chômage en Afrique est actuellement estimé à seulement 6,75% (WDI, 2023). Toutefois, ce chiffre ne tient pas compte des personnes qui, bien qu'employées, occupent des emplois en deçà de leur niveau d'instruction, c'est-à-dire des personnes sous-employées par rapport à leurs qualifications, des personnes dont les heures de travail sont insuffisantes par rapport à une situation d'emploi plus souhaitable, ainsi que d'autres formes de sous-emploi. C'est ainsi que beaucoup de ceux qui travaillent se retrouvent dans les rangs des travailleurs pauvres, c'est-à-dire qu'ils vivent dans des ménages dont les revenus sont inférieurs au seuil de pauvreté. En 2021, environ 61% des personnes employées vivaient sous le seuil de pauvreté modérée, soit USD 3,10 par jour (en parité de pouvoir d'achat) (ILO, 2023c). De plus, une grande partie d'africains se trouve dans le secteur informel, principalement dans l'agriculture[1], un secteur qui est presque entièrement informel, avec un taux d'informalité estimé à 98% (Kiaga and Leung, 2020). Dans l'ensemble, les chiffres indiquent qu'en 2022, environ 87% des personnes employées en Afrique occupaient un emploi

[1] Les emplois dans l'agriculture y représente 51.57% du total des emplois (Données de 2021, Source : WDI (2023)).

informel (ILO, 2023c).

En fait, l'Afrique est confrontée à un double défi : d'une part, créer des opportunités d'emploi afin de répondre à la croissance rapide de sa population en âge de travailler, et d'autre part, créer des emplois adéquats. En effet, la population en âge de travailler de la région devrait augmenter plus fortement que celle de toute autre région, avec un ajout estimé à 740 millions d'individus de 2020 à 2050 (Figure 0.1). Chaque année, 8 à 11 millions de jeunes devraient rejoindre la population active au cours des dix prochaines années, alors que le marché du travail actuel ne peut fournir qu'environ 3 millions de nouveaux emplois salariés formels chaque année (Banque Mondiale, 2023). Cette situation souligne le besoin pressant d'une création d'emplois plus importante et de meilleure qualité pour faire face à l'augmentation de la population.

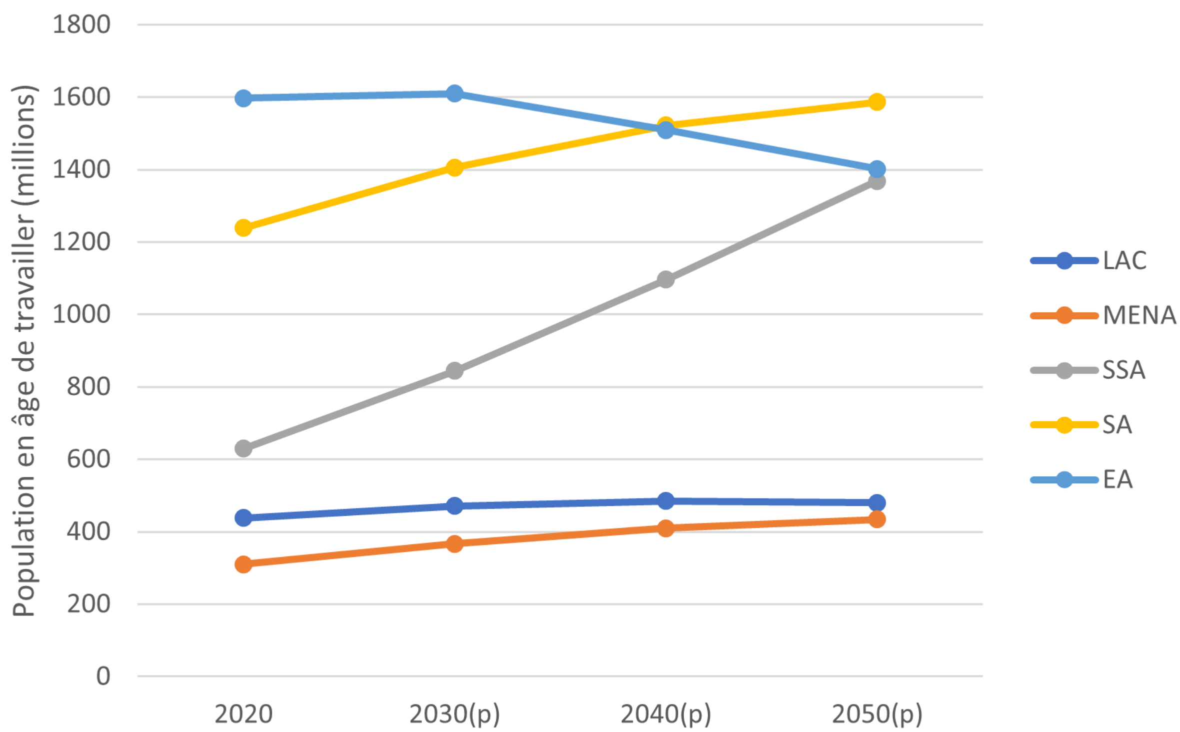
En résumé, le marché du travail africain se caractérise bien souvent par diverses formes de sous-emploi ainsi qu'une forte prévalence de l'informalité. Cet état du marché du travail touche particulièrement les jeunes, majoritaires dans la population, durant leur transition de l'école au travail.

ii Transition école-travail

Au cours des deux dernières décennies, les inscriptions dans l'enseignement supérieur ont plus que doublé en Afrique, avec des taux de croissance encore plus prononcés que la moyenne africaine au Burundi et en Ethiopie (Figure 0.2). Cette population de jeunes instruits en forte augmentation est non seulement à la recherche d'emplois, mais elle aspire également à des postes correspondant à ses qualifications académiques. Cette section présente l'état actuel des connaissances concernant la transition des jeunes africains de l'école vers le monde du travail en se focalisant sur la littérature économique.

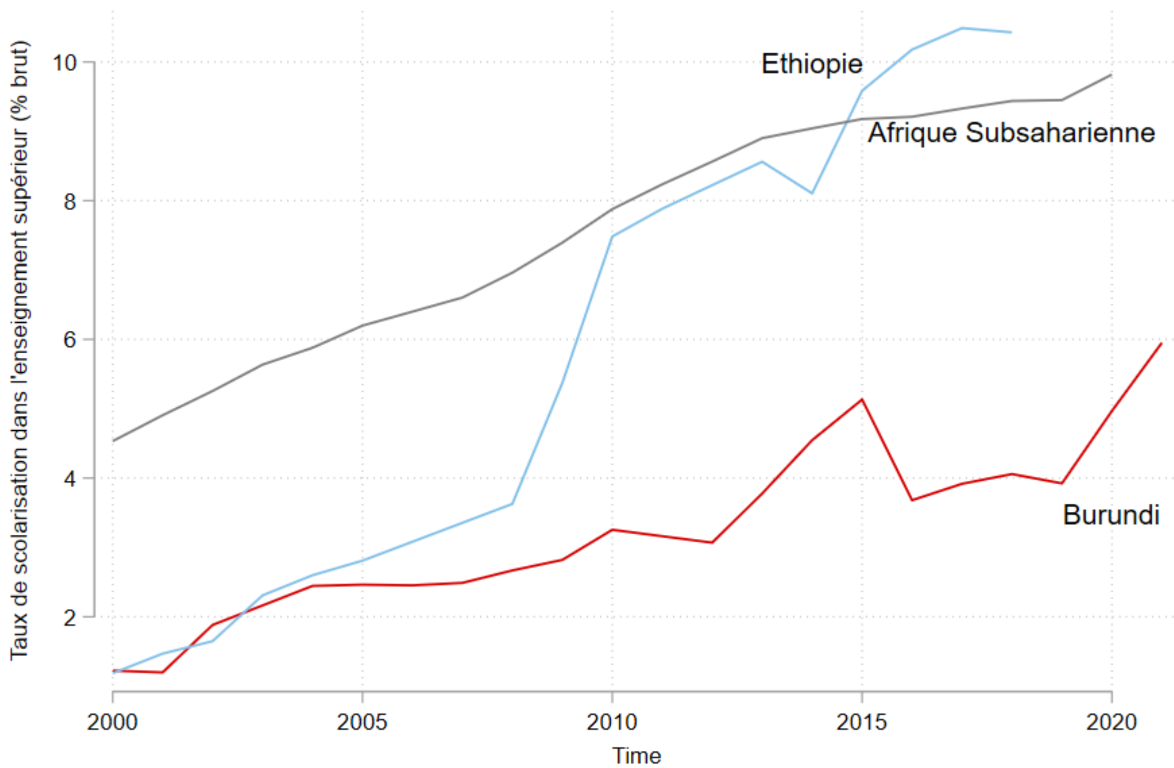
Les indicateurs de transition école-travail de l'Organisation Internationale du Travail (OIT) fournissent une ventilation détaillée de la transition des jeunes (individus âgés de 15 à 29 ans) sur le marché du travail. Il existe deux indicateurs principaux : le stade de la transition entre l'école et le travail et la forme que prend cette transition. Les indicateurs de stade

Figure 0.1: Projections de la population en âge de travailler



Source: Banque Mondiale (2023)
Note : EAP – East Asia and Pacific (Asie de l'Est et Pacifique), LAC – Latin America and Caribbean (Amérique Latine et Caraïbes), MENA – Middle East and North Africa (Moyen Orient et Afrique du Nord), SSA – Sub-saharan Africa (Afrique Sub-saharienne), SA – South Asia (Asie du Sud), ECA – Europe and Central Asia (Europe et Asie Centrale), NA – North America (Amérique du Nord), (p) – projections.

Figure 0.2: Evolution du taux de scolarisation dans l'enseignement supérieur au Burundi, en Éthiopie et en Afrique Subsaharienne : 2000-2021



Source: WDI (2023)

classent les jeunes en trois segments en fonction de leur avancement dans la transition : (I) transité, (II) en transition, et (III) pas encore commencé la transition. Les indicateurs de forme se concentrent sur les résultats spécifiques de ceux qui ont achevé la transition, en faisant la distinction entre un emploi salarié stable et un emploi indépendant satisfaisant ou un emploi temporaire satisfaisant[2].

Suivant ces indicateurs, l'Afrique affiche une proportion relativement élevée de jeunes en transition par rapport à d'autres régions (ILO, 2023a). Les dernières données de l'OIT sur la transition, recueillies dans quatre pays - Kenya, Rwanda, Sénégal et Ouganda - révèlent qu'au Kenya et au Rwanda, près de la moitié des jeunes (Agés de 15 à 29 ans) sont considérés comme étant en transition. En Ouganda, le ratio est plus proche d'un sur trois, tandis qu'au Sénégal, il est d'environ un sur quatre. Dans tous ces pays, entre 40 et 45% des jeunes, soit une fraction particulièrement importante, n'ont pas encore entamé leur transition. Au Kenya et au Rwanda, à peine 10% des jeunes ont réussi leur transition (ILO, 2023a).

Dans une revue des études portant sur la transition école-travail dans les pays en développement, Nilsson (2019) identifie divers déterminants de la transition vers le marché du travail dans le contexte africain. Des recherches menées dans le contexte du Mali ont montré que les jeunes Maliens ayant fait des études supérieures passent en moyenne plus de temps (6 ans) à trouver un premier emploi que les diplômés du primaire et du secondaire (3 ans), mais ont besoin de moins de temps pour trouver un emploi satisfaisant (9 ans contre 12 ans) (Boutin, 2013).

La revue de Nilsson (2019) souligne que la génération actuelle est confrontée à un marché du travail différent de celui de leurs aînés en ce qui concerne l'attente d'emplois dans le secteur public. Alors que les personnes bien éduquées des générations précédentes avaient un accès relativement facile à l'emploi dans le secteur public, l'augmentation de leur nombre combinée à des crises économiques et à des réformes structurelles a signifié que cette option n'est plus efficace.

On note également dans l'étude ci-haut citée qu'il y a peu de preuves sur le chômage lié

[2]Le critère de satisfaction est pris en compte dans la définition de la transition à l'exception des emplois non satisfaisants qui répondent à tous les autres critères d'un travail décent (ILO, 2009).

au salaire de réserve en Afrique, à l'exception de l'Afrique du Sud où des taux de chômage élevés ont suscité un débat sur les origines du chômage des jeunes. Une étude sur le cas précis de l'Afrique du Sud révèle que, en distinguant les petites et grandes entreprises, entre 70% et 80% des jeunes hommes sud-africains ont des attentes salariales plus élevées que ce qu'ils sont susceptibles de gagner en travaillant dans une petite entreprise, suggérant que le chômage pourrait être en partie causé par des jeunes attendant un emploi dans de grandes entreprises (Rankin and Roberts, 2011).

Concernant le genre, une littérature principalement descriptive a trouvé que les femmes sont généralement désavantagées dans la transition de l'école au travail (Nilsson, 2019). Les femmes connaissent également des transitions plus longues en général, que ce soit la transition vers un emploi salarié stable ou vers un auto-emploi satisfaisant. De plus, être une femme est associé à des parts plus élevées de travail familial et d'emploi informel, et à des salaires plus bas lorsqu'elles sont en emploi salarié.

Une enquête de la Banque mondiale menée dans plusieurs pays en développement, dont le Kenya et le Ghana, a révélé que les compétences socio-émotionnelles facilitent la transition de l'école au travail (Valerio et al., 2014). Les travailleurs qui rapportent une transition plus fluide de l'école au travail possèdent des compétences socio-émotionnelles différentes de ceux qui ont mis plus de temps à trouver leur premier emploi : ils ont tendance à être plus consciencieux, émotionnellement stables et à avoir plus de persévérance[3]. Le premier chapitre de la thèse examine entre autres le rôle de la persévérence du demandeur d'emploi dans la recherche d'emploi.

Un nombre croissant de recherches expérimentales menées en Afrique explorent les difficultés liées à la recherche d'un emploi. Ces recherches mettent en lumière l'impact sur les demandeurs d'emploi de diverses initiatives visant à réduire les coûts de la recherche d'emploi et à améliorer la visibilité des compétences. Dans une étude réalisée par Abebe et al. (2021), deux approches ont été testées pour aider les jeunes chômeurs d'Addis-Abeba, en Éthiopie, à surmonter les obstacles géographiques et informationnels : l'octroi d'une subvention pour

[3]La recherche a également examiné si la probabilité de transition est liée à la spécialisation choisie au niveau universitaire, à la fréquentation d'une institution privée, aux liens avec des figures administratives ou politiques de premier plan et autres facteurs (Voir revue de Nilsson (2019)).

le transport et l'organisation d'un atelier de candidature à un emploi. Sur le court terme, les deux stratégies ont amélioré de manière significative la probabilité d'obtenir un emploi formel. L'atelier, en particulier, a permis d'augmenter les chances d'obtenir un emploi stable et à long terme. Au bout de quatre ans, les participants à l'atelier ont enregistré une nette amélioration de leurs revenus, de leur satisfaction professionnelle et de la durée de leur emploi, alors que les avantages de l'aide au transport n'étaient plus évidents. L'étude souligne que les jeunes demandeurs d'emploi possèdent des compétences précieuses, mais souvent invisibles. Lorsque ces compétences sont rendues visibles pour les employeurs, les gains qui en résultent compensent largement les coûts de ces interventions.

Dans le même ordre d'idées, les études de Bassi and Nansamba (2022) et Carranza et al. (2022) soulignent l'idée que la fourniture d'informations crédibles sur les compétences peut améliorer les résultats sur le marché du travail. L'expérience de terrain de Bassi and Nansamba (2022), en Ouganda, a montré que la divulgation des certifications de compétences non cognitives lors des entretiens d'embauche modifiait positivement les attentes des employeurs et des demandeurs d'emploi, ce qui s'est traduit par des revenus anticipés plus élevés chez les travailleurs et une plus grande appréciation de leurs compétences par les employeurs. Dans une expérience proche de cette dernière menée en Afrique du Sud, Carranza et al. (2022) ont montré que si le simple fait de fournir aux demandeurs d'emploi des informations sur leurs compétences n'a qu'un effet limité sur le comportement de recherche d'emploi et les résultats en matière d'emploi, aider les demandeurs d'emploi à faire connaître leurs compétences aux employeurs améliore nettement leur taux d'emploi et leurs revenus. Ces études suggèrent collectivement que si des lacunes d'information existent des deux côtés du marché du travail, ce sont principalement les frictions du côté de la demande qui sont cruciales pour les résultats du marché du travail.

En analysant la candidature à un poste d'un demandeur d'emploi sans expérience professionnelle antérieure, les entreprises doivent inférer la productivité du travailleur à partir des peu d'informations dont elles disposent. Un tel élément d'information qui reçoit une attention particulière dans le premier chapitre est l'expérience dans des emplois peu qualifiés, c'est-à-dire des emplois ne nécessitant pas de diplôme universitaire.

Dans ce chapitre, nous examinons les préférences des employeurs par rapport aux expériences en emplois peu qualifiés dans le contexte du Burundi. Théoriquement, il y a des raisons de croire que l'expérience post-universitaire dans des emplois peu qualifiés peut soit augmenter, soit diminuer les chances d'obtenir un emploi correspondant à ses qualifications. D'une part, les jeunes diplômés peuvent tirer profit de ces emplois, car ils permettent d'augmenter le revenu courant et de mettre en évidence certaines compétences non techniques telles que l'adaptabilité. D'autre part, certains pourraient éviter ces emplois de peur d'y rester bloqués et de voir leurs compétences académiques dépréciées, entre autres raisons. Nous postulons que sur un marché du travail où les emplois qualifiés sont rares, les employeurs pourraient apprécier la ténacité des diplômés qui acceptent des postes moins qualifiés. Mais sur un marché où les postes qualifiés sont nombreux, cette expérience pourrait être perçue négativement.

Nous avons mené une expérience sur le terrain en utilisant des CV d'étudiants de l'Université du Burundi, dans la faculté d'économie et de gestion. Ces CV ont été modifiés pour y ajouter des expériences professionnelles peu qualifiées. Les résultats montrent qu'après un an sur le marché du travail, les CV mentionnant des expériences peu qualifiées sont mieux notés par les employeurs en comparaison aux CV dépourvus de toute expérience post-universitaire. Les entretiens menés après l'expérience révèlent que ces employeurs perçoivent les personnes ayant une expérience peu qualifiée comme étant travailleuses, disciplinées et persévérantes.

Cette recherche se distingue des études antérieures en proposant une variante d'une méthode expérimentale introduite pas Kessler et al. (2019), applicable à la fois dans les pays à hauts et à bas revenus. Elle contribue également à la littérature en examinant l'impact des expériences de faible qualification après les études sur l'intérêt des employeurs à embaucher, alors que des recherches précédentes ont étudié l'impact de ces expériences pendant les études (Baert et al., 2016; Kessler et al., 2019). Enfin, cette étude alimente le débat sur le sous-emploi lié aux compétences, un sujet qui a reçu peu d'attention dans le contexte africain (Barnichon and Zylberberg, 2019). La recherche souligne la nécessité de comprendre les préférences des employeurs pour mieux guider les demandeurs d'emploi.

iii Les faces cachées de l'emploi

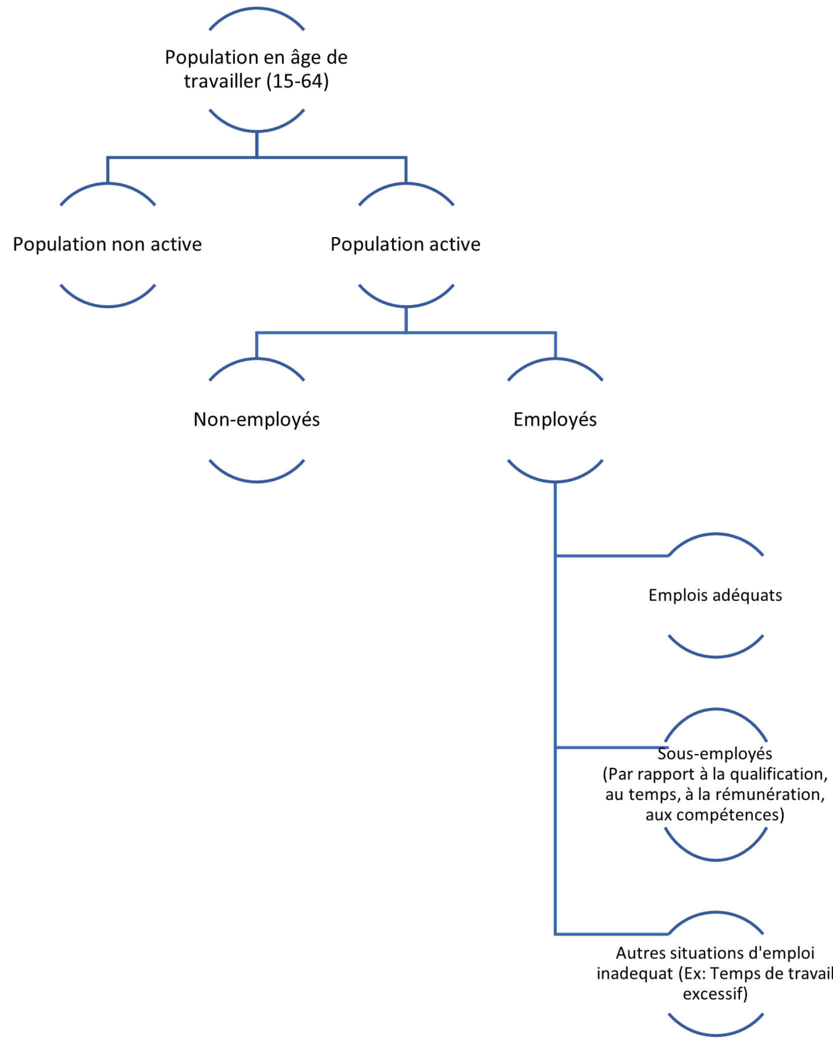
Nous tournons à présent l'attention sur l'emploi qui, comme nous l'avons évoqué au début, dissimule souvent diverses formes de sous-emploi. Selon l'OIT, le sous-emploi est un sous-ensemble d'un concept plus large de sous-utilisation du potentiel productif de la population employée. Peut-être pour des raisons de facilité de mesure, les normes internationales de l'OIT se sont limitées pendant longtemps à un seul aspect du sous-emploi, à savoir le sous-emploi lié au temps, qui se caractérise par des personnes employées pour un nombre d'heures inférieur à la durée de travail souhaitée et pour laquelle elles seraient disponible (OIT, 2008). Cependant, le paysage de l'emploi inadéquat s'étend au-delà des seules préoccupations liées au temps de travail. Une perspective holistique reconnaît diverses formes d'inadéquation de l'emploi, englobant le sous-emploi lié aux qualifications, aux compétences, aux revenus ainsi que les préoccupations liées aux heures de travail excessives. Ces nuances remettent en question les analyses de l'état du marché du travail dans les pays en dévéloppement basées sur les statistiques du chômage qui, bien que largement diffusées (Ndayikeza, 2020), sont critiquables parce qu'elles ne rendent pas pleinement compte de la complexité des questions liées à l'emploi. Le cadre de mesure de la main d'oeuvre (*Labor force framework*) ci-dessous, qui se réfère à celui de OIT (2008), met en évidence la catégorie d'individus qui nous intéresse dans cette thèse, à savoir le sous-emploi lié aux qualifications, et précise ses différences et ses similitudes avec d'autres concepts relatives au marché du travail.

Le sous-emploi lié aux qualifications survient lorsque les acquis scolaires dépassent les exigences de l'emploi. Ce sous-emploi reflète un rendement sous-optimal des investissements dans l'éducation. Ce concept correspond à ce que l'OIT appelle la « suréducation » (*Overeducation*). Le terme de « sous-emploi » (*Underemployment*) est préféré au terme de « suréducation » dans cette thèse car le premier fait référence directement à la problématique d'emploi alors que le second fait penser que le problème se situerait au niveau de l'éducation. Notre choix de terminologie est également appliquée dans d'autres études [4].

Par ailleurs, la conceptualisation du sous-emploi lié à la qualification par l'OIT est relativement récente. La 20è Conférence Internationale des Statisticiens du Travail

[4] Par exemple Barnichon and Zylberberg (2019); Jackson (2023); Ferhat and Joubert (2023).

Figure 0.3: Cadre de mesure de la main d'oeuvre



Note: Développé à partir du cadre de mesure de la main d'oeuvre d'OIT (2008), Page 3, en ajoutant différentes catégorisations des personnes employées.

(CIST), qui s'est tenue en 2018, a introduit des précisions dans la mesure du concept général d'inadéquation des qualifications de la main-d'œuvre en proposant trois approches différentes: l'approche normative, l'approche statistique et l'auto-évaluation. L'approche normative recommande de fixer des exigences en matière d'éducation pour des emplois ou des groupes professionnels spécifiques. L'approche statistique utilise le niveau d'éducation moyen, médian ou modal des employés au sein d'une profession pour évaluer l'inadéquation. Enfin, l'approche fondée sur l'auto-évaluation s'appuie sur la perception qu'ont les individus de l'adéquation entre leur formation et les exigences de l'emploi. L'OIT a examiné les avantages et les inconvénients de chaque méthode, reconnaissant les limites de l'approche statistique et la subjectivité de l'approche par auto-évaluation, pour finalement plaider en faveur de la méthode normative fondée sur des évaluations approfondies des emplois [5]. Ainsi, la suite de notre analyse se base sur l'approche normative.

En outre, le sous-emploi lié aux qualifications doit être distingué du sous-emploi lié aux compétences. L'OIT définit la qualification comme une confirmation officielle, généralement sous la forme d'un document, obtenue par la réussite d'un programme d'éducation complet, la réussite d'une étape, d'un programme d'éducation, ou la validation des connaissances, aptitudes et compétences acquises indépendamment de la participation à un programme d'éducation (OIT, nd). D'autre part, les compétences, plus difficiles à mesurer, sont définies par la même institution comme la capacité innée ou acquise d'appliquer des connaissances acquises par l'expérience, l'étude, la pratique ou l'instruction, et d'accomplir les tâches et les fonctions requises par un emploi donné. Ces compétences peuvent être spécifiques à un emploi ou techniques, il peut s'agir de compétences de base telles que la lecture, l'écriture et le calcul, et il peut s'agir de compétences transférables, compétences que nous appelons dans le chapitre 3 compétences générales (*General skills*) suivant la tradition en économie du travail (Becker, 1964; Acemoglu, 1997). Ces compétences générales sont pertinentes pour un large éventail d'emplois et peuvent être facilement transférées d'un emploi à l'autre.

Néanmoins, qu'il soit lié aux qualificiations ou aux compétences, le sous-emploi entraîne divers coûts pour les différents agents économiques et la société (Stoevska, 2017). Les

[5] Voir une discussion détaillée sur les avantages et les inconvénients des différentes approches dans OIT (2018), Points 51 à 56.

travailleurs surqualifiés sont confrontés à des salaires et à une satisfaction professionnelle moindres (Pascual-Saez and Lanza-Leon, 2023; Sam, 2020) et tendent à chercher continuellement un emploi pendant qu'ils sont en poste (Ferhat and Joubert, 2023), augmentant ainsi le turnover. En conséquence, les employeurs souffrent d'une perte de productivité et d'un ralentissement de la croissance. Il s'en suit une diminution des recettes de l'impôt sur le revenu et, comme il en ressort de notre analyse dans le deuxième chapitre, la société supporte le fardeau du sous-investissement conséquent dans l'éducation.

De manière analogue au calcul du taux de chômage, nous calculons ci-dessous le taux de sous-emploi comme le nombre de personnes sous-employées[6] par rapport à la taille de la population active en utilisant toutes les données disponibles pour l'Afrique. Nous présentons les chiffres du sous-emploi calculé de deux façons. Nous calculons d'abord le sous-emploi de la manière suivante :

$$\text{Taux de sous-emploi} = \frac{\text{Nombre de personnes sous-employées}}{\text{Population active}} \times 100 \tag{1}$$

où la population active est le nombre total de personnes employées ou au chômage à un moment donné. Un dénominateur plus pertinent est le sous-ensemble de personnes qui peuvent potentiellement être en situation de sous-emploi, c'est-à-dire, suivant l'OIT, la population active ayant au moins terminé le premier cycle de l'enseignement secondaire[7]. Nous calculons ce deuxième indicateur comme suit.

$$\begin{array}{c}\text{Taux de sous-emploi avec au moins}\\ \text{un niveau d'éducation secondaire}\end{array} = \frac{\text{Nombre de personnes sous-employées}}{\begin{array}{c}\text{Population active ayant au moins terminé}\\ \text{le premier cycle de l'enseignement secondaire}\end{array}} \times 100 \tag{2}$$

[6] C'est-à-dire les personnes occupant un emploi en deçà de leur niveau de qualification, selon l'approche normative établie par l'OIT. Voir Figure A2.1.

[7] Plus précisément, la population ayant un niveau d'instruction de niveau CITE 11_2 (premier cycle de l'enseignement secondaire) à la CITE 11_8 (doctorat ou niveau équivalent). L'Organisation des Nations Unies pour l'Education, la Science et la Culture (UNESCO) a élaboré la Classification Internationale Type de l'Education (CITE) au début des années 1970. Ce cadre a été créé pour faciliter la collecte, la compilation et la présentation de statistiques et d'indicateurs sur l'éducation qui soient comparables à la fois au sein de chaque pays et à l'échelle internationale. Nous utilisons la dernière classification introduite en 2011.

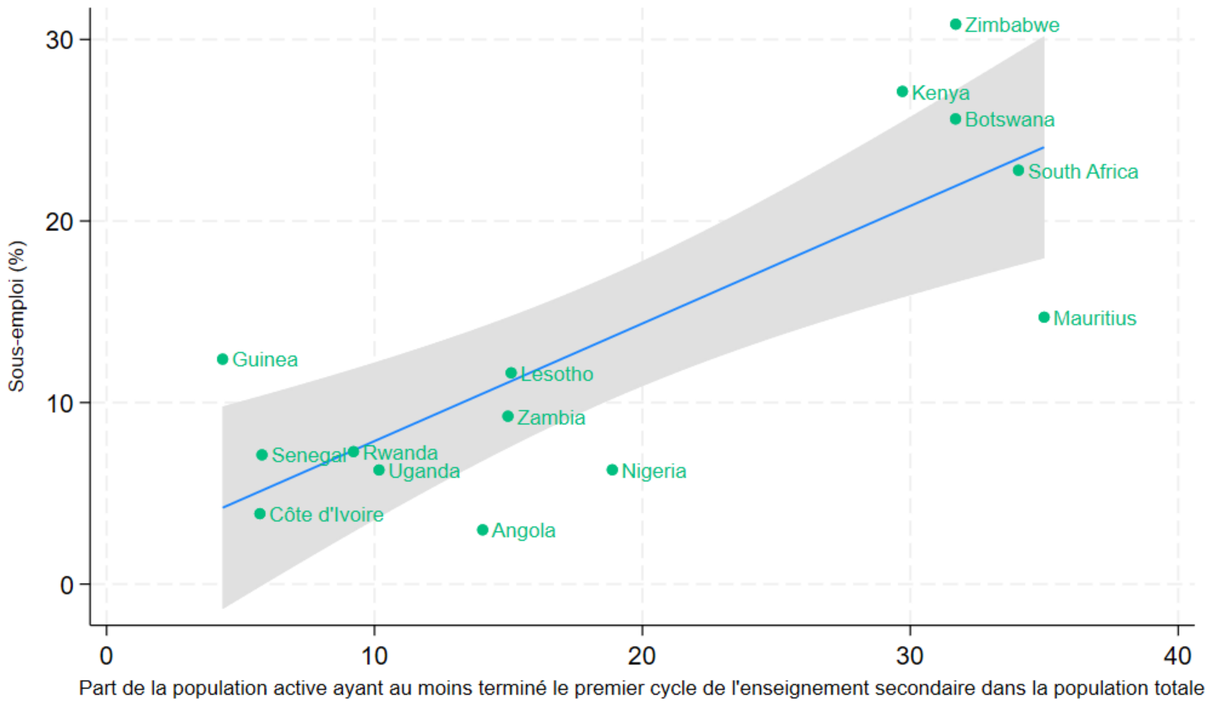
Bien que le manque de données ne permette pas l'évaluation du phénomène de sous-emploi pour l'Afrique entière, nous donnons une image du phénomène en utilisant les dernières données de l'OIT. Nous présentons dans la Table 0.1 les statistiques du sous-emploi pour l'année 2019 afin de faciliter la comparaison car la plupart des pays d'Afrique n'ont pas mis à jour ces données depuis cette année. La première remarque est que le sous-emploi (en moyenne de 27% ou 13% selon, respectivement, que l'on tient compte du niveau d'instruction de la population active ou pas) est plus élevé que le chômage dans cette région, proche de 7% (WDI, 2023). Cependant, il existe des variations importantes entre les pays. Sans tenir compte du niveau d'éducation, le sous-emploi varie de 3% en Angola à 31% au Zimbabwe. En tenant compte du niveau d'éducation, le sous-emploi varie de 8% en Angola à 70% en Guinée.

Table 0.1: Le sous-emploi en Afrique en 2019

Pays	**Sous-emploi par rapport à la population active**	**Sous-emploi par rapport à la population active ayant au moins terminé le premier cycle de l'enseignement secondaire**
Angola	2.99	7.76
Botswana	25.62	31.69
Côte d'Ivoire	3.88	23.76
Guinea	12.39	70.13
Kenya	27.14	32.86
Lesotho	11.64	25.58
Mauritius	14.7	19.11
Nigeria	6.3	11.11
Rwanda	7.3	26.32
Senegal	7.12	35.21
Uganda	6.29	23.75
South Africa	22.8	27.68
Zambia	9.25	18.59
Zimbabwe	30.84	31.37
Moyenne	**13.45**	**27.49**

Note: Cette table montre les statistiques du sous-emploi en 2019 en Afrique suivant l'approche normative. L'approche normative se base sur une catégorisation des occupations et des niveaux d'instruction préétablis par l'OIT. La comparaison est faite uniquement pour 2019 car la plupart de ces pays n'ont pas encore mis à jour leurs données depuis cette année.

Figure 0.4: Corrélation entre le niveau d'instruction et le sous-emploi (2019)



Note: Ce graphique utilise des données de 2019 car la plupart de ces pays n'ont pas encore mis à jour leurs données depuis cette année. Le sous-emploi en ordonnées est calculé par rapport à la population active (Suivant l'equation 1).

En outre, la Figure 0.4 montre que le niveau d'éducation au niveau national est positivement associé au sous-emploi. Face à cette corrélation qui interpelle, il est légitime de se demander s'il vaut la peine d'investir dans l'éducation dans un contexte où les personnes qui l'ont fait n'ont pas été en mesure d'employer les qualifications accumulées. Le deuxième chapitre aborde indirectement cette question en cherchant à savoir si la transition d'une situation d'emploi adéquat à une situation de sous-emploi de la part des adultes d'un ménage influence l'investissement dans l'éducation des enfants vivant dans le même ménage.

Cependant, la finalité de l'éducation ne saurait être que l'obtention d'un travail lié à ses études. Ainsi, un questionnement connexe et plus général est de savoir si le système éducatif doit s'adapter aux besoins du marché du travail ou s'il doit contribuer à la création de nouvelles compétences pour stimuler le marché du travail. Nous analysons cette question après avoir présenté les problèmes auxquels est confronté le système éducatif africain.

iv Les défis contemporains du système éducatif africain

L'Afrique est diverse, mais de nombreux défis liés à l'éducation sont communs à l'ensemble du continent. Malgré des progrès significatifs, de nombreux enfants ne sont toujours pas scolarisés. Parmi toutes les régions du monde, l'Afrique est en tête de liste de l'exclusion en matière d'éducation. Selon les données de l'UNESCO en 2019, 19% des enfants âgés de 6 à 11 ans n'étaient pas scolarisés. Ce pourcentage passe à 37% pour ceux âgés de 12 à 14 ans, et à 58% pour la tranche d'âge de 15 à 17 ans (UNESCO, 2019). Même lorsque les enfants sont scolarisés, nombre d'entre eux n'acquièrent pas les compétences fondamentales, ce qui a entraîné ce que l'on a appelé la "crise de l'apprentissage" dans cette région (UNESCO, 2014; World Bank, 2018b; Pritchett and Viarengo, 2023). L'évaluation PASEC 2019, menée dans 14 pays d'Afrique francophone, révèle qu'à la fin du cycle primaire, plus de 52% et près de 62% des élèves n'atteignent pas le niveau "suffisant" en lecture et en mathématiques, respectivement (CONFEMEN, 2020). Ce problème de qualité de l'éducation a été associé en partie à l'expansion des programmes d'éducation gratuite qui se sont multipliés à partir des années 90, car l'augmentation de la fréquentation scolaire qui s'en est suivie n'a pas été accompagnée d'une augmentation proportionnelle des autres intrants éducatifs dans de nombreux pays (Riddell, 2014; UNESCO, 2014).

Le premier rapport de la Banque Mondiale qui s'est penché sur la question de la qualité des apprentissages distingue les causes immédiates des causes profondes de cette dernière (World Bank, 2018b). Les causes immédiates sont liées au manque de préparation des élèves à l'apprentissage[8], au faible niveau et à la motivation insuffisante des enseignants, aux intrants insuffisants ou non effectivement utilisés, ainsi qu'à la gouvernance scolaire à améliorer. Les causes profondes, quant à elles, sont liées à la superstructure chapeautant le système éducatif, exigeant d'aligner divers éléments du système éducatif sur l'apprentissage. Ainsi, non seulement il y a des défis techniques, tels que l'amélioration des systèmes de recrutement des enseignants, une meilleure mesure des acquis des élèves, l'amélioration du

[8] Dans le sens où ils mangent à leur faim, ne sont pas obligés de faire trop de travaux ménagers et ainsi de suite.

fonctionnement des marchés publics, etc., mais également des défis politiques. Concernant ces derniers, il s'agit de s'assurer que les intérêts et les actions des politiciens, des entreprises privées fournisseuses d'intrants, des bailleurs de fonds internationaux et d'autres parties prenantes ne contredisent pas les objectifs de l'apprentissage.

S'il n'y a pas de solution miracle aux causes profondes, on peut néanmoins se référer aux succès observés dans différents pays, comme en Corée du Sud et au Vietnam, deux pays dont la rapidité de l'amélioration de la qualité des apprentissages a surpris le monde (Voir World Bank (2018b)), afin d'adopter une approche qui convient. On peut aussi se référer aux nombreuses connaissances accumulées au fil du temps concernant l'efficacité de certaines interventions. Par exemple, agir sur certaines des causes immédiates en mettant en place des programmes de cantines scolaires permettrait de mieux préparer les élèves à l'apprentissage. Il est nécessaire dans plusieurs contextes de mieux former les enseignants et d'augmenter leurs rémunérations. Enfin, la gouvernance scolaire pourrait être améliorée en permettant une plus grande autonomie de décision des écoles, accompagnée d'une supervision des parents et de la collectivité.

L'enseignement supérieur est confronté à ses propres défis. Tout d'abord, le taux brut de scolarisation dans l'enseignement supérieur, estimé à 10%, est très faible par rapport à une moyenne mondiale proche de 90% (WDI, 2023). Malgré ce faible taux d'inscription dans l'enseignement supérieur, les dépenses publiques par étudiant dans l'enseignement supérieur étaient le double de celles des élèves de l'école primaire, selon les dernières estimations de 2013 (UNESCO, 2023a). En outre, le coût de l'enseignement supérieur pèse lourdement sur de nombreux étudiants. Même lorsque les frais de scolarité sont abordables, la nécessité de s'installer plus près des universités entraîne des dépenses supplémentaires. L'incertitude quant à l'obtention d'un emploi bien rémunéré après l'obtention du diplôme est un obstacle supplémentaire à l'inscription dans l'enseignement supérieur.

En outre, les bas salaires et le manque de financement de la recherche découragent les universitaires qualifiés de rester dans les universités africaines (Devarajan et al., 2011). Par conséquent, ces institutions deviennent moins attrayantes pour les meilleurs étudiants africains, dont beaucoup choisissent de poursuivre leurs études et leur carrière dans d'autres parties du monde. Cette fuite de cerveaux entraine un manque de dynamisme au sein des universités africaines, reprochées par ailleurs de transmettre souvent des compétences non calibrées aux besoins du marché du travail (Morsy and Mukasa, 2019). Cependant, l'adaptation des programmes universitaires aux besoins du marché du travail ne fait pas l'unanimité comme nous le précisons dans la section suivante.

v S'adapter ou transformer ? Le rôle de l'enseignement supérieur dans la réduction du sous-emploi

La question de savoir si le système éducatif doit s'adapter aux exigences courantes du marché du travail ou jouer un rôle transformateur en inculquant des compétences qui contribuent à l'expansion du marché du travail n'est pas nouvelle. Elle remonte même à Aristote, qui se demandait si les jeunes devaient "cultiver les connaissances utiles à la vie, ou celles qui tendent à la vertu, ou enfin les connaissances sortant de l'ordinaire"[9]. Le contexte actuel d'une hausse de la fréquentation de l'université[10] en Afrique (Graphique 0.2) et d'une forte croissance de la population en âge de travailler (Graphique 0.1), risquant de grossir les rangs des sous-employés (Table 0.1), fait que cette question mérite d'être re-posée aujourd'hui [11].

En effet, les universités africaines sont de plus en plus appelées à jouer un rôle central dans la résolution des problèmes de chômage et de sous-emploi, en particulier chez les jeunes. Toutefois, cela n'a pas toujours été le cas. Bénéficiant de financements publics et opérant dans un contexte de forte demande de main-d'œuvre qualifiée, les universités de la période postcoloniale immédiate étaient quelque peu à l'abri de la pression exercée pour former à l'employabilité (UNESCO, 2012). Aujourd'hui, l'enseignement supérieur est de plus en

[9] Cité dans Trouvé (2015)

[10] Le mot "université" est ici utilisé comme terme générique regroupant toutes les institutions de l'enseignement supérieur.

[11] La question se pose moins pour les niveaux secondaire et inférieurs, tout au moins pour les élèves ayant les aptitudes scolaires requises. Ainsi, cette section se focalise sur le niveau universitaire.

plus coûteux, principalement en raison des frais de scolarité et du coût de la vie pour les étudiants, et cela se produit dans un contexte où la demande de travail ne suit pas le rythme de croissance de la population active (Banque Mondiale, 2023). Ainsi, même dans un pays tel que le Burundi, où le taux de scolarisation dans l'enseignement supérieur, à 6,5% (Graphique 0.2), figure parmi les plus bas du monde, il n'est pas rare d'y entendre qu'il y aurait un excès d'universitaires compte tenu du nombre restreint d'emplois disponibles. Ce *zeitgeist* incite l'université africaine à s'éloigner des disciplines "déconnectées" du monde qui les entoure (Wedekind and Mutereko, 2016). Comme corrolaire, l'apprentissage dans le monde universitaire est poussé à devenir plus utilitaire, ce qui se traduit entre autres par le développement des relations entre l'université et l'industrie (Outamha and Belhcen, 2020; World Economic Forum, 2023).

Cette tendance utilitaire de l'enseignement supérieur présente des avantages et des inconvénients. Côté négatif, elle pourrait mettre en péril la mission des universités et réduire leur autonomie, en particulier si celles-ci cherchent à établir des partenariats avec le secteur industriel en raison de contraintes financières (Wedekind and Mutereko, 2007). En dispensant un enseignement général qui ne se limite pas aux compétences actuellement demandées par le marché du travail, les universités peuvent cultiver une main-d'œuvre qui façonne l'avenir plutôt que de s'y adapter. En particulier, un virage utilitariste pourrait être problématique pour les sciences sociales, qui offrent moins de possibilités de travailler dans le secteur industriel[12]. En outre, les universités peuvent avoir d'autres priorités importantes, telles que la promotion de la recherche scientifique fondamentale, pouvant contribuer à trouver des remèdes à certaines maladies, ou la bio-ingénierie des plantes, pouvant contribuer à éradiquer la famine dans le monde, mais qui peuvent ne pas être compatibles avec la perspective utilitaire.

Par ailleurs, nous devons des avancées remarquables à des scientifiques dévoués et à des

[12] A titre illustratif, alors que le prix Nobel d'économie de 2023 a été décerné à Claudia Goldin pour ses travaux portant sur les différences entre les sexes sur le marché du travail, le président ougandais Museveni a formulé la même année la critique suivante à l'égard des études de genre : "Il est impossible de ne pas financer l'enseignement des sciences. Mais lorsque vous apportez [...] des études sur les femmes, que vous étudiez les femmes pendant trois ans et que vous obtenez un diplôme sur les femmes, c'est là que le budget est dépassé" [Traduit de l'anglais par l'auteur]. Voir le discours sur YouTube à partir de 2:23, https://www.youtube.com/watch?v=dZZhPtu8NGU

personnalités politiques qui ont préféré le progrès sociétal à l'enrichissement personnel. Des innovateurs comme Nikola Tesla, connu pour ses travaux pionniers en électricité et en magnétisme ou Srinivasa Ramanujan, mathématicien indien autodidacte, sont tous décédés avec peu ou pas de fortune[13]. S'ils avaient choisi de mettre leur talent au profit de la poursuite de l'argent, l'humanité n'aurait peut-être pas bénéficié de leur ingéniosité. De même, de nombreux leaders des mouvements d'indépendance africains et des progrès sociétaux post-coloniaux étaient pleinement conscients des risques associés à leurs actions. Ces personnalités, telles que Patrice Lumumba et Thomas Sankara, ont choisi de se confronter à des questions sociétales difficiles plutôt que de poursuivre des positions lucratives dans les secteurs public ou privé, malgré leurs talents évidents (Mba, 2017). Cela suggère qu'un système éducatif qui se concentrerait uniquement sur la préparation des individus à travailler pour les autres limiterait potentiellement la pleine expression et le développement de l'intelligence humaine.

On peut également se demander s'il n'est pas contradictoire de vouloir adapter la formation des étudiants aux exigences du marché, compte tenu de la nature fluctuante de celui-ci (Trouvé, 2015). En effet, un système éducatif réactif, qui rattrape continuellement les tendances du marché peut inhiber la réflexion stratégique à long terme et étouffer l'innovation.

En outre, le revers de la médaille de la course mondiale aux talents, renforcée par la pandémie de Covid-19 et l'ouverture accrue au travail à distance, est qu'elle accentue la vision des étudiants en tant que futurs travailleurs plutôt que sur la vision idéaliste d'un enseignement supérieur formant des citoyens du monde dotés de l'esprit d'entreprise et des compétences nécessaires pour résoudre des problèmes tels que les droits de l'homme, la réduction de la pauvreté, la protection de l'environnement et le développement durable (Brookings, 2022).

Cela étant, les arguments en faveur de l'alignement de l'enseignement supérieur sur les besoins du marché du travail en Afrique sont convaincants. Les partisans de cette approche

[13]Voir les biographies de O'Neill (2007) pour Nikola Tesla et Rao (2021) pour celle de Srinivasa Ramanujan.

soutiennent que les programmes d'enseignement doivent être pragmatiques, se concentrer sur les métiers sous tension, et qu'il est normal que le succès des universités dépende du succès des diplômés (Aranda et al., 2022). Sous cette vision, la nécessité pour le système éducatif africain d'évoluer en réponse aux besoins du marché du travail est évidente compte tenu de la forte prévalence du sous-emploi en Afrique, non seulement lié à la formation, mais aussi à la rémunération, au temps de travail et aux compétences. En outre, adapter l'éducation aux pénuries de certaines compétences, même si ces pénuries ne se trouvent pas sur le territoire national, peut contribuer à attirer des investissements étrangers dans des secteurs en quête de main-d'œuvre prête à être employée. Bien que cette stratégie visant à répondre aux besoins à court terme du marché puisse restreindre les catégories de secteurs dans lesquels il est possible d'innover, elle offre toujours la possibilité d'innover dans les compétences demandées, ce qui est peut-être la meilleure stratégie pour l'Afrique, compte tenu de ses besoins pressants de croissance économique et réduction de la pauvreté.

Comme évoqué plus haut, la possibilité de travailler à distance ainsi qu'une plus grande ouverture à la mobilité de la main-d'œuvre pour combler la pénurie de certaines compétences dans les pays développés constituent des arguments en faveur de la promotion de la fonction utilitaire de l'enseignement supérieur. Parmi les compétences les plus demandées actuellement dans les pays développés figurent les compétences en informatique. Le monde connaît une crise des talents dans ce domaine, une situation qui s'aggrave, et les entreprises dominantes dans ce secteur n'ont pas encore tiré pleinement parti de la possibilité de trouver des informaticiens en Afrique (Brookings, 2022). C'est ainsi que des pays comme le Kenya et l'Afrique du Sud ont rendu obligatoire l'enseignement de la programmation dans les écoles primaires et secondaires (The Informer, 2022) mais plusieurs autres pays ne les ont pas encore emboités le pas. De plus, si de nombreux acteurs privés et ONG tentent de mettre les entreprises en contact avec des talents du continent, le nombre d'africains travaillant à distance pour des organisations américaines et européennes est loin d'avoir atteint l'ampleur des embauches actuelles en Inde ou en Europe de l'Est (Brookings, 2022). Dans ce contexte, mettre l'Afrique en position de résoudre la pénurie mondiale de talents en adaptant les programmes d'études afin de préparer les lauréats des universités à travailler à distance pourrait alléger la pression sur le marché du travail et réduire le sous-emploi.

En outre, l'adaptation de l'éducation à des pénuries immédiates de compétences peut favoriser une corrélation plus rapide entre l'investissement dans l'éducation et les rendements financiers, un argument convaincant pour les familles qui recherchent des résultats tangibles suite à leurs dépenses d'éducation. Nous nous penchons sur cette problématique dans le chapitre 2, qui aborde la question de l'influence du marché du travail sur l'education primaire.

Ce chapitre examine comment le sous-emploi des adultes peut influencer la scolarité des enfants du niveau primaire, non seulement par le biais du revenu, mais aussi par le canal de la motivation, se différenciant des études antérieures qui se sont penchés sur l'impact du sous-emploi uniquement sur le revenu (Pascual-Saez and Lanza-Leon, 2023; Chuang and Liang, 2022) et sur la satisfaction au travail (Bender and Roche, 2013; Sam, 2020). Nous testons l'hypothèse que le sous-emploi a une incidence négative sur la fréquentation scolaire des enfants et augmente le temps que ces derniers consacrent aux travaux ménagers.

La recherche utilise des données individuelles collectées en Éthiopie entre 2011 et 2016. Ces données de panel permettent d'étudier la relation dynamique entre le sous-emploi et l'éducation. L'étude compare les enfants vivant dans des ménages avec des adultes sous-employés à ceux vivant dans des ménages avec des adultes occupant des emplois correspondant à leurs études. Afin d'éviter le problème d'endogénéité, l'analyse est basée sur la méthode de différence de différences, une approche méthodologique qui la distingue des études antérieures analysant le lien entre le marché du travail et l'éducation.

Les résultats montrent que le sous-emploi a un impact significatif sur les travaux ménagers des enfants, en particulier sur les tâches agricoles et d'autres corvées telles que la collecte d'eau et de bois. Toutefois, le lien avec l'absentéisme scolaire prolongé est faible. En outre, les données indiquent que les enfants relativement âgés et les enfants des classes relativement avancées sont plus susceptibles d'être impliqués dans le travail agricole en raison du sous-emploi des adultes du ménage.

L'étude apporte une nouvelle perspective à la littérature existante en se concentrant sur l'influence du sous-emploi sur l'éducation, plutôt qu'en analysant l'impact du chômage sur l'éducation. Comme nous l'avons expliqué plus haut, dans les pays à faible revenu, le marché du travail est davantage caractérisé par le sous-emploi que par le chômage, ce dernier étant généralement faible simplement parce que la plupart des individus ne peuvent pas se permettre de rester sans emploi.

vi De la formation scolaire à la formation en entreprise, la problématique du développement des compétences générales

Les compétences générales peuvent être définies comme des compétences "qui peuvent être utilisées de manière productive dans différents contextes d'emploi" (OIT, 2007). Ces compétences peuvent être techniques, comme l'utilisation d'une machine, ou élémentaires, comme la lecture et l'écriture, et contrastent avec les compétences qui sont entièrement liées à l'emploi ou spécifiques à l'entreprise. Le chapitre 3 traite des compétences générales liées à la plantation et à l'application d'engrais dans le contexte du Burundi rural.

Les compétences générales améliorent l'employabilité des individus qui sont mieux à même de passer d'un emploi à l'autre. Cet avantage s'accompagne d'un défi. Les entreprises peuvent être réticentes à investir dans les compétences générales, car elles risquent de perdre le travailleur et par là leur investissement. Les politiques de formation doivent donc s'attaquer à ce problème, car il peut entraîner un niveau sous-optimal d'investissement dans ce type de compétences.

Des politiques visant à introduire un partage des coûts entre les entreprises formatrices, non formatrices et les salariés, telles que les fonds de formation, ont été mises en place dans les pays en développement comme dans les pays développés pour inciter les entreprises à investir davantage dans les compétences transférables, par exemple le Fonds de Développement de la Formation Professionnelle en Côte d'Ivoire (UNESCO, 2022), ou le Compte Personnel de Formation en France (Perez and Vourc'h, 2020). Ces fonds sont sectoriels, régionaux ou nationaux. Ils sont le plus souvent alimentés par des prélèvements sur les entreprises, plus spécifiquement sur les salaires des employés, et visent principalement à financer la formation des employés et des apprentis. Moins fréquemment, ils servent à financer la formation des chômeurs, des personnes désavantagées, et d'autres groupes. Il existe différentes modalités pour l'utilisation des fonds de formation : ils peuvent soit rembourser les employeurs qui investissent dans la formation de leurs employés et apprentis, soit financer directement diverses formations, soit combiner ces deux approches. L'intervention que nous mettons en œuvre au Burundi relève du premier cas, où il s'agit de rembourser les entreprises pour leurs dépenses en formation.

Les évidences disponibles concernant l'impact des fonds de formation, qui reposent pour la plupart sur des corrélations, des perceptions ou de simples comparaisons avant-après, sont faibles (UNESCO, 2022). En outre, les évaluations menées dans différents pays aboutissent à des résultats sensiblement divergents. Quelques rares données probantes issues d'études quasi-expérimentales montrent un impact positif sur la formation des travailleurs en Malaisie, tandis que des effets non significatifs ont été observés au Canada et aux Pays-Bas (UNESCO, 2022). Par ailleurs, il fréquent de constater des problèmes de gouvernance au sein de ces institutions, notamment en termes de coûts d'administration excessifs.

La question du transfert des compétences générales se pose avec d'autant plus d'acuité que les gains et les pertes potentiels liés à la mobilité du travailleur augmentent. C'est particulièrement vrai dans le contexte du football et dans d'autres sports. Lors de l'affaire Bosman, dont l'arrêt de 1995 a permis aux footballeurs de l'Union Européenne (UE) de rejoindre un club de l'UE sans indemnité de transfert, les clubs de football ont fait valoir que l'arrêt réduirait l'incitation à former les joueurs (Morris et al., 1996). Il n'est pas certain que la décision ait eu cet effet, mais un peu plus tard, la FIFA a établi une indemnité de formation en 2001, qui est payée par le nouveau club au club, ou aux clubs, qui ont formé le joueur entre 12 et 21 ans (Papantoniou, 2017). L'obligation de payer l'indemnité de formation entre en vigueur lorsqu'un joueur signe son premier contrat en tant que professionnel et à chaque fois qu'un professionnel est transféré au niveau international jusqu'à la fin de la saison de son 23e anniversaire. Le calcul de l'indemnité, qui est assez compliqué, prend notamment en compte le montant nécessaire à la formation du joueur professionnel multiplié par un "facteur joueur" qui est égal au ratio des joueurs qui doivent être formés pour produire un joueur professionnel.

Ce système serait bien sûr trop compliqué à appliquer aux entreprises ordinaires, en plus de restreindre la libre circulation des personnes. Néanmoins, le cas du football illustre bien l'importance de la problématique de formation en compétences générales, problématique qui n'a pas de solution simple.

Dans le chapitre 3, nous examinons l'impact d'une solution basée sur l'incitation financière et ayant pour objectif d'augmenter la probabilité qu'une personne formée travaille pour un employeur pendant une période convenue après la formation. Dans cette étude, les employeurs sont des agriculteurs qui font appel à la main-d'œuvre externe au ménage pour des travaux de plantation, et le marché du travail se situe au niveau du village. Il faut préciser que le contexte spécifique de notre étude facilite l'étude de l'impact de la formation et d'une intervention visant à accroître la transmission de compétences générales, par rapport à l'alternative de faire une étude pareille auprès de firmes urbaines. Nous observons que, malgré le fait que les compétences agricoles analysées soient encouragées depuis longtemps par le gouvernement, via les moniteurs agricoles, et les ONG, leur application n'est pas largement répandue au niveau national. Notre hypothèse est donc que les employeurs hésitent à former les travailleurs à ces compétences générales car ils ne sont pas certains de leur disponibilité lors de la période de plantation.

Nos résultats apportent une preuve empirique que les avantages de la formation s'étendent au-delà des employeurs qui la dispensent. Si ceux qui forment les travailleurs emploient effectivement un plus grand nombre de personnes formées, d'autres employeurs sur le même marché du travail embauchent ces travailleurs qualifiés. Par conséquent, tant les employeurs qui dispensent la formation que ceux qui ne le font pas voient leurs bénéfices augmenter. Cet investissement dans la formation entraîne une augmentation du surplus social total, mais seul un quart de ce surplus est capté par les employeurs à l'origine de la formation. Sur le surplus restant, deux tiers bénéficient à d'autres employeurs et un tiers bénéficie aux travailleurs formés.

En outre, notre étude montre que la redistribution d'une partie du surplus de formation aux formateurs, en l'occurrence les agriculteurs, les motive à former. Pour ce faire, nous avons offert un contrat visant à améliorer la probabilité perçue que les travailleurs retournent travailler pour les employeurs après la formation. L'introduction de ce contrat stimule considérablement la formation et le transfert de compétences, nos résultats montrant que les agriculteurs sont 50% plus enclins à former des travailleurs lorsqu'on leur présente ce contrat.

vii Conclusion

Cette introduction générale aborde les défis complexes liés au travail et à l'éducation dans le contexte africain, jetant les bases pour une analyse plus approfondie de questions spécifiques dans les parties suivantes de la thèse.

D'entrée de jeu, nous soulignons que le marché du travail africain est souvent caractérisé par le sous-emploi et des conditions de travail précaires. Cette situation touche particulièrement la jeunesse en constante augmentation, notamment durant leur transition de l'école au travail. Nous observons que l'Afrique présente une proportion relativement élevée de jeunes en phase de transition, comparée à d'autres régions. Dans ce contexte, un nombre croissant de recherches expérimentales menées en Afrique s'intéressent aux difficultés de l'insertion professionnelle, proposant des pistes pour faciliter la transition école-travail. Ces études révèlent que les jeunes demandeurs d'emploi possèdent des compétences précieuses, mais souvent non reconnues par eux-mêmes ou par les employeurs, et que la mise en évidence de ces compétences peut améliorer leurs perspectives sur le marché du travail. Ce constat introduit le premier chapitre qui analyse l'impact du signalement de l'expérience en emplois peu qualifiés sur l'intérêt pour l'embauche des employeurs.

Cette introduction précise également différents concepts clés de cette thèse, notamment le sous-emploi et sa méthode de calcul, la qualification et la compétence. Nous mettons aussi en évidence une corrélation entre le niveau d'instruction et le sous-emploi, soulevant ainsi la question de l'adaptation du système éducatif aux besoins du marché du travail, ou de sa contribution à la création de nouvelles compétences pour dynamiser ce marché. Après avoir examiné les défis du système éducatif africain, nous confrontons les deux visions de l'enseignement supérieur : vision utilitariste et vision idéaliste. Nous proposons une réponse de politique éducative intégrant ces deux stratégies et mettons en garde contre la négligence potentielle de certaines disciplines importantes mais moins demandées sur le marché. Cette discussion établit un lien avec le second chapitre, qui analyse l'impact du sous-emploi sur l'éducation.

Face aux défis rencontrés par le système éducatif standard, nous tournons l'attention sur un autre vecteur de formation crucial en cas de faiblesse du système scolaire : l'entreprise. Plus précisément, nous discutons de la problématique de la formation en compétences générales, définies comme des compétences transversales utiles dans divers contextes professionnels. Bien que ces compétences accroissent l'employabilité des individus, les rendant plus capables de naviguer entre différents emplois, elles posent un dilemme pour les employeurs réticents à investir dans une formation qui pourrait bénéficier à d'autres entreprises. Cette discussion fait le lien avec le troisième chapitre de la thèse, qui examine l'impact d'une intervention visant à montrer l'impact de la formation en compétences générales et d'une autre intervention visant à augmenter la probabilité que le travailleur formé soit disponible pour l'employeur dans le futur.

Chapter 1

Underemployment of college graduates: is doing anything better than doing nothing?

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1 Introduction

Over the past two decades, enrollment in tertiary education has substantially increased in low-income countries, going from 4.5% to 9.3% in 2020 (WDI, 2022). However, a significant number of students graduate into low-skill jobs, meaning jobs that do not require a college degree[1]. This underemployment[2] issue is of concern to policy makers as well as graduates themselves who invest important sums of money in higher education. Be that as it may, there are reasons to think that post-graduation low-skill experience may increase or diminish the likelihood of obtaining a job that is commensurate with one's qualifications.

On one hand, there are arguments to suggest that recent college graduates may benefit from taking on low-skill jobs during the transition from college to a high-skill job[3]. For instance, low-skill jobs increase current income, can potentially signal soft skills to employers such as perseverance and may improve matching by allowing individuals to better understand their career preferences. Such jobs may also increase appreciation for high-skill jobs and build discipline. On the other hand, people may avoid taking up a low-skill employment for fear of being trapped in a low equilibrium as the low-skill job reduces the time available to search for jobs that require a college degree. Furthermore, the knowledge gained in college may decay during the low-skill employment period, decreasing chances of obtaining a college-level job in the future. Low-skill experience may also be viewed as a negative signal by employers, who may infer lower ability from this information. Additionally, individuals aspiring to high-profile jobs, such as top government positions, may be hesitant to take on low-skill jobs due to concerns about social reputation. The focus of this paper is on preferences of employers for low-skill job experience.

In a labor market where high-skill jobs and low-skill jobs are scarce, employers may value the

[1]Statistics on the number of recent college graduates affected by underemployment in low-income countries are currently lacking. The latest estimates of underemployment in Africa for the general population, typically lower than underemployment of young college graduates, are 30% in Botswana, 27% in Rwanda and 27% in South Africa in 2022 (Underemployment defined as the share of people whose level of education is above the average requirement of their occupation among people with at least a lower secondary education.).

[2]Unless otherwise indicated, underemployment refers to persons whose highest level of education is above the educational requirements for their occupation.

[3]Manacorda et al. (2017) estimated the average duration to first employment in sub-Saharan Africa countries at 26 months, in a sample which included Benin, Madagascar, Tanzania, Togo and Uganda.

tenacity and resilience shown by a graduate's decision to work in low-skill roles. Conversely, with many high-skill job offers, low-skill job experience may not be as favorably viewed. Here, employers might question why a graduate with a college degree would opt for a job that doesn't utilize their academic qualifications. This could be interpreted as a lack of ambition or ability, potentially leading to a decrease in the perceived value of the graduate's profile. Our study delves into what it means for a graduate to take up a low-skill job during this time in comparison to being unemployed[4] from the standpoint of employers[5].

To elicit preferences of employers with respect to low-skill experience, we conducted a variant of the Incentivised Resume Rating (IRR) experiment, introduced by Kessler et al. (2019) to address the issue of deception inherent in audit studies. We started with a group of real resumes of students who were one month from finishing their bachelor studies at the University of Burundi[6], in the faculty of economics and management. By using graduates' actual resumes, we obtained a variety of formats and other idiosyncrasies that reflect the material that hiring managers typically review. These resumes were modified such that the period since graduation corresponded to one year and they do not mention any post-graduation experience. Starting from this pool of resumes, we created a new set of resumes which was similar to the first one, except with the addition of low-skill experience. We used data on the types of low-skill jobs past graduates have done after graduation to generate types of low-skill jobs that we randomly populated the resumes with. Our implementing partner, a well-established human resource (HR) firm, sent the resumes to various employers in the country with whom it usually collaborates for recruitment, informing them that their evaluations will be used to improve the quality of future matches. A total of 712 resumes were evaluated by 37 employers, among the largest in the country, who rated them on a scale of 1 to 10 with respect to hiring interest.

[4]We provide a discussion in appendix 6 on how realistic this comparison is in the African context, following a presentation of the current knowledge on young graduates' transition into the labor market, and provide some complementary information on school-to-work transition.

[5]Understanding these preferences doesn't fully clarify whether it's more advantageous for recent tertiary education graduates to accept low-skilled positions or to seek high-skilled roles while remaining unemployed. The ideal way to address this would be through an experiment where individuals are randomly assigned to low-skilled jobs. However, conducting such an experiment would be ethically questionable.

[6]We focus on students finishing their undergraduate studies since less than 10% of bachelor's graduates pursue master's studies (MENRS, 2024).

Results of the experiment show that resumes with low-skill experience received a higher score on average compared to resumes devoid of any post-graduate experience, with a statistically significant difference ($p < 0.01$). Moreover, results indicate a stochastic dominance of a job search strategy which consists of signaling low-skill experience in comparison to presenting a resume devoid of any post-graduate experience. The latter finding means that employers prefer job seekers with low-skill experience rather than individuals with no experience at all, irrespective of the quality of the job seekers as indicated by the score given to his or her resume. We analyze the heterogeneity of the low-skill experience treatment with respect to resume and evaluator characteristics. Main results are robust to different specifications and we benchmark the effect size against other effects identified in the literature. Post experiment interviews are consistent with experimental results and reveal that employers perceive people with low-skill experience as hard working, disciplined and persevering individuals rather than individuals with financial difficulties, incompetent or less qualified compared to classmates.

This study contributes to the literature on the influence of career histories in securing a high-skill employment. Several experimental studies have delved into the impact of unemployment duration on the likelihood of obtaining a high-skilled position (Kroft et al., 2013; Eriksson and Rooth, 2014; Farber et al., 2019; Cahuc et al., 2021). Closer to this study is Nunley et al. (2017), which compares underemployment and employment, while this study compares periods of underemployment and unemployment. Nunley et al. (2017) found that underemployed college graduates face a 30% reduction in callback rates compared to their adequately employed counterparts. Relatedly, Farber et al. (2016) found that college-educated females engaged in "interim" jobs at a lower skill level than the job for which they are applying for are markedly less likely to receive callbacks for administrative support positions, while finding no relationship between callback rates and the duration of unemployment. In a departure from these findings, Adermon and Hensvik (2022) found in the Swedish context that having "gig-experience" is more advantageous than being unemployed. Other experiments and audit studies have evaluated the value of gaining work experience during school via internships (Nunley et al., 2017; Kessler et al., 2019), summer jobs (Gelber et al., 2016; Davis and Heller, 2020), or year-long employment (Baert et al., 2016; Le Barbanchon et al., 2023).

Conceptually, the signaling of low-skill experience can have either a positive or negative impact. Consequently, recent graduates might choose to exclude this information from their resumes, even if it could be advantageous. A study examining a similar strategic behavior among college graduates in Peru shows that, despite a correspondence study indicating that signaling that the job seeker is a laureate of a highly selective scholarship for poor and talented students increases callback rates by 20 percent, 92 percent of beneficiaries avoid listing this award when applying for jobs (Agüero et al., 2023). This behavior is consistent with beneficiaries perceiving a negative labor market return from sending a signal indicative of a lower social background. Similarly, Rivera and Tilcsik (2016) conducted an audit study to investigate the effect of social class signals (such as name, awards and personal interests) on entry into large US law firms. The authors found that law firms prefer higher-class men relative to lower-class men, lower-class women and even higher-class women[7]. In the context of this study, since low-skill experience is often a consequence of low income, it could be that employers deduce from such a signal that the job candidate is from a lower-class. Part of this research investigates this.

More generally, our work supplements previous research which has investigated the impact different resume signals, including race (Bertrand and Mullainathan, 2004; Kline et al., 2022), marital status (Arceo-Gomez and Campos-Vazquez, 2014), religion (Valfort, 2020), resume mistakes (Sterkens et al., 2023) and gender (Bohren et al., 2022). Researchers are typically interested in investigating preferences that employers do not indicate in job adverts either because it is forbidden[8] (some countries have prohibited discrimination in recruitment based on race, religion, sexual orientation, etc)[9] or because of social desirability (for instance, employers might not be willing to admit in interviews that they prefer higher-

[7]The study suggests that higher-class in itself confers an advantage because of the elite culture and clientele of large law firms. In the case of higher-class women however, the class advantage is dampened by a negative stereotype that portrays them as less committed to full-time, intensive careers.

[8]For example, the US law prohibits discrimination based on race, national origin, gender, pregnancy, religion, disability, age, military service or affiliation, wealth, genetic information and citizenship status (Baert, 2018)

[9]See for instance Bertrand and Mullainathan (2004) for racial discrimination, Valfort (2020) for discrimination based on religion and Drydakis (2009) for sexual orientation.

class employees).

In this chapter, we examine the value of low-skill jobs, which may signal varied skills to employers, influencing their hiring interest. Echoing this objective, there exists a body of literature that delves into the worth of skill signals made apparent to employers. Abebe et al. (2021) show that young people possess valuable skills that are unobservable to employers and that helping them signal these skills to employers generates large and persistent improvements in their labor market outcomes. In a similar vein, studies by Bassi and Nansamba (2022), as well as Carranza et al. (2022), underscore the idea that providing credible skill information can improve labor market outcomes. Overall, the existing literature has established that unemployment spells, work experience, and skill signals matter for securing employment.

Our research distinguishes itself from the aforementioned literature by concentrating on a comparative analysis of underemployment and unemployment spells in the quest for high-skilled jobs and by focusing on recent college graduates. Another distinguishing feature of our study is its setting - we base our experiment in a low-income country, contrasting with the previous audit type of studies which are focused on high-income countries.[10]

Our analysis of the impact of low-skill experiences also feeds into the literature on qualification-related underemployment, a topic which has received little attention in the economic literature (Barnichon and Zylberberg, 2019) particularly the demand side of the problem (Brunello and Wruuck, 2021). The issue of underemployment has been mainly investigated from the perspective of high skilled workers rather than employers. It has been advanced that high skilled workers search for low-skill jobs in order to maximize chances of obtaining a job quickly by avoiding relatively tense competition for high-skill jobs (Barnichon and Zylberberg, 2019). The migration literature has also documented the issue of underemployment of high skilled workers who migrate to developed countries (Lo et al., 2019; Chiswick and Miller, 2009). We contribute to this literature by analyzing underemployment of recent college graduates from the perspective of employers.

[10] In low-income countries, sending fictitious applications via email for experimental purposes is generally not feasible, as this is not the typical method of applying for jobs. Additionally, it is more challenging to find enough open job offers to achieve adequate statistical power.

Understanding preferences of employers with respect to low-skill experience is also important for policy. Previous research suggests that expectations about how workers will be treated in the labor market may affect their investment (Lang and Lehmann, 2012). In the specific case of low-skill jobs, preconceptions may affect their take-up or their signaling in interviews or on resumes. Hence, this study is of interest for organizations in charge of advising job seekers as well as job seekers themselves.

The rest of the paper proceeds as follows. In the following section, we present the context of the study. In Section 3, we provide details on the study design and present results in Section 4. We conclude in Section 5.

2 Context of the study

With a population of approximately 12 million people and a gross national income per capita of USD 800 (PPP), Burundi is currently ranked among the poorest countries in the world (World Bank, 2022b). The majority of Burundians is young, with an estimated 65% of the population below the age of 25 (WPP, 2024). In what follows, we present the labor market and higher education contexts.

The general labor market

As is generally the case in low-income countries, the level of unemployment in Burundi is low in absolute terms (2.8%)[11], and slightly lower than average unemployment in low-income countries, estimated at 5.5% in 2022 (WDI, 2023). However, unemployment is higher in urban areas compared to rural areas, with respective rates of 17.2% and 1.1%. Furthermore, unemployment increases with the level of education (see Table 1.1).

However, the Burundian labor market, like that of other developing countries, is better described by underemployment rather than unemployment. In fact, 53.4% of the employed are actually underemployed with respect to time, *i.e.* they work for less than 40 hours per week. Time-related underemployment[12] is predominant in rural areas where the main

[11] Unless otherwise mentioned, labor market statistics come from the most recent survey of the national statistics institute of Burundi (INSBU, 2022).

[12] Qualification-related underemployment data is not available for Burundi. In the remainder of this

economic activity is agriculture. In urban areas, it is estimated at 27.7%, with Bujumbura being the least affected (18.5%). Underemployment decreases with the level of education, with a rate of 57.9% among people with no education and 25.4% among people with higher education, suggesting that relatively educated persons might be less willing to take on bad jobs.

Table 1.1: Summary statistics on education and the labor market in Burundi

Level of education	Unemployment (%)	Underemployment (%)	Enrollment
None	1.0	57.9	-
Primary (or Fundamental)	1.6	51.9	2 756 241
Secondary (or Post-Fundamental)	10.3	45.3	239 645
Higher education	18.2	25.4	63 428

Notes: (1) The unemployment rate measures the number of people who want to work but do not, even though they are available for work and are actively looking for work, as a proportion of the labor force. The rate used is the broad unemployment rate, that is, it includes persons who at the time of the survey were available for work but did not look for work and persons who looked for work but were not immediately available to work. (2) The underemployment rate is calculated with respect to the number of hours worked, using an official reference of 40 hours per week. (3) Enrollment by level of instruction has been calculated based on the fundamental and post-fundamental levels, whereas other statistics use the primary and secondary levels of education. Fundamental education begins at age 6 and lasts 9 years, after which students take a national exam for entry into post-fundamental education, which lasts 3 years. Before this reform was introduced in 2013, primary school lasted 6 years after which students took a national exam to enter secondary school which also lasted 6 years.
Sources: INSBU (2022), MENRS (2021a) and MENRS (2021b).

Arrival rates

Employers' preferences concerning low-skill job experience of recent college graduates may be influenced by the arrival rates of high-skill and low-skill jobs. When both arrival rates are low, meaning that the labor market is tight for all types of jobs, employers should value any type of experience over no experience at all. For instance, employers may interpret experience in low-skill jobs in such a labor market context as a sign of perseverance and adaptability. On the contrary, in a situation where the arrival rate of high-skill jobs is high and the arrival rate of low-skill jobs is low, employers should favor graduates who do not have low-skill job experience, interpreting the low-skill experience signal negatively. For instance, employers may interpret such a signal as lack of ambition or lower ability compared to classmates.

Low economic growth (an average of 1.7% of annual GDP growth over the past decade (WDI, 2023) and relatively high unemployment rate of individuals with higher education (18.2%)[13]

section, underemployment refers to time-related underemployment.

[13]As a comparison, unemployment of individuals with secondary education is estimated at 10.3%, 1.6%

suggest that the arrival rate of high-skill jobs is low. As for low-skill jobs, discussions with recent university graduates highlight the difficulty in obtaining such positions. For instance, several of them reported joining a waiting list in order to become a security guard. In our survey of a cohort from the Faculty of Economics and Management at the University of Burundi, one year after completing their undergraduate studies, we found that only 18% had obtained a job requiring their qualifications.

Education

For what concerns the higher education system, Burundi had 63 428 students in 2021 (a 73% increase since 2011) distributed over 49 institutions of higher learning (MENRS, 2021b). The University of Burundi, that we worked with for our experiment, is a public and tuition free university, and the largest higher learning institution in the country. Most of its campuses are located in Bujumbura where it attracts students mainly from poor backgrounds from all over the country. While the number of students in the higher education system is considerably lower than the number of students in primary schools (2 756 241)[14], government expenditure per student (PPP) in primary school was last estimated at USD 95 in 2013 compared to USD 2794 per student in tertiary education (UNESCO, 2023a). In addition, the small number of students in higher education should not obscure the importance of this sector, as these young people are a particularly critical group. If they are not employed, they may engage in activities that pose a risk to themselves and to society. Moreover, the number of students should be assessed in relation to the jobs available. The government employs only 2.9% of the working age population, private enterprises and associations 6.3% and NGOs 0.1%. Households employ the remaining labor (90.7%), mainly in the agricultural sector, a sector in which higher education graduates tend to refrain from engaging in.

for those with primary education and 1% for persons with no education (INSBU, 2022).

[14]Gross enrollment in tertiary education was estimated at 6.52% in 2022, in comparison to 103.9% for primary education (World Bank, 2024). Gross enrollment rate is the number of children enrolled in a certain education level as a percentage of the number of children who should be studying officially in that level. This indicator can be higher than 100% due to class repetition and early or late enrollment.

3 Study design

Our experimental approach is a variant of the Incentivized Resume Rating (IRR) introduced by Kessler et al. (2019), which involves incentivizing employers to evaluate resumes in the absence of a job offer, thereby avoiding the deception issue associated with traditional audit studies. However, instead of researchers engaging directly with employers as in Kessler et al. (2019), a HR company we partnered with, Infinity Group (IG)[15], sent printed resumes to employers with whom they had a professional relationship[16]. Prior to evaluating the resumes, IG informed the employers that their evaluations would be used to send them workers in the future that correspond to preferences they have indicated[17]. Therefore, in our case, the incentive for employers to indicate their true preferences is the promise of better matches in the future.

A total of 800 resumes were sent to 40 employers for evaluation. Out of the 40 employers that we targeted, 37 provided us with their evaluations and responded to follow-up questions. Those who did not respond were not available in the period that our data collection partner, IG, contacted them. Each employer was given 20 randomly selected resumes to evaluate. We stratified the sampling such that each employer receives 10 resumes with low-skill experience, 10 resumes without low-skill experience, 10 resumes of males and 10 resumes of females. The set of 20 resumes evaluated by each employer was randomly drawn without replacement such that it does not contain duplicates. Consequently, for each individual evaluator, all resume characteristics varied across the 20 resumes, ensuring that he or she could not identify our treatments of interest.

We targeted employers who are among the largest in the country. This list of employers includes Brarudi, an affiliate of Heineken International, multinational banks, NGOs, manufacturing firms and services firms [18]. Nonetheless, the small sample of employers does

[15] IG's services include human resources hiring and management, marketing, communication and project management. Since the company was created in 2018, it has provided its services to the corporate sector (Bank, Industry, Large construction companies), International NGOs and other organizations.

[16] Meaning employers who had either hired a worker through IG or employed a worker under an IG contract.

[17] We show the template of the letter that was sent to employers by IG in appendices A1.2 and A1.3, as well as the verbatim translation in appendix A1.4.

[18] The full list of employers who participated in the experiment is the following: Action Aid,

not allow a within group analysis. For instance, it would have been interesting to analyze the results by sector of activity. However, the sample may be viewed as representative of the largest employers in the country given that the study covered almost all the employers in the database of the implementing partner (Approximately 90% of employers that work with IG) and that the distribution of firms is skewed to the left with very few employers in the formal sector (See details in the context section).

3.1 Creating a pool of resumes

In March 2022, we surveyed economics and management graduates of 2021 from the University of Burundi with the main goal of collecting data on the kind of low-skill jobs they had been doing in the one year after finishing their undergraduates studies. Out of 139 students surveyed in a cohort of 203 students, 18% had done a high-skill job and 34% had done the following low-skill jobs after graduation: Phone credit sales agent (13), Data Entry Agent and Enumerator (7), Cashier (3), Waiter (3), Petty trader (3), Welder (2), Call center agent (1), Clothing salesperson (1), Milk seller (1), TukTuk driver (1), Security guard (1), Chicken trader (1), Driver (1), Photographer (1), and other low-skill jobs (8). The rest of the students (48%), had no experience whatsoever.

In May 2022, we hired a training firm[19] to train students that were finishing their bachelor studies in June 2022 on how to make a resume. The training had a general objective of developing the participants' skills on how to navigate the hiring process in a training session called "How to attract the recruiter's attention?". More specifically, the training aimed to teach participants the basic rules of making a good resume and touched on how to write a cover letter and how to succeed in a job interview. The methodological approach followed in the training was a participatory one with the use of an inductive method, starting with the trainer's presentation, exercises and then discussions. The training took place in the

Akeza.Net, Banque Burundaise de Commerce et d'investissement, Banque de Crédit de Bujumbura, Banque Commerciale du Burundi, Best imprimerie, Bi-Switch, Bicor, Brarudi, Clinique de l'œil, DHL, Ecobank, DIFO, Ercon, Finbank, FSCJ Microfinance, Groupement ADP-MD2P, Hope Design, International Rice Research Institute, Jimbere Magazine, Kenya Commercial Bank, Kaz'O'Zah, Liquides, Modern Dairy Burundi, Memisa, Metalusa, Mutualité Santé Plus, Play International, SOFEPAC, Savonor, Socabu, Socar AG, Socar Vie, Sogerbu, TwoFiveSeven Arts, Université du Lac Tanganyika and Zebra Electronics.

[19] Called *Cabinet MARC*.

computer room of the Faculty of Economics and Management of the University of Burundi over a period of 10 days, with 6 hours per day. In the end, 249 students benefited from this training and 248 of them provided their resumes[20].

We subsequently randomly selected 200 resumes among the 248 that were collected and used, with consent, in the experimental approach. This strategy provided us with a starting pool of resumes that reflects idiosyncrasies that are realistic and that employers typically review. We then created three other copies of these initial resumes that are similar except for low-skill experience and gender. We thus obtained 200 resumes of males with low-skill experience, 200 resumes of males without low-skill experience, 200 resumes of females with low-skill experience and 200 resumes of females without low-skill experience[21]. Additionally, the duration of low-skill experience was randomized by introducing either a short duration (less than three months) or a long duration (between nine and twelve months) of low-skill experience.

Contrary to what is often done in audit studies, our experimental design started with multiple real resumes and manipulated only three characteristics (low-skill experience, duration of the low-skill experience and gender), rather than starting with a limited set of resume samples and randomizing numerous characteristics. This strategy mitigates the risk of inadvertently incorporating incompatible elements or uncommon combinations into the resume. For example, we excluded the resume of a woman with welding experience to avert potential skepticism as this would be uncommon. Moreover, names, contact information and other identifying information were hidden prior to sending the resumes for evaluation (See sample resume in appendices A1.7 and A1.8).

3.2 The "low-skill treatment"

To test the preferences of employers with respect to low-skill experience against the counterfactual of doing nothing, the resumes were modified such that they appear to

[20] The resumes used in our experiment were edited by the trainer but not the experimenters. This approach reflects the reality, as young graduates often have their resumes reviewed by experienced adults and more importantly, the HR firms normally reviews resumes before sending them to employers.

[21] We illustrate the randomization process in appendix A1.1.

employers as corresponding to job candidates who have been on the market for a year. Among the 800 resumes in our sample, 400 were "treated" with a low-skill experience, *i.e* we added a work experience section on the resume, randomly chosen from the list of different types of experiences, with more weight given to more common experiences. The other 400 resumes served as a control group. The low-skill experiences themselves were grouped in two categories. The first group consisted of experiences which lasted between one to three months, which we call short duration low-skill experiences. The second group consisted of experiences which lasted between 9 to 12 months, which we call long duration low-skill experiences. The starting dates of the jobs corresponded to actual starting dates obtained from our survey of past experiences of graduates. We show in appendices A1.7 and A1.8 a sample of resumes sent out for evaluation. The part that was added to half of the resumes is section 12 under the heading "Expérience".

3.3 Resume evaluation and employers' interviews

Since employers were aware that there would be no immediate recruitment following their evaluation, we were concerned about ensuring that their choices are as close as possible to their true preferences. We made sure in the letter that was sent to employers as well as in oral contacts that IG managers had with them that resume evaluators are aware that the value of the proposed incentive (future job candidates propositions from IG that correspond to indicated preferences) is positively correlated with the accuracy with which they report their preferences. No other incentive was provided and prior to evaluating the resumes, employers were not informed that we are interested in estimating the impact of low-skill experiences.

Employers were asked to rate resumes on a scale of 1 to 10, assuming that a job seeker with such a profile would accept the offer. The precise wording of the evaluation form (See appendix A1.5 for original form and appendix A1.6 for the English translation) was the following : "On a scale of 1 to 10, how interested are you in hiring this candidate? Evaluate only the quality of the candidate. Assume that the candidate would accept an offer if he/she received one." Considering that the experiment invited employers to suggest up to three jobs that an individual with such a resume could be hired for, it is reasonable to assume that they would suggest jobs they think the job seeker would accept[22]. After evaluating the resumes, each employer was invited to respond to a questionnaire designed to obtain further information on employers' perception of low-skill experience. The employers were asked to choose between employing an individual without post-graduation experience or an individual who has been doing different types of low-skill jobs, chosen among the 15 from our earlier survey. On the positive side, we asked whether employers think that people with low-skill experience have grit and discipline. On the negative side, we asked whether they think such individuals are of lower ability compared to their peers or if they think they have financial difficulties.

The order of the questions was randomized to take into account potential preview or priming effects (Kahneman et al., 1992). The first kind of randomization concerned the following question which was asked for 15 different types of low-skill jobs: "Would you hire a job candidate: (a) without experience in any type of employment or (b) with 12 months of experience in [. . .] after graduation". For half of employers, choice (a) appeared first and for the other half choice (b) appeared first.

The second type of randomization was related to the idea that employers may value low-skill experience more or less depending on whether they are taking into account that such experiences may affect soft skills development. Hence, half of the employers were made to reflect on the importance of soft skills in their organization by asking them to respond to two questions: (1) How important are soft skills (such as communication skills, interpersonal skills and being on time) in your organization? (2) Which soft skills do you look for when making a hiring decision? After responding to these questions, they were asked to indicate their preference relative to low-skill experience. The other half of employers were first asked to indicate their preference relative to low-skill experience and then were asked to respond to the two questions that relate to the importance of soft skills.

The third kind of randomization concerned attributes employers associate with low-skill

[22] Employers also had the option to suggest a starting salary, but few chose to do so. Those who did not provide this information indicated that salary decisions were beyond their authority.

experience. Employers had to score between 1 and 10 the following attributes: perseverance, hardworking, discipline, financial difficulties, incompetent and less qualified compared to classmates. The order in which the attributes appeared on the screen was different for each employer.

We provide the English translation of the questionnaire (originally in French) in Appendix A1.10. The set of choices was randomized with Stata and displayed on a tablet using SurveyCTO.

3.4 Data

The data on resume evaluations that we use in this study was collected between July and August 2022 in Burundi, on a sample of 37 employers and each employer evaluated 20 resumes[23]. Each resume was given a score which ranges from 1 to 10, corresponding to hiring interest for a specific job. The employer could rate a resume with respect to a maximum of 3 jobs an individual with the given profile could occupy in the organization. The list of proposed jobs are shown in Appendix A1.7.

3.5 Methodology for regression analysis

The regression analysis focuses initially on how low-skill experience affects hiring interest of employers using the simplest specification. The hiring interest is measured with a score ranging from 1 to 10, that employers gave to resumes when asked to evaluate whether they would be interested in hiring the candidate, supposing that the job offer would be accepted. Hence, our baseline specification is the following ordinary least square model:

$$resumescore_{i,m,j} = \alpha_0 + \alpha_1 LSExperience_i + \alpha_2 Gender_i + \alpha_3 Pages_i + \varepsilon_{i,m,j} \tag{1.1}$$

with $resumescore_i, m, j$ the score given to resume i by a hiring manager m for a specific

[23]The final dataset we use has 712 observations instead of 740 observations for two reasons. First, 10 resumes were mistakenly not scored. Second, for 18 other resumes, individuals did not indicate either their year of birth, their marital status or where they went for high school. We show that our results are robust to including the 18 observations without controls, and by imputing averages for missing observations.

job j, $LSExperience_i$ a variable equal to 1 if the resume mentions post-graduate low-skill experience and 0 if the resume does not indicate any post-graduate professional experience, $Gender_i$ a variable equal to 1 for a resume of a female individual and 0 for a resume of a male individual. Since the length of the resume increases when we add a low-skill experience section, we systematically control for this confounding effect by adding the variable $Pages_i$, which is the number of pages of resume i. $\varepsilon_{i,m,j}$ is an idiosyncratic error.

In the full specification (Equation (2)) we add control variables (vector X) and employer/evaluator fixed effects (ϕ_m) to the baseline specification.

$$resumescore_{i,m,j} = \beta_0 + \alpha_1 LSExperience_i + \alpha_2 Gender_i + \beta_3 Pages_i + X\theta + \phi_m + e_{i,m,j} \tag{1.2}$$

X includes the year of birth of the job candidate and whether the individual is married or not. We also control for whether the job candidate went to a secondary school in the economic capital Bujumbura[24]. X also includes the number of extra curricular training programs indicated on the resume, the gender of the evaluator, the size of the evaluating organization measured in terms of the number of employees and the number of years since the organization started its activities in Burundi. We include employer fixed effects to allow employers to have different mean ratings. Given the design of the experiment, adding fixed effects and control variables should not affect our estimates of interest α_1 and α_2 in Equation (1) as these additional controls should be orthogonal to the treatments we introduced on the resumes, *i.e.* low-skill experience and gender. Furthermore, we analyze the heterogeneity of the low-skill experience and gender treatments along resume and evaluator characteristics.

[24]In field preparation meetings we had with HR experts from IG, they indicated that employers frequently express demand for individuals who are fluent in French and English, and that those skills are not well taught outside the capital.

4 Results

4.1 Descriptive statistics

Table 2.3 shows summary statistics for the dependent variable, treatment variables and independent variables grouped into resume characteristics and evaluator characteristics.

Although hiring managers had the option of providing up to three different evaluations for three different types of jobs, we provide in Table 2.3 statistics for the evaluations of the first job only. This is because the second and third evaluations contain substantial missing observations. We show that treatment effects become more noisy as we include the second and third score, which is consistent with evaluators paying relatively more attention to the first job proposed.

Table 2.3 shows that the average resume score is 4.6 and the scores range from 1 to 10. Approximately half of resumes are resumes of females. We do not obtain a perfect 50-50 split because we did not obtain evaluations for all 800 resumes. The duration of low-skill experience variable was generated such that 25% of the resumes showed a duration of three months or less and 25% of resumes showed a period between 9 and 12 months. The resumes had between one and three pages. They showed that individuals were born between 1986 and 1998, considering that the normal age if the individual had not repeated a school year and had started primary school at age 6, was 1998. Approximately 4% of resumes are of married individuals and 15% are of individuals who went to a high school in Bujumbura. Most individuals mentioned two extracurricular training programs or less on their resumes and one individual mentioned 10 training programs. Approximately half of the 712 resumes were evaluated by women.

Even though we do not have evaluation data for all 800 resumes, we still have balance on almost all our covariates. These are balanced for the low-skill experience treatment except for the *number of pages* variable which is on average higher for the treatment group than the control group (Table 1.3), highlighting the need to control for the length of the resume

Table 1.2: Summary Statistics

Variable	Obs	Mean/Median	Std. Dev.	Min	Max
Dependent variable					
Resume score	712	4.628	2.241	1	10
Treatment variables					
Female (=1)	712	0.499	0.5	0	1
Low-skill experience	712	0.5	0.5	0	1
3 months or less of low-skill experience	712	0.243	0.429	0	1
9 months or more of low-skill experience	712	0.257	0.437	0	1
Resume characteristics					
Number of pages	712	1.949	0.26	1	3
Year of birth	712	1994	1.914	1986	1998
Married (=1)	712	0.044	0.204	0	1
High school in Bujumbura	712	0.15	0.358	0	1
Training	712	1.086	1.165	0	10
Evaluator characteristics					
Gender of evaluator	712	0.486	0.5	0	1
Number of employees	712	149.513	340.436	6	2000
Years in Burundi	712	23.709	19.01	1	70

Notes: For *Year of birth*, we show the median, and show the mean for all the other variables. Training is the number of extra curricular training programs mentioned on resumes such as IT or leadership training, that individuals took before entering the job market. *Years in Burundi* is the number of years the organization has been operating in Burundi.

when estimating the impact of the low-skill experience treatment[25]. Table A1.1 shows that when we split the low-skill treatment group into a high-duration group (9-12 months) and low-duration (0-3 months) group, we obtain less balance of covariates. In fact, this lack of balance concerns all covariates except *training*, *year of birth* and *married*. As a result, heterogeneity analysis of the *low-skill experience* treatment by its duration includes the list of covariates as controls but may be biased by unobservable confounders. To verify that we are comparing comparable groups for the heterogeneity analysis with respect to gender, we check for balance of covariates along the four groups that are generated by the interaction of the *low-skill experience* and *gender* treatments. This randomization test does not show any statistically significant difference among covariates except for the number of pages (See Table A1.3).

[25]We show balance for the gender treatment in Table A1.2.

Table 1.3: Balance tests for the *Low-skill experience* treatment

		(1)		(2)	t-test
		0		1	p-value
Variable	N	Mean/SE	N	Mean/SE	(1)-(2)
Number of pages	356	1.916	356	1.983	0.001
		[0.016]		[0.010]	
Year of birth	356	1993.826	356	1993.854	0.845
		[0.103]		[0.099]	
Married (=1)	356	0.042	356	0.045	0.855
		[0.011]		[0.011]	
High school in Bujumbura	356	0.160	356	0.140	0.464
		[0.019]		[0.018]	
Training	356	1.098	356	1.073	0.773
		[0.065]		[0.059]	
Gender of evaluator	356	0.486	356	0.486	1.000
		[0.027]		[0.027]	
Number of employees	356	150.315	356	148.711	0.950
		[18.058]		[18.053]	
Years in Burundi	356	23.809	356	23.610	0.889
		[1.013]		[1.003]	

Standard errors in brackets

4.2 Regression results

We show in column (1) of Table 1.4 parameter estimates of our baseline model. We find that having a low-skill experience increases the hiring interest of employers and gender does not have a significant effect. Given our study design, these results are robust to the inclusion in the model of controls for resume characteristics (Column (3)), evaluator characteristics

(Column (4)) and evaluator fixed effects (Column (5)).[26]

Table 1.4: Impact of low-skill experience

VARIABLES	(1) Resume Score	(2) Resume Score	(3) Resume Score	(4) Resume Score	(5) Resume Score
Low-skill experience	0.458***	0.462***	0.469***	0.479***	0.473***
	(0.141)	(0.147)	(0.150)	(0.151)	(0.153)
Female (=1)	-0.009	-0.009	-0.039	-0.038	-0.014
	(0.135)	(0.135)	(0.129)	(0.128)	(0.128)
Number of pages		-0.061	-0.132	-0.196	0.108
		(0.246)	(0.239)	(0.231)	(0.175)
Year of birth			0.088**	0.109***	0.032
			(0.037)	(0.035)	(0.028)
Married (=1)			-0.086	-0.044	-0.250
			(0.464)	(0.446)	(0.204)
High school in Bujumbura			0.023	0.077	-0.114
			(0.291)	(0.257)	(0.159)
Training			0.153*	0.126	0.145**
			(0.088)	(0.077)	(0.067)
Gender of evaluator				0.440	
				(0.574)	
Number of employees				-0.001**	
				(0.000)	
Years in Burundi				0.038**	
				(0.018)	
Mean dependent (Male, Without low-skill experience)	4.342	4.342	4.342	4.342	4.342
Observations	712	712	712	712	712
Adjusted R-squared	0.008	0.006	0.013	0.112	0.648
Resume characteristics	NO	NO	YES	YES	YES
Evaluator characteristics	NO	NO	NO	YES	NO
Evaluator FE	NO	NO	NO	NO	YES

Standard errors are clustered at the employer level
*** p<0.01, ** p<0.05, * p<0.1

Referring to the most robust and our preferred specification in column (5), results show that mentioning a low skill experience on one's resumes increases the Likert score approximately by 0.47[27] and the impact is statistically significant at 1%. This result implies that, all else equal, a person with a low-skill experience is preferred to a person with no experience. If

[26] Although some of the other covariates are significant, they cannot be given a causal interpretation. For instance, younger students tend to be born in the capital Bujumbura which induces a positive correlation between *Year of birth* and *High school in Bujumbura*. Had we not controlled for where the person went for high school, the coefficient on *Year of birth* would have been biased. Similarly, the data suggests that older, more established organizations in the market tend to employ women more in management positions, inducing a positive correlation between *Gender of evaluator* and *Years in Burundi*. Generally, we cannot rule out the presence of unobserved confounders while interpreting the effect of control variables.

[27] Which corresponds to approximately a 10% increase in comparison to the mean of resumes of males without low-skill experience.

employers typically select the most competitive candidates, then the coefficient's magnitude is not crucial in this context. However, if employers lean towards delaying hiring until they find a sufficiently qualified candidate, then the extent of the change in the Likert score caused by low-skilled experience becomes important. The coefficient on *Low-skill experience* is relatively large compared to coefficients on other covariates. In fact, the magnitude of the effect of *Low-skill experience* is the largest among all independent variables. The coefficient on *Low-skill experience* is also in the range of coefficients found by Kessler et al. (2019) who examined the impact of low-skill jobs during college studies [28].

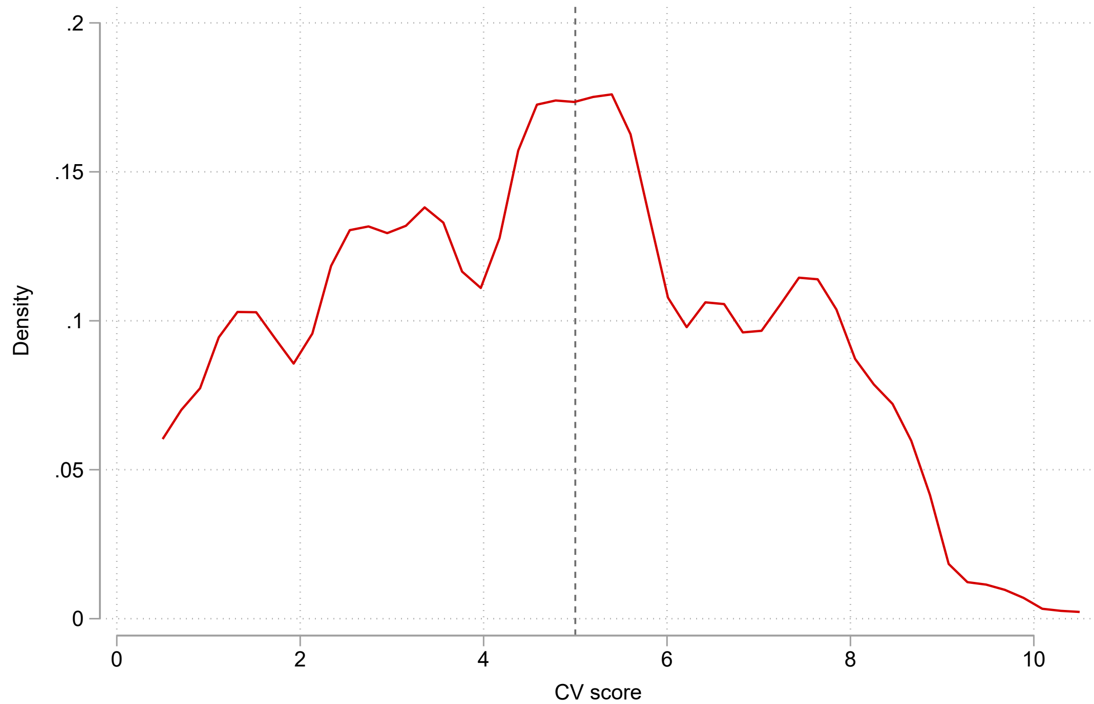
Correspondence between resume scores and callback rates

Unlike the outcome indicator we use in this study, *i.e.* a resume score, audit studies typically employ the callback rate for interviews as an indicator of an employer's interest in a candidate. However, in the context of Burundi, it is not possible to implement such a study notably because employers typically require job applicants to submit documents such as a criminal record, diplomas and proof of residence in a particular city at the time of application. To approximate the results that might have been obtained had an audit study with the callback rate as the outcome variable been implemented, various callback thresholds are hypothesized. These thresholds may change contingent upon labor market conditions, employer behavior, and other factors.

We change the coding of the dependent variable by making it binary with a cutoff at the Likert point of 5. In fact, it could be that evaluators were using "system 1" (Morewedge and Kahneman, 2010) when scoring the resumes, meaning that, instead of making a fine distinction between the resumes, they tended to score the resumes above or below the cutoff of 5 depending on whether they are interested in the profile or not. In fact, Figure 1.1 shows that resume scores are concentrated around the score of 5.

[28] Similarly to this study, Kessler et al. (2019) used a 10 points Likert score as a dependent variable and found, in the context of the US, the following impacts of resume signals: GPA (2.13), Top Internship (0.90), Second Internship (0.47), Work for Money Jobs during studies (0.12), Technical Skills (0.047), Female and White (-0.15), Male and Non-White (-0.17), Female and Non-white (-0.009). The effect of low-skill experience is similar to the effect of a second internship and is superior to the effect of "work for money" jobs during studies.

Figure 1.1: Distribution of resume scores



Results from logistic regressions in Table 1.5, Column (4), suggest that, if the callback threshold corresponds to the Likert score of 5, individuals who show a low-skill experience on their resume would have a probability of being called back which is approximately 13 percentage points higher that individuals who do not show any experience. If the callback threshold were set at 7, where we observe another peak in the score distribution, we estimate that including low-skill experience on one's resume would augment the callback probability by almost 5 percentage points (See Table A1.4).

These callback findings bear similarities to results from prior literature. For instance, Valfort (2020) observed that the callback rate for applicants with Muslim inherited affiliations was 6.7 percentage points lower than that of their Christian counterparts in France. In the context of the United States, Kline et al. (2022) found that distinctively Black names decreased employer contact probability by 2.1 percentage points relative to distinctively white names. Arceo-Gomez and Campos-Vazquez (2014) found that married women had a callback rate 2.8 percentage points lower than that of single women within the Mexican context. These

Table 1.5: Impact of low-skill experience: binary dependent variable

	(1)	(2)	(3)	(4)
VARIABLES	OLS	OLS	Logistic	Logistic
Low-skill experience	0.108***	0.110***	0.109***	0.128***
	(0.031)	(0.032)	(0.031)	(0.038)
Female (=1)	-0.015	-0.016	-0.015	-0.022
	(0.030)	(0.029)	(0.030)	(0.033)
Mean dependent	0.28	0.28	0.28	0.28
(Male, Without low-skill experience)				
Observations	712	712	712	712
Adjusted R-squared	0.009	0.526		
Resume characteristics	NO	YES	NO	YES
Evaluator characteristics	NO	NO	NO	YES
Evaluator FE	NO	YES	NO	NO

The dependent variable is equal to 1 for scores above 5 and equal to 0 otherwise.
Standard errors are clustered at the employer level
*** p<0.01, ** p<0.05, * p<0.1
We report marginal effects at the mean for the logistic regressions.

results suggest that the callback threshold in the context of the present study would likely correspond to the score of 7 rather than 5.

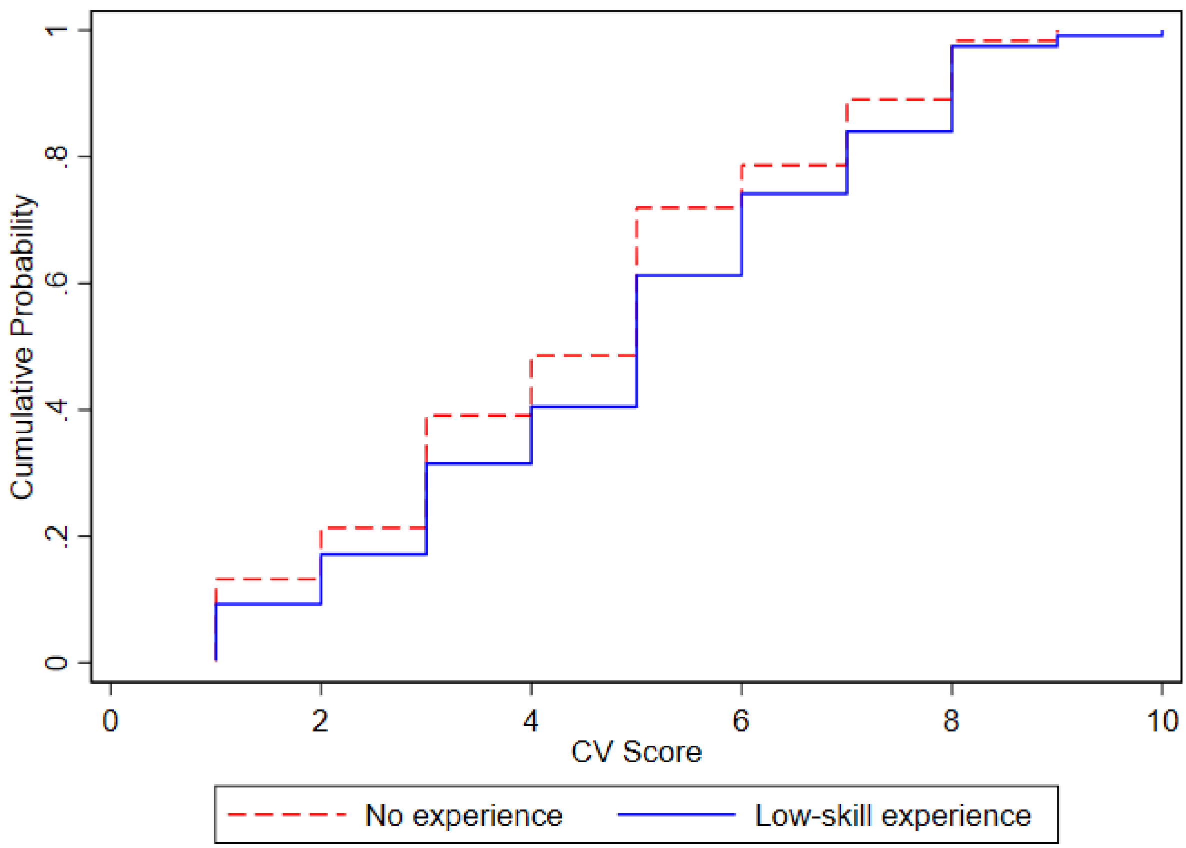
Low-skill experience and quality of job seeker

The empirical evidence further suggests that signaling low-skill experience not only increases hiring interest on average, but also, irrespective of the candidate's quality as measured by the resume score, it is invariably more advantageous to signal low-skill experience than to present a resume devoid of any experience at all. This result is depicted in Figure 1.2, which illustrates the stochastic dominance of a job search strategy that incorporates the signaling of low-skill experience. The cumulative distribution function (CDF) of scores assigned to resumes exhibiting low-skill experience (in blue) is consistently beneath the CDF of scores associated with resumes that do not feature low-skill experience across the full spectrum of the Likert scale.

Is there a case for gender discrimination?

The non-significance of the gender effect as shows Table 1.4 can be interpreted as a lack of gender-based discrimination at an early stage of the hiring process and for early career job candidates. However, this may not be the case for other stages of the hiring process,

Figure 1.2: Cumulative distribution functions for resumes with and without low-experience



for example during interviews, or for relatively senior positions. Nonetheless, this result is surprising given that the average age in our sample is 28, in a country context where the median age of women at first union is 20.3 and median age of women at first birth is 21.5 (DHS, 2018)[29]. One might expect that employers would discriminate against women who are likely to be pregnant and have childcare responsibilities, as it has been observed in other contexts (Becker et al., 2019). However, the result is consistent with the literature that found that discrimination against women increases as the level of responsibility of the occupation increases (Valfort, 2020). In fact, employers scored resumes with respect to entry-level positions such as Accountant, Administrative Assistant, Teller, Financial Officer, HR Assistant, Logistics Officer, Sales Agent, although some relatively small organizations proposed relatively senior positions such as Administrative and Finance Director, Branch Manager and Head of Accounting Department (refer to Table A1.7 for a comprehensive list). Furthermore, results indicate that the positions matched to an applicant do not differ based on gender or presence of low-skill experience on the resume.

Heterogeneity with respect to resume and evaluator characteristics

Our heterogeneity analysis shows that the effect of low-skill experience for males (0.59) is higher than the general effect found previously (0.47) and is statistically significant at 1% (See Column (1) of Table A1.5). Conversely, the effect of low-skill experience for females (0.36) is lower than the average of both genders and statistically significant at 1%. However, the difference of the effects for males and females (0.231) is not statistically significant. Results further suggest that the longer the duration of the low-skill experience the more hiring interest increases but the difference between the corresponding two coefficients is not statistically significant (p=0.105). We do not find significant differences of the treatment effects with respect to the year of birth of an individual, whether they are married or not, whether they went to a high school in Bujumbura or not, the number of training programs attended, the gender of the evaluator, the number of employees of the evaluating organization nor the number of years the organization has been present in the country. It could be that the latter dimensions of heterogeneity are not important in the assessment of the value of

[29] Estimates from the latest demographic and health survey conducted between 2016 and 2017.

low-skill experience. However, we cannot rule out that this absence of significance is due to a lack of statistical power.

It would have been interesting to estimate the heterogeneity of the low-skill treatment with respect to the types of low-skill experiences individuals typically do but since the design of the experiment does not allow that, we have asked directly the question to hiring managers. We discuss the corresponding results in sub-section 4.3 below.[30]

Robustness checks

In Table 1.6, we estimate the impact of the treatment variables while combining scores given by the employers considering the first, the second and the third type of job for which they indicated that they would be interested in hiring the profile being evaluated[31]. In Column (1), we reproduce the main result obtained in Table 1.4 where the dependent variable is the score attributed for the first type of job. In Column (2), the dependent variable is the score assigned for the second type of job and in Column (3), the score given for the third type of job. Column (4) shows results for the three types of jobs after pooling all the scores in the dataset. The effect of low-skill experience is largest and most significant in Column (1) and decreases in magnitude and in significance from column (2) to (4). These results are consistent with evaluators being less attentive in their evaluations for the second and third job compared to the first job, thus inducing attenuation bias in the estimates. Relatedly, it could be argued that attention may wane from the first to the 20th resume evaluated. However, one might contend that paying reduced attention to subsequent resumes or jobs might more accurately mirror real-world practices, if employers' hasty decisions reflect their biases more than their meticulous evaluations. Be that as it may, our primary findings are based on the results for the first job, as this provides the most complete data across all employers.

We also conducted a robustness check where we added the 18 observations we deleted because

[30] We do not investigate how preferences of employers vary with respect to different types of low-skill job experiences, different fields of study of jobs seekers or different high-skill jobs being applied for because such an analysis requires a sample that is larger than the one used here. The limiting factor in expanding the sample size is finding enough employers to evaluate many resumes.

[31] This additional complexity in the design was not mentioned earlier to simplify exposition.

of missing observations for control variables. We show in Table A1.6 that our results are robust to the inclusion of these and replacing missing observations with means.

Table 1.6: Impact of low-skill experience: three types of jobs

VARIABLES	(1) Resume Score	(2) Resume Score	(3) Resume Score	(4) Resume Score
Low-skill experience	0.473***	0.287***	0.275*	0.388***
	(0.153)	(0.100)	(0.145)	(0.103)
Female (=1)	-0.014	-0.033	-0.062	-0.025
	(0.128)	(0.172)	(0.224)	(0.128)
Mean dependent	4.342	4.397	4.102	4.311
(Male, Without low-skill experience)				
Observations	712	410	277	1,399
Adjusted R-squared	0.648	0.752	0.741	0.684
Resume characteristics	YES	YES	YES	YES
Evaluator characteristics	NO	NO	NO	NO
Evaluator FE	YES	YES	YES	YES

Standard errors are clustered at the employer level
*** p<0.01, ** p<0.05, * p<0.1
Note : In Column (1), the dependent variable is the score assigned to the first type of job. The dependent variable in Column (2) is the score attributed to the second type of job, while in Column (3), it's the score for the third type of job. Column (4) presents the results for all three types of jobs combined.

4.3 Eliciting employers' preferences directly

After evaluating resumes, the hiring managers were invited to express directly their preferences with respect to low-skill experience. Employers were asked to choose between hiring: (a) an individual without any type of post-graduate professional experience or (b) an individual with 12 months of low-skill experience after graduation. They were asked to respond to the question in the context of a college graduate who has been 12 months on the market. The types of low-skill jobs were randomly chosen from the set of experiences used in the IRR. The managers had the option of expressing their hiring interest with respect to up to five types of existing jobs in their organizations. Among 645 choices expressed, 75% were in favor of low-skill experience, which is consistent with the IRR results. Furthermore, this qualitative data does not suggest that employers care about which type of low-skill experience a person has, as long as the alternative is, in a sense, staying at home.

Next, we asked employers to evaluate on a Likert scale how they perceive in general post-graduate experience in the low-skill jobs. We show their responses in Table 1.7. The results suggest that employers perceive job seekers with low-skill experience as perseverant, hard working and disciplined, rather than people with financial difficulties[32], generally incompetent or relatively incompetent compared to classmates. The list includes purposely qualifiers that have a close meaning, such as perseverance and hard working, to check the consistency of responses.

Table 1.7: Employers' perception of low-skill experience

Experience in low-skill jobs suggests that the job seeker is:	Mean of a 10 points Likert Scale
Persevering	8.05
Is a hard worker	7.22
Has discipline	5.59
Has financial difficulties	3.51
Incompetent	2.27
Is less qualified compared to classmates	1.86

Note: The order of these attributes in the survey was randomized

In pre-survey interviews with out of sample employers, they insisted on the importance of developing soft skills of young job seekers such as communication skills, showing up on time at work (discipline) and others. We therefore investigated whether low-skill jobs might be a way of developing such soft skills. We first asked employers about the importance of soft skills in their organization. We found that they value soft skills with an average of 7.5 of the Likert score. We then asked them to indicate which low-skill experiences teach soft skills that are directly relevant to their organization. Their answers are shown in Figure A1.9. The interpretation of the results is not straightforward, however, the figure suggests that employers might be valuing jobs that involve speaking to clients such as sales jobs more than jobs that do not require this skill such as enumerator and data entry jobs.

Lastly, it is reasonable to assume that employers would value low-skill experiences related to the high-skill job they are offering. However, it is less certain whether they would value

[32] It is possible that low-skill experience could still signal some degree of "gettability". However, the fact that employers disagreed that low-skill experience mainly signals financial difficulties, goes against this idea.

unrelated low-skill experiences. Qualitative evidence suggests that they might. For instance, a manager at a microfinance institution indicates that experience as a security agent is more valuable than no experience at all when hiring for a credit analyst position. However, whether these two experiences are related is debatable. In general, distinguishing between low-skill jobs that are related or unrelated to high-skill jobs is not as straightforward as it may seem. Nevertheless, the fact that employers widely agree that low-skill experience can develop personality traits such as perseverance and discipline, as well as soft skills, regardless of whether the experience is related to the high-skill job, supports the idea that low-skill experiences are valuable regardless of their direct relevance to high-skill employment.

5 Conclusion

Using an experimental approach which avoids deception, this paper investigated preferences of employers with regard to low-skill experience of recent college graduates. The focus was on examining the impact of various types of low-skill experiences, such as working as a phone credit sales agent, a waiter, a security guard and other positions that do not necessitate a college degree, on the hiring interest of employers in a high-skill job.

We find that individuals who mention a low-skill experience on their resume are more likely to be hired than individuals who do not mention any post-graduate experience. This main finding holds irrespective of the quality of the resume. Post-experiment interviews with employers suggest that they value low-skill experiences because they signal grit, discipline and a hard-working character rather than financial difficulties or relative incompetence.

Overall, this research could help recent college graduates and career services offices to understand the importance of low-skill jobs as stepping stones to high-skill jobs. Additionally, it may challenge societal perceptions about low-skill work and emphasize its value. Considering that expectations of how employers will perceive different experiences can affect their uptake and signaling, graduates should be informed that signaling such experiences to potential employers may improve their chances of being hired.

In fact, it is crucial for young graduates to perceive a particular value of low-skill jobs.

Underemployment was a significant factor contributing to the popular uprisings that occurred in many countries of the Arab world starting in 2010, as reported by the International Labour Organization (ILO, 2011). The sense of frustration among the youth was exacerbated by the fact that their parents had invested significant amounts of money in their education, with the hope of providing them with a better future, only to see them end up in low-skill jobs or no job at all. It is therefore important that young people who are forced to take on low-skill jobs do not feel alienated from the career they aspire to, especially in contexts where social security coverage, particularly unemployment insurance, is limited or does not exist.

An important direction for future research would be to examine how employers' preferences vary across different labor markets, particularly where high-skill and low-skill jobs are more or less scarce. We also highlight the need to collect detailed data on the time use of university graduates in low-income countries. Current standard school-to-work surveys sample university graduates in proportion to their share of the population, resulting in a small sample size of this group. It would be beneficial to oversample university graduates to enable thorough studies of this subcategory of young people, as they are at the forefront of governance and have a relatively high capacity to cause disruption if dissatisfied with their condition.

6 Appendix

School-to-work transition of young graduates

The school-to-work transition indicators of the International Labor Organization (ILO) provide a detailed breakdown of the transition of young people (individuals aged 15 to 29) into the labor market. There are two families of indicators: the stage of transition from school to work and the form this transition takes. Stage indicators classify young people into segments according to their stage of transition: (1) transitioned, (2) in transition, and (3) not yet in transition. The form indicators focus on the specific outcomes of those who have completed the transition, distinguishing between stable salaried employment, satisfactory self-employment or temporary employment (ILO, 2009).

What do we know about the school-to-work transition of young graduates in Sub-Saharan Africa?

Africa has a relatively high proportion of young people in transition compared to other regions of the world (ILO, 2023a). The latest ILO data on transition, available for four countries only in Sub-Saharan Africa - Kenya, Rwanda, Senegal and Uganda -, reveal that in Kenya and Rwanda, almost half of young people are considered to be in transition. In Uganda, the ratio is closer to one in three, while in Senegal it is around one in four. In all these countries, between 40% and 45% of young people, a particularly high proportion, have not yet begun their transition. In Kenya and Rwanda, barely 10% of young people have made the transition (ILO, 2023a).

What do young university graduates do when they are not doing low-skill jobs?

Standard school-to-work surveys conducted with the support of the International Labor Organization do not provide an answer to this question. This is because the number of university graduates surveyed is too low (usually below 3% for samples of around 1,000 individuals). While the ideal dataset would be a representative sample of recent university graduates, the preparatory data collection, whose main purpose was to gather information on the types of low-skill jobs recent graduates do, tracked 139 students from the Faculty of

Economics and Management at the University of Burundi who had completed their bachelor's degree (fewer than 10% of students pursue a master's education). For this cohort, we find that 34% of university graduates who have been on the market for about one year have been working in low-skill jobs, 18% have done work related to their qualifications, and 48% indicated that they haven't worked at all since graduating.

It is challenging to have a solid discussion on the time use of recent college graduates in the absence of comprehensive survey data, but the quick survey we conducted and observations on the ground suggest that many of the graduates, if not in low-skill jobs, are likely at home, helping on the farm or in other household activities—activities they cannot include on a resume. If young graduates are not in high-skill jobs or education, they could be in low-skill jobs, in training, or volunteering. Thus, one might consider other interesting comparisons beyond the one made in this study, such as comparing time spent on training versus unemployment. However, it should be noted that training and volunteering are costly and may not be accessible to many graduates who are liquidity-constrained. Furthermore, the low-skill versus unemployment comparison is particularly pertinent to the study population, i.e. university graduates, who could be tempted to wait for the job they studied for. Finally, it seems reasonable to assume that, when available, training and high-skill employment should typically be better options for recent college graduates compared to low-skill jobs. Therefore, the less obvious comparison is between low-skill employment and unemployment.

A few determinants of a successful transition

In a review of studies on the school-to-work transition in developing countries, Nilsson (2019) identifies various determinants of school-to-work in the African context. In particular, research conducted in the context of Mali shows that young people with tertiary education spend on average more time (6 years) to find their first job than primary and secondary school graduates (3 years), but need less time to find a satisfactory job (9 years vs.12 years) (Boutin, 2013). The review also points out that the current generation of young Africans faces a different labour market from that of the previous generation when it comes to waiting for jobs in the public sector. Whereas the well-educated of previous generations had relatively easy access to employment in the public sector, the increase in their numbers combined with economic crises and structural reforms has meant that this option is no longer effective.

A World Bank survey conducted in several developing countries, including Kenya and Ghana, revealed that socio-emotional skills facilitate the transition from school to work (Valerio et al., 2014). Workers who report a smoother transition from school to work have different socio-emotional skills than those who took longer to find their first job: they tend to be more conscientious, emotionally stable and persistent. In a way, this study examines the role of job-seeker perseverance in the job search as reflected in their take-up of low-skill jobs.

Table A1.1: Balance tests for the *Duration of low-skill experience* treatment

		(1)		(2)		(3)	t-test	t-test	t-test
		None		3 months or less		9 months or more	p-value	p-value	p-value
Variable	N	Mean/SE	N	Mean/SE	N	Mean/SE	(1)-(2)	(1)-(3)	(2)-(3)
Number of pages	356	1.916	173	1.988	183	1.978	0.003	0.016	0.624
		[0.016]		[0.012]		[0.017]			
Year of birth	356	1993.826	173	1993.769	183	1993.934	0.752	0.533	0.406
		[0.103]		[0.147]		[0.135]			
Married (=1)	356	0.042	173	0.035	183	0.055	0.681	0.514	0.365
		[0.011]		[0.014]		[0.017]			
High school in Bujumbura	356	0.160	173	0.104	183	0.175	0.083	0.663	0.055
		[0.019]		[0.023]		[0.028]			
Training	356	1.098	173	1.156	183	0.995	0.608	0.323	0.171
		[0.065]		[0.091]		[0.075]			
Gender of evaluator	356	0.486	173	0.538	183	0.437	0.266	0.283	0.058
		[0.027]		[0.038]		[0.037]			
Number of employees	356	150.315	173	209.867	183	90.896	0.096	0.023	0.001
		[18.058]		[35.372]		[9.006]			
Years in Burundi	356	23.809	173	27.757	183	19.689	0.030	0.013	0.000
		[1.013]		[1.554]		[1.220]			

Standard errors in brackets

Table A1.2: Balance tests for the *Gender* treatment

		(1)		(2)	t-test
		Male		Female	p-value
Variable	N	Mean/SE	N	Mean/SE	(1)-(2)
Number of pages	357	1.950	355	1.949	0.988
		[0.013]		[0.014]	
Year of birth	357	1993.751	355	1993.930	0.213
		[0.103]		[0.100]	
Married (=1)	357	0.039	355	0.048	0.571
		[0.010]		[0.011]	
High school in Bujumbura	357	0.148	355	0.152	0.892
		[0.019]		[0.019]	
Training	357	1.039	355	1.132	0.286
		[0.059]		[0.064]	
Gender of evaluator	357	0.485	355	0.487	0.942
		[0.026]		[0.027]	
Number of employees	357	150.199	355	148.823	0.957
		[18.007]		[18.104]	
Years in Burundi	357	23.768	355	23.651	0.935
		[1.011]		[1.005]	

Standard errors in brackets

Table A1.3: Balance tests for the interaction of the gender and low-skill experience treatments

		(1)		(2)		(3)		(4)	t-test	t-test	t-test	t-test	t-test	t-test
		Male+Low-skill		Female+Low-skill		Male+No Low-skill		Female+No Low-skill	p-value	p-value	p-value	p-value	p-value	p-value
Variable	N	Mean/SE	N	Mean/SE	N	Mean/SE	N	Mean/SE	(1)-(2)	(1)-(3)	(1)-(4)	(2)-(3)	(2)-(4)	(3)-(4)
Number of pages	179	1.989	177	1.977	178	1.910	178	1.921	0.587	0.003	0.012	0.017	0.047	0.730
		[0.014]		[0.016]		[0.023]		[0.023]						
Year of birth	179	1993.698	177	1994.011	178	1993.803	178	1993.848	0.116	0.611	0.465	0.301	0.415	0.828
		[0.144]		[0.136]		[0.147]		[0.146]						
Married (=1)	179	0.039	177	0.051	178	0.039	178	0.045	0.594	0.991	0.784	0.602	0.795	0.793
		[0.015]		[0.017]		[0.015]		[0.016]						
High school in Bujumbura	179	0.128	177	0.153	178	0.169	178	0.152	0.515	0.289	0.529	0.682	0.982	0.666
		[0.025]		[0.027]		[0.028]		[0.027]						
Training	179	0.994	177	1.153	178	1.084	178	1.112	0.180	0.447	0.316	0.599	0.756	0.828
		[0.074]		[0.092]		[0.092]		[0.091]						
Gender of evaluator	179	0.492	177	0.480	178	0.478	178	0.494	0.830	0.791	0.959	0.960	0.790	0.751
		[0.037]		[0.038]		[0.038]		[0.038]						
Number of employees	179	149.575	177	147.836	178	150.826	178	149.803	0.962	0.972	0.995	0.934	0.957	0.977
		[25.439]		[25.697]		[25.566]		[25.582]						
Years in Burundi	179	23.849	177	23.367	178	23.685	178	23.933	0.811	0.936	0.967	0.874	0.779	0.903
		[1.431]		[1.410]		[1.433]		[1.437]						

Standard errors in brackets

Table A1.4: Impact of low-skill experience: binary dependent variable at 7

	(1)	(2)	(3)	(4)
VARIABLES	OLS	OLS	Logistic	Logistic
Low-skill experience	0.050**	0.050*	0.050**	0.048**
	(0.025)	(0.025)	(0.025)	(0.024)
Female (=1)	-0.005	-0.004	-0.005	-0.006
	(0.029)	(0.030)	(0.029)	(0.027)
Mean dependent	0.112	0.112	0.112	0.112
(Male, Without low-skill experience)				
Observations	712	712	712	712
Adjusted R-squared	0.001	0.434		
Resume characteristics	NO	YES	NO	YES
Evaluator characteristics	NO	NO	NO	YES
Evaluator FE	NO	YES	NO	NO

The dependent variable is equal to 1 for scores above 7 and equal to 0 otherwise.
Standard errors are clustered at the employer level
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A1.5: Heterogeneity of gender and low-skill experience treatments

VARIABLES	(1) Resume Score	(2) Resume Score	(3) Resume Score	(4) Resume Score	(5) Resume Score	(6) Resume Score	(7) Resume Score	(8) Resume Score	(9) Resume Score
Low-skill experience	0.589***		144.422	0.498***	0.464***	0.391*	0.584***	0.449***	0.332
	(0.182)		(117.177)	(0.161)	(0.165)	(0.202)	(0.155)	(0.163)	(0.272)
Female (=1)	0.101	-0.014	-25.231	0.002	-0.009	-0.037	-0.067	-0.031	0.132
	(0.134)	(0.126)	(102.715)	(0.132)	(0.136)	(0.181)	(0.138)	(0.139)	(0.159)
Female*Low-skill	-0.231								
	(0.194)								
3 months or less of low-skill experience		0.326							
		(0.201)							
9 months or more of low-skill experience		0.612***							
		(0.168)							
Low-skill*Yearofbirth			-0.072						
			(0.059)						
Female*Yearofbirth			0.013						
			(0.052)						
Low-skill*Married				-0.565					
				(0.360)					
Female*Married				-0.349					
				(0.384)					
Low-skill*HighSchoolinBujumbura					0.066				
					(0.283)				
Female*HighSchoolinBujumbura					-0.042				
					(0.273)				
Low-skill*Training						0.076			
						(0.120)			
Female*Training						0.018			
						(0.133)			
Low-skill*MaleEvaluator							-0.215		
							(0.290)		
Female*MaleEvaluator							0.056		
							(0.264)		
Low-skill*NumberofEmployees								0.000	
								(0.000)	
Gender*NumberofEmployees								-0.000	
								(0.000)	
Low-skill*YearsinBurundi									0.006
									(0.008)
Female*YearsinBurundi									-0.007
									(0.006)
Mean dependent (Male, Without low-skill experience)	4.342	4.342	4.342	4.342	4.342	4.342	4.342	4.342	4.342
Observations	712	712	712	712	712	712	712	712	712
Adjusted R-squared	0.648	0.649	0.648	0.648	0.647	0.647	0.110	0.110	0.111
Resume characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Evaluator characteristics	NO	NO	NO	NO	NO	NO	YES	YES	YES
Evaluator FE	YES	YES	YES	YES	YES	YES	NO	NO	NO

Standard errors are clustered at the employer level
*** p<0.01, ** p<0.05, * p<0.1

Table A1.6: The impact of low-skill experience: taking into account missing observations

VARIABLES	(1) Resume Score	(2) Resume Score	(3) Resume Score	(4) Resume Score
Low-skill experience	0.035	0.023	0.020	0.023
	(0.128)	(0.125)	(0.126)	(0.125)
Female (=1)	0.451***	0.459***	0.464***	0.436***
	(0.150)	(0.151)	(0.150)	(0.155)
Mean dependent	4.333	4.333	4.333	4.333
(Male, Without low-skill experience)				
Observations	730	730	730	730
Adjusted R-squared	0.006	0.007	0.054	0.643
Resume characteristics	NO	YES	YES	YES
Evaluator characteristics	NO	NO	YES	NO
Evaluator FE	NO	NO	NO	YES

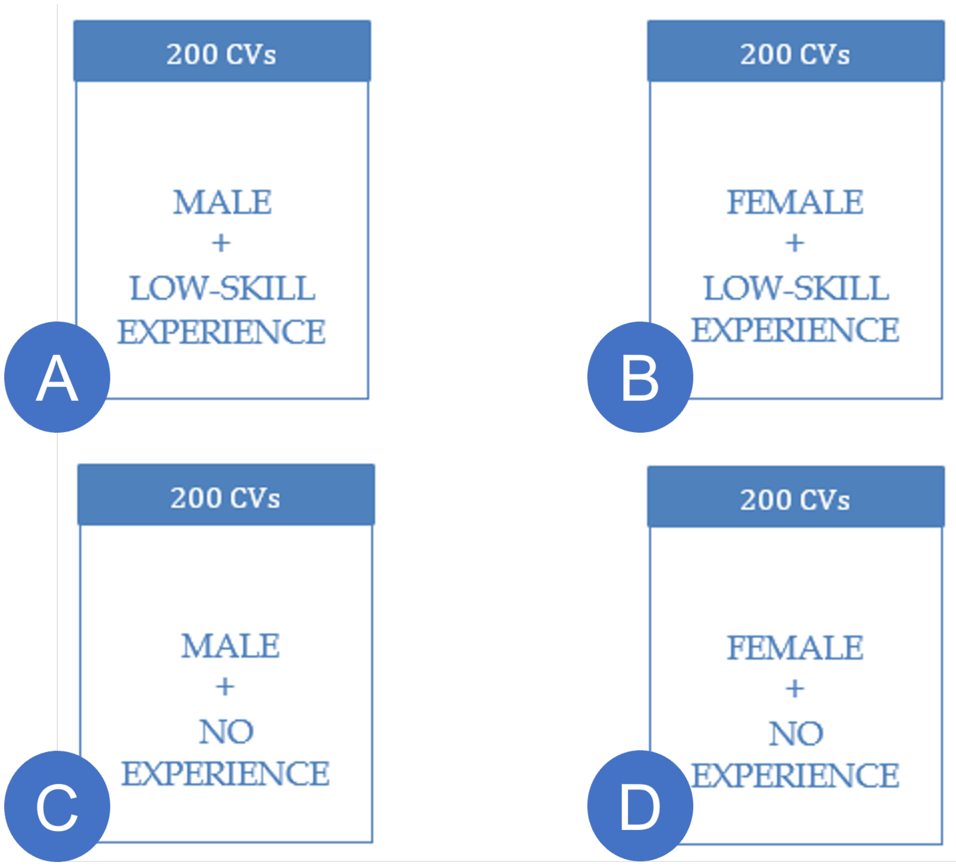
Standard errors are clustered at the employer level
*** p<0.01, ** p<0.05, * p<0.1
Note : From columns (2) to (4), missing observations for Year of birth, Maried and High school in Bujumbura are replaced with means.

Table A1.7: Types of high-skill jobs suggested by resume evaluators

Accountant	Financial Analyst
Accounting and Financial executive	Monitoring and Evaluation
Accounting and HR Manager	Grant Accountant
Accounting Department Executive	Head of Accounting Department
Accounting Internship	Head of Credit Department
Administration and Finance Assistant	Head of Operations
Administration Assistant	HR Assistant
Administration Executive	HR Assistant
Administrative and Financial Director	Human Resources Clerk
Administrative and Financial Intern	Internal Auditor
Administrative Manager	Inventory Manager
Administrative Secretary	Journalist
Assistant Accountant	Local Purchasing Agent
Assistant Manager	Logistics
Automotive Underwriter	Logistics Manager
Bank Operation Officer	Logistics Officer
Billing and Collection Department	Logistics/security Department
Branch Manager	Logistics/Security Manager
Business Banker	Management and Warehouse Department
Teller	Management Control Department
Claims Department	Marketing Agent
Collection officer	Marketing/Commercial Officer
Collection Service	Miscellaneous Operations Officer
Collections Controller	Order Manager
Commercial Attache	Personnel Manager
Commercial Department Executive	Production Agent
Communication Officer	Production Manager
Community Manager	Program Manager
Cooperative Facilitator	Project Manager
Credit Analyst	Public Relations
Credit Department	Sales Agent
Credit Officer	Sales Manager
Credit Risk Officer	Sales Representative
Customer Service Agent	Sales Representative Internship
Customer Service and Marketing	Team Leader
Data Entry in Accounting	Technical Sales Executive
Direct Sales Representative	Treasury Custody
Finance Officer	Underwriter trainee

Note : All the high-skill jobs listed by employers require an undergraduate degree within their organization. The degree requirement criterion is the only one used to distinguish between low-skill and high-skill jobs in this study.

Figure A1.1: Resume modification



Note: This figure illustrates the randomization process. From an initial set of real 200 resumes, we generated four groups of resumes (A, B, C and D) that are similar except for gender and low-skill experience. Each employer was invited to evaluate a total of 20 resumes drawn from all 4 groups by randomly selecting 5 resumes in each group. The randomization algorithm included an instruction to not select twice a resume from the same person.

Figure A1.2: Template of the letter sent to employers (Page 1)

Bujumbura, le 30 mai 2022

A Monsieur/Madame le Directeur Général de ....

à Bujumbura

Objet : Etude des préférences des organisations partenaires/collaborateurs

Réf. : ....../IG/MK/05/2022

Madame/Monsieur le Directeur Général,

Je vous présente mes compliments et sollicite votre participation à une évaluation que nous conduisons sur les préférences des employeurs burundais. Cette évaluation permettra à INFINITY GROUP de vous fournir à l'avenir et au besoin, des travailleurs correspondant aux préférences que vous aurez indiquées.

L'insertion professionnelle des jeunes ! Une équation à « n » inconnues que l'Etat, le Système Educatif, les Pourvoyeurs d'Emplois – acteurs des Secteurs tant Public que Privé, les Bailleurs de Fonds Internationaux, etc... tentent de résoudre par tous les moyens. Les Jeunes se plaignent de ne pas avoir suffisamment accès à l'emploi, alors que les Employeurs potentiels se plaignent de n'avoir pas une main d'œuvre, adéquatement préparée pour le milieu professionnel. INFINITY GROUP souhaite apporter sa pierre à la résolution de ce problème sur base d'une théorie de changement selon laquelle : Si les pourvoyeurs d'emplois communiquent mieux leurs besoins en ressources et participent à la mise à niveau des jeunes à travers leur responsabilité sociale et que les capacités des jeunes sont renforcées et adaptées aux besoins du marché, alors les jeunes auront un meilleur accès au marché du travail burundais.

En effet, dans le cadre de l'amélioration continue de nos services et pour mieux préparer nos formations à l'endroit de certains lauréats, potentiels employés de demain, nous souhaitons mieux connaître les profils de candidats qui vous intéressent le plus. Nous vous demandons ainsi d'évaluer les 20 CVs en annexe sur une

Figure A1.3: Template of the letter sent to employers (Page 2)

échelle de 1 à 10 en utilisant la fiche d'évaluation également en annexe. Pour ce lot spécifique de CVs, il s'agit de profils de candidats ayant terminé leur Baccalauréat en Sciences Economiques et de Gestion en mai 2021 à l'Université du Burundi. Après avoir terminé l'évaluation des CVs, nous vous demandons de répondre à quelques questions supplémentaires pour nous aider à mieux comprendre les besoins de votre entreprise/organisation/institution. Cette activité prend environ 20 minutes. Plus vous évaluerez soigneusement les CVs, mieux nous pourrons vous proposer les profils adéquats. Il serait préférable que les CVs soient évalués par un haut cadre qui participe habituellement dans les décisions d'embauche afin d'augmenter la précision de nos recommandations.

En espérant une suite favorable, je vous prie d'agréer, Madame/Monsieur le Directeur Général, l'expression de ma haute considération.

Irvine Floréale Murame
Managing Director

CPI :

- A Monsieur / Madame l'ADGA
- A Monsieur / Madame le DRH

7, Avenue de France, Rohero
Bujumbura-Burundi
NIF: 4001100017
+257 22 280 320
+257 75 317 000 / +257 61 917 000
info@infinitygroup.bi
www.infinitygroup.bi
RC: 12607/18

Figure A1.4: Verbatim translation of the letter sent to employers

Dear …,

I would like to offer you my compliments and ask for your participation in an evaluation we are carrying out on preferences of Burundian employers. This evaluation will enable INFINITY GROUP to provide you with workers corresponding to the preferences you have indicated.

The professional integration of young people! An equation with "n" unknowns that the country, the Education System, the Job Providers - both in the Public and Private sectors, International Financial Organizations, etc...are doing their utmost to solve the problem. Young people complain that they do not have sufficient access to employment, while potential Employers complain that they do not have a workforce that is adequately prepared for the workplace. INFINITY GROUP wants to help solve this problem, based on the theory of change that: If job providers better communicate their resource needs and participate in the upskilling of young people through their social responsibility and young people's capacities are strengthened and adapted to market needs, then young people will have better access to the Burundian labor market.

In fact, as part of the continuous improvement of our services, and to better prepare our training courses for certain graduates, potential employees of tomorrow, we'd like to know more about the candidate profiles you are most interested in. We therefore ask you to evaluate the 20 CVs attached on a scale of 1 to 10, using the attached evaluation form. For this specific batch of CVs, candidates have completed their Bachelor in Economics and Management in May 2021 at the University of Burundi. After completing the CV assessment, we ask you to answer a few additional questions to help us better understand the needs of your company/organization/institution. This activity takes about 20 minutes. The more carefully you evaluate the CVs, the better we will be able to suggest suitable profiles. It would be preferable for the CVs to be evaluated by a senior executive who is usually involved in hiring decisions, to increase the accuracy of our recommendations.

We look forward to hearing from you. Please accept, Madam/Sir, the assurances of my highest consideration.

Irvine Floréale Murame
Managing Director

Figure A1.5: Evaluation form used by employers (Original)

Infinity
WE PROVIDE SOLUTIONS GROUP

OUTIL D'EVALUATION DE CVs

INFINITY GROUP réalise une étude qui vise à améliorer l'adéquation entre les travailleurs et les entreprises et autres employeurs du Burundi. Nous vous demandons d'évaluer sur une échelle de 1 à 10 les CV joints de jeunes diplômés en économie et gestion de l'Université du Burundi. Vos choix seront utilisés pour vous fournir des recommandations de travailleurs qui pourraient convenir à votre organisation. Plus vous évaluerez les CV avec soin, plus nous serons en mesure de trouver des candidats appropriés pour votre organisation. Les noms des candidats ainsi que de leurs référents ont été rendus anonymes pour des raisons de confidentialité.

Nom de l'évaluateur de CVs

Nom de l'organisation

Titre de l'évaluateur de CVs

Date

Intitulé du poste ou des postes qui pourrait(ent) être occupé(s) par un détenteur d'un diplôme de Baccalauréat en Economie et Gestion sans expérience connexe.

Poste 1

Poste 2

Poste 3

SCORE DE CHAQUE CV

Sur une échelle de 1 à 10, quel intérêt portez-vous à l'embauche de ce candidat ?

(Encerclez le chiffre correspondant : 1 est "Pas du tout intéressé" et 10 est "Très intéressé").

N'évaluez que la qualité du candidat. Supposez que le candidat accepterait une offre s'il en recevait une.

Poste 1
1 2 3 4 5 6 7 8 9 10

Poste 2
1 2 3 4 5 6 7 8 9 10

Poste 3
1 2 3 4 5 6 7 8 9 10

Quel montant recommanderiez-vous comme salaire mensuel de départ si le candidat est offert le poste ?

Poste 1

Poste 2

Poste 3

Figure A1.6: Evaluation form used by employers (English translation)

Infinity GROUP

Resume evaluation form

INFINITY GROUP is carrying out a study aimed at improving the match between workers and other employers in Burundi. We are asking you to rate on a scale of 1 to 10 the attached CVs of young graduates in economics and management from the University of Burundi. Your choices will be used to provide you with recommendations of workers who might be suitable for your organization. The more carefully you evaluate the CVs, the more likely we are to find suitable candidates for your organization. The names of the candidates and their referees have been made anonymous for reasons of confidentiality.

Name of CV evaluator ....

Organization name ....

Resume evaluator title ....

Date ....

Job title(s) that could be filled by a holder of a Bachelor's degree in Economics and Management without related experience.

Job 1 ....

Job 2 ....

Job 3 ....

SCORE FOR EACH RESUME

On a scale of 1 to 10, how interested are you in hiring this candidate?

(Circle the corresponding number: 1 is "Not at all interested" and 10 is "Very interested").

Evaluate only the quality of the candidate. Assume that the candidate would accept an offer if he/she received one.

Job 1

1 2 3 4 5 6 7 8 9 10

Job 2

1 2 3 4 5 6 7 8 9 10

Job 3

1 2 3 4 5 6 7 8 9 10

What would you recommend as a starting monthly salary if the candidate is offered the position?

Job 1 ....

Job 2 ....

Job 3 ....

Figure A1.7: A sample of the resumes sent for evaluation (Page 1)

CURRICULUM VITAE

1. **Nom de famille** :
2. **Prénom** :
3. **Contact** :
4. **E-mail** :
5. **Date de naissance** : **1995**
6. **Genre** : **Féminin**
7. **Nationalité** : **Burundaise**
8. **Etat civil** : **Célibataire**
9. **Profession** : **Sans**

10. Formation :

Établissements fréquentés	**Périodes**	**Diplômes**
Université du Burundi	**2019-2021**	**Baccalaureat**
Lycée communal MUSIGATI	2015-2017	DiplomeA2 en gestion et comptabilité
Lycée communal NGARA	2011-2015	Certificat du tronc commun
Ecole primaire NGARA I	2004-2011	

11. Formations parascolaires

Institutions	**Périodes**	**Certificats/Attestations**
Formation de l'entrepreneuriat : club new vision new genereration(2020)	3mois	Certificat d'entrepreneuriat
Université du Burundi	2 Mois	Stage académique
Lycée technique de la foi	En cours de faire	Bénévole : enseignant du cours de comptabilité générale

12. Expérience

Type	**De**	**A**
Agent Lumicash	Juin 2021	Aujourd'hui

13. Niveaux des langues connues (par compétence de 1 à 5, 5 étant le maximum) :

Langue	Lu	Parlé	Ecrit
Kirundi	5	5	5
Français	4	4	3
Anglais	3	2	2
Swahili	4	3	3

14. Connaissances informatiques : Outils bureautique (Word, Excel, PowerPoint, Access…).

15. Centre d'Intérêts et loisirs : Cinéma

16. Les personnes de référence :

Les personnes qui peuvent témoigner la véracité de notre expérience susmentionnée sont :

1. , Enseignant-Chercheur à la FSEG (Université du Burundi)
   Téléphone :
   E-mail :
2. , Enseignant-Chercheur à la FSEG (Université du Burundi)
   Téléphone :

1

Figure A1.8: A sample of the resumes sent for evaluation (Page 2)

E-mail :

3.

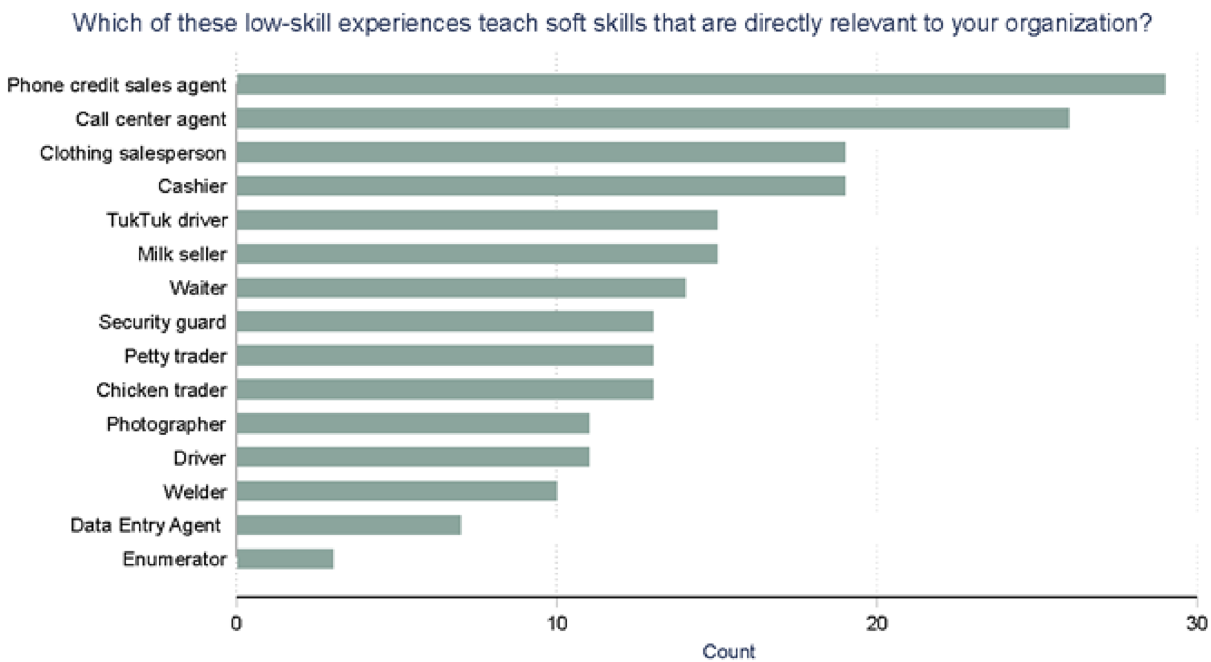
Téléphone :

E-mail :

Fait à Bujumbura, le 16 mai 2022

Prénom et nom

Figure A1.9: Ranking of low-skill jobs by employers



Source: Authors' computations using the present study's survey data.

Figure A1.10: Questionnaire for employers

Survey of employers

Field	Question	Answer
note_start	(After CV evaluation) We'll now ask you a series of questions designed to understand your preferences in relation to the people you'd like to recruit. This interview should last about 10 minutes. If at any point you don't hear or understand the question, please ask me to clarify. Your answers will be treated in the strictest confidentiality.	
TO BE COMPLETED BY THE CONSULTANT BEFORE STARTING THE FACE-TO-FACE INTERVIEW		
q101 *(required)*	Organization name	
q102 *(required)*	Address	
q103 *(required)*	Organization's economic sector	
QUESTIONS TO ASK THE RESPONDENT		
q201	In what year did the organization start its activities in Burundi?	
q202	Number of employees	
QUESTIONS TO BE ASKED > Group2_1		
q204	Can you provide rough estimates (in percentages) of employees' field of study?	
q205	Economics and Management	
q206	Law	
q207	Geography	
q208	History	
q209	Literature	
q210	Civil Engineering	
q211	Other Engineering Studies	
q212	IT	
q213	Sport	
q214	Chemistry	
q215	Physics	
q216	Biology	
q217	Psychology	
q218	Mathematics	
q219	Medicine	
q220	Public Health	
q221	Clinical Sciences	
q222	Without	
EMPLOYER PREFERENCES 1		
q301 *(required)*	Has your organization hired or does it plan to hire graduates in Economics and Management? Management without experience? (Consider first permanent positions, temporary positions and then internships).	1 Yes 0 No
q302 *(required)*	For which position? *Question relevant when: selected(${q301} , '1')*	
q303	Answer the following questions by referring to the position indicated above. *Question relevant when: selected(${q301} , '1')*	
EMPLOYER PREFERENCES 1 > First type of position *Group relevant when: selected(${q301} , '1')*		
q304	For each pair of candidate profiles, which one would you hire?	
q316_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as a photographer after undergraduate studies.
q307_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as a cashier after undergraduate studies.
q317_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as a welder after undergraduate studies.
q311_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job.

		2 with 12 months' experience as a waiter after undergraduate studies.
Field	**Question**	**Answer**
q312_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as a security guard after undergraduate studies.
q305_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as a telephone credit sales agent after undergraduate studies.
q310_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as a Tuktuk driver after undergraduate studies.
q313_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as a small retailer after undergraduate studies.
q306_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as a call center agent after undergraduate studies.
q319_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as an enumerator agent after undergraduate studies.
q315_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as a driver after undergraduate studies.
q308_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as a clothing salesperson after undergraduate studies.
q314_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as a chicken trader after undergraduate studies.
q318_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job. 2 with 12 months' experience as a data entry agent after undergraduate studies.
q309_1 *(required)*	Would you hire a job candidate :	1 without experience in any kind of job.

		2 with 12 months' experience as a milk salesman after undergraduate studies.
q320 *(required)*	Is there any other position for which your organization has already hired or plans to hire Economics and Management graduates? (First consider permanent positions, temporary positions and then internships).	1 Yes 0 No

Field	Question	Answer
	Question relevant when: selected(${q301} , '1')	
q321 *(required)*	Which one? *Question relevant when: selected(${q320} , '1')*	
q322	Answer the following questions by referring to the position indicated above. *Question relevant when: selected(${q320} , '1')*	
EMPLOYER PREFERENCES 2		
q401	In the following section, we ask you to describe in general how you perceive the post-graduate experience of college graduates into low-skill jobs (jobs which do not require a college degree).	
q404 *(required)*	Experience in "low-skill jobs" suggests that the job seeker is disciplined.	1 1. Strongly disagree 2 2. 3 3. 4 4. 5 5. Neutral 6 6. 7 7. 8 8. 9 9. 10 10. Totally agree
q402	Experience in "low-skill jobs" suggests that the job seeker is incompetent.	1 1. Strongly disagree 2 2. 3 3. 4 4. 5 5. Neutral 6 6. 7 7. 8 8. 9 9. 10 10. Totally agree
q407 *(required)*	Experience in "low-skill jobs" suggests that the job seeker is less qualified than his or her classmates.	1 1. Strongly disagree 2 2. 3 3. 4 4. 5 5. Neutral 6 6. 7 7. 8 8. 9 9. 10 10. Totally agree
q403 *(required)*	Experience in "low-skill jobs" suggests that the job seeker is perseverant.	1 1. Strongly disagree 2 2. 3 3. 4 4. 5 5. Neutral 6 6. 7 7. 8 8. 9 9. 10 10. Totally agree
q405	Experience in "low-skill jobs" suggests that the job seeker is a hard worker.	1 1. Strongly disagree 2 2. 3 3. 4 4. 5 5. Neutral 6 6. 7 7. 8 8. 9 9. 10 10. Totally agree
q406 *(required)*	Experience in "low-skill jobs" suggests that the jobseeker has financial difficulties.	1 1. Strongly disagree 2 2. 3 3.

Field	Question	Answer
		4 4. 5 5. Neutral 6 6. 7 7. 8 8. 9 9. 10 10. Totally agree
q408	Do any of the following experiences teach soft skills that are directly relevant to your organization? Select them if so.	1 Credit sales agent telephone 2 Call center agent 3 Cashier 4 Clothing salesman 5 Milk seller 6 TukTuk driver 7 Server 8 Security agent 9 Small retailer 10 Chicken dealer 11 Driver 12 Photographer 13 Welder 14 Data entry agent 15 Enumerator
q409 *(required)*	How important are soft skills in your organization?	1 1. Not at all important 2 2. 3 3. 4 4. 5 5. 6 6. 7 7. 8 8. 9 9. 10 10. Very important
q410 *(required)*	Which soft skills are you looking for when making a hiring decision?	
RESPONDENT INFORMATION		
q501	Respondent job title	
q502	Number of years with the organization.	
q503	Phone number	
q504	Email	
q505	Type *Select without asking*	1 Male 0 Female
q506	Age	
note_end	Thank you for your time and participation in our survey.	

Chapter 2

The impact of underemployment on schooling: evidence from Ethiopia

1 Introduction

As more and more students in Africa are graduating to jobs which do not require their level of education, the issue of underemployment has garnered increasing attention among academic researchers and policy makers (ILO, 2022). Despite the growing interest, research on the impact of underemployment has focused on its effect on income (Pascual-Saez and Lanza-Leon, 2023; Chuang and Liang, 2022) and job satisfaction (Bender and Roche, 2013; Sam, 2020) but has overlooked the potential impact on schooling. This paper examines whether underemployment of adults affects the schooling of children in their households not only through an income channel but also through a motivation channel.

This study holds particular relevance in light of the ongoing "learning crisis" afflicting developing countries, where, despite a significant increase in school enrollment over the past decades — from an average of 2.0 years of schooling completed in 1950 to 7.2 years in 2010 — the level of learning achieved from schooling is alarmingly low (World Bank, 2018a; Pritchett and Viarengo, 2023). Part of this learning crisis can be attributed to the motivation for learning from school of children, which can be influenced by their parents as well as other influential figures in the household.

The literature has argued that enhancing perceived returns to education amplifies incentives for schooling. For example, Avitabile and De Hoyos (2018) observed a positive and significant impact on standardized test scores and self-reported effort measures following an intervention which provided 10th-grade students with information about the average earnings associated with different educational attainments. Similarly, Jensen (2010) found that 8th grade students at randomly selected schools who were given information on returns to secondary education that were higher than what they expected, completed on average 0.20–0.35 more years of school over the next four years. Moreover, it has been posited that parents can spur greater effort from their children, leading to positive gains from schooling (Bergman, 2021; Rogers and Feller, 2017).

In this study, we examine how underemployment impacts children's schooling. Underemployment is defined as a situation whereby the highest level of education of an individual is above educational requirements for their occupation. We explore its effects on children in primary education. Specifically, we test the hypothesis that underemployment negatively affects children's school attendance and increases their engagement in household activities.

The theoretical underpinning of this hypothesis is that individuals whose qualifications are above the requirements for their jobs may not be inclined to motivate children in their households to attend school, owing to their own perceived unsuccessful educational outcomes. Similarly, witnessing educated adults who are underemployed might discourage children from working hard in school. As the household members start to question the value of school or the probability of educational returns, school absenteeism of children could increase and they could become more engaged in household chores, negatively affecting their education outcomes.

To examine the impact of underemployment on schooling, this paper uses individual level panel data with national coverage, collected in Ethiopia for the period 2011 to 2016. One benefit of this panel dataset over more prevalent cross-sectional datasets is that it allows an examination of the dynamic relationship between underemployment and schooling. The main treatment effect we estimate represents the difference between the average outcomes for children in households with one or more underemployed adults, compared to the same children when previously living in matched households, meaning households where all adults have an occupation which corresponds to their studies. Given the varying timeframes for household treatment, our identification strategy leverages recent developments in the Difference-in-Differences literature. These developments highlight that a simple two-way fixed effects (TWFE) estimator with a single treatment indicator, in the presence of variation in treatment timing, is typically biased as it uses units already subjected to treatment as control groups (Goodman-Bacon, 2021). To sidestep this issue, we employ an Extended TWFE (ETWFE) approach, as proposed by Wooldridge (2021), as well as Callaway and Sant'Anna (2021), allowing for treatment effect heterogeneity by cohort and timing.

Results show significant impacts of underemployment on children's out-of-school activities and to a lesser extent on extended school absenteeism, *i.e.* school absence of more than a week. Specifically, underemployment increases children's involvement in household agricultural activities and other out-of-school activities such as collecting water and firewood. However, the effect on extended school absenteeism is not significant in most specifications, suggesting that this measure exhibits a relatively minor response to underemployment. We examine the heterogeneity of these main results with respect to children's grade level, their age, their relationship with the underemployed adult and migration. This analysis suggests that older children and those in higher educational levels are more likely to engage in agricultural activities as a reaction to underemployment within their household, possibly due to a growing awareness of the disparity between educational achievements and adult job opportunities. The study also highlights that children are more affected by their parents' underemployment than by other household members, indicating a deeper dependency on parental employment status. We find that the addition or departure of household members, does not significantly alter children's involvement in household tasks nor school absenteeism. Additionally, the research examines the sensitivity of the main results to varying definitions and classifications of agricultural work.

This study contributes to the literature on the relationship between labor market conditions and education outcomes first by examining the influence of underemployment on children's schooling, while previous research focused on the impact of underemployment on income and job satisfaction. Second, the study departs from previous, high-income focused research, which has analyzed the impact of *unemployment* on schooling (Peraita and Pastor, 2000; Clark, 2011; Lavrijsen and Nicaise, 2015; Reiling and Strøm, 2015; von Simson, 2015; Sievertsen, 2016; Witteveen, 2021). In the context of low-income countries, analyzing the effect of *underemployment* on schooling is more relevant. This is primarily because unemployment rates in these regions are typically low[1], as most individuals cannot financially afford to remain unemployed.

The paper proceeds as follows. In the next section, we provide further details on the related literature. We then present the conceptual framework in Section 3. We discuss the economic, labor and education context of the study in Section 4. Section 5 presents the data used in

[1]Currently estimated at 6.75% (WDI, 2023).

the study. Section 6 provides a descriptive analysis of the effect of underemployment on schooling. Section 7 presents the identification strategy and Section 8 the results. We conclude in Section 9.

2 Literature review

The literature has explored the influence of labor market conditions on education outcomes, including primary enrollment and dropout rates. One strand of literature has analyzed the effect of unemployment on schooling. In this literature, Clark (2011) analyzed the impact of youth unemployment on enrollment in post-compulsory education in eight regions in England from 1975 to 2005. The study found that youth unemployment increases enrollment. Similar to Clark (2011), Sievertsen (2016) analyzed the effect of local unemployment on high-school enrollment in Denmark and found that local unemployment has both a short and long-run effect on school enrollment and completion, with the short-run effect causing students to advance their enrollment of additional schooling, and the long-run effect causing students who would never have enrolled to enroll and complete schooling.

The finding that unemployment increases school enrollment is not universal and may be a function of two opposing forces: the opportunity cost of studying on the one hand and expected returns on education on the other hand. While studies conducted in Europe suggest that the opportunity cost of schooling has a greater influence on schooling compared to expected returns (Clark, 2011; Reiling and Strøm, 2015; von Simson, 2015; Sievertsen, 2016) the opposite appears to be happening in the United States (Witteveen, 2021). The latter study found that youth unemployment increases enrollment in Europe but decreases enrollment in the US. The author explains the difference between Europe and the United States as due to the fact that education is relatively more expensive in the US.

Studies have also examined the impact of the labor market conditions on dropping out of school and on educational aspirations. Peraita and Pastor (2000) found, in the context of Spain, that unemployment has a negative impact on primary school dropout rate. Directing at a different outcome, *i.e.* educational aspirations, Lavrijsen and Nicaise (2015) analyzed the influence youth unemployment in 27 European countries. The authors found that youth unemployment seems to affect negatively the educational aspirations of disadvantaged students more in comparison to students with high-educated parents.

The literature has also examined the impact of underemployment on income and satisfaction. Pascual-Saez and Lanza-Leon (2023) analyze, in the context of Spain, the effect of underemployment, or over-education, on income. The authors estimate an annual average earnings drop attributable to underemployment of 7000 euros for women and 5 000 euros for men. Similarly, Chuang and Liang (2022) point to significant wage loss due to underemployment in the context of Taiwan. Researchers have also investigated the impact of underemployment on job satisfaction. Bender and Roche (2013) found no decrease in job satisfaction among the self-employed persons in the US who are mismatched. However, Sam (2020) found that underemployment adversely affects job satisfaction of university graduates in Cambodia.

On one hand, this study contributes to the literature on the relationship between labor market conditions and education outcomes by focusing on the impact of underemployment and by departing from previous research which has focused on the impact of unemployment. In developing countries, it is deemed more pertinent to analyze the effect of underemployment rather than unemployment, as unemployment rates in these countries are often low, as individuals cannot afford to remain unemployed. On the other hand, this study fills a gap in the literature by examining an impact of underemployment which has been overlooked, *i.e.* the impact of underemployment on education. Overall, this study provides valuable insights into the relationship between employment mismatch and education outcomes.

3 Conceptual framework

This section discusses the potential mechanisms through which underemployment may affect children's schooling, focusing on two key channels: the income channel and the motivation channel. These channels provide a conceptual framework for understanding the implications of underemployment, viewed as a shock on expected returns to education affecting adults and children in a household. While this study primarily concentrates on the motivation channel, treating the income channel as a control variable, we believe that it is crucial to clearly outline the mechanism through which the income effect operates as it is often the initial factor considered when thinking about the impact of underemployment.

Income Channel

One potential mechanism through which underemployment may affect schooling is the income channel. This channel assumes that household income significantly influences the educational outcomes of children. When a working individual in the household is employed in a job that is below their qualifications, their income may be negatively affected if prior employment was in a matched position. Indeed, previous literature has shown that underemployment results in reduced income (Pascual-Saez and Lanza-Leon, 2023; Chuang and Liang, 2022). As household income decreases, children might be pushed to spend more time helping their parents with household or farm activities which, in turn, may lead to increased absenteeism.

The research design of this study introduces a nuanced perspective compared to the previous literature. Unlike previous research that compared individuals in matched and mismatched employment, this study analyses within-individual variation as opposed to inter-individual comparisons. Here, the income effect can vary depending on the type of an individual's transition into underemployment. If a person shifts from unemployment or schooling to underemployment, their income would likely increase, positively impacting household income. Conversely, if the transition is from a matched employment position to underemployment, a decrease in income is expected. Additionally, underemployed individuals joining a household from outside should lead to an increase in the household's overall income.

Motivation Channel

Another theoretical mechanism linking underemployment to schooling is the motivation channel. This channel, which is the focus of this study, considers the psychological and social aspects of underemployment on children's schooling. On one hand, underemployed adults might be less motivated to encourage household children to go to school. This could result from a perception that their own educational qualifications have not translated into desirable job outcomes. On the other hand, children themselves might be less motivated to attend school if they observe that people who have completed their education still end up in jobs that do not require their degrees. This observation may lead to a belief that the returns to education are low or very uncertain, and thus, the children may disengage from formal schooling. The reduced motivation for learning from school should increase children's participation in out-of-school activities and simultaneously increase school absenteeism. More time spent on household chores could mean that children arrive to school tired and not ready to learn. It could also mean that they do not have enough time to do their homework. Both of these effects, in addition to school absenteeism, are likely to translate in lower education outcomes. This may seem counterintuitive, but research has found that the involvement of children in household activities, such as domestic chores and paid activities, is associated with a reduction of hours of study and different measures of school performance, in the context of Ethiopia, India and Vietnam (Borga, 2019), Ghana (Heady, 2003) and Tanzania (Akabayashi and Psacharopoulos, 1999).

4 Economic, labor and education context

With a gross national income per capita of $960, Ethiopia is classified as a low-income country (World Bank, 2022a). Over the past two decades, the country has experienced rapid economic growth, with an average real GDP growth of 8.6% per annum (IMF, 2022). The sustained high rate of economic growth has led to significant improvements in poverty, although the ongoing civil conflict which started in 2020, centered in the northern region of Tigray, threatens to reverse the economic and social progress (World Bank, 2022a).

Approximately 2 million individuals are reaching the working age each year, which is putting significant pressure on the labor market's ability to absorb these new workers (World Bank, 2022a). The latest Ethiopian labor force survey shows that 65% of employed persons are working in the agriculture sector, 30% in the service sector and 5% in manufacturing, construction, mining and quarrying (CSA, 2021). Agricultural employment is more prevalent in the rural sector (77%) while service jobs are more observed in the urban sector (73%). Similar to other low-income countries, the unemployment rate, at 8%, is relatively low, since most people cannot afford to remain without work, but underemployment, defined as the share of people whose level of education is above the average requirement of their occupation among people with at least a lower secondary education, was last estimated at 22% in 2013 (ILO, 2023b).

The education system in Ethiopia has undergone significant expansion in the last two decades, with the number of pupils in primary education going from approximately 6 million in 2000 to 18 million in 2021 (World Bank, 2022c). Despite considerable efforts to provide schooling for a rapidly growing population, there are still significant shortcomings in educational outcomes, as well as large regional disparities (Federal Ministry of Education, Ethiopia, 2021). Gross enrollment rate[2] for primary school was estimated at 106% in 2021. However, the survival rate to the final grade of primary education[3] was a mere 33% in 2021, which signifies a high prevalence of dropouts. The Ethiopian government has implemented various programs and initiatives, including free education and digitization, aimed at increasing access to primary education and improving the quality of education. However, more needs to be done to ensure that all children in Ethiopia have access to quality education. Assessments have shown that many pupils do not achieve expected competencies in fundamental subjects like reading and math, despite spending years in school (Oketch et al., 2021). This disconnect between years of schooling and actual learning highlights the learning crisis affecting Ethiopia like many other low-income countries. However, the average years of schooling, estimated at 2.38 in 2019 (UNESCO, 2023b), is still very low. Hence, primary education faces at least two major challenge: attracting a greater number of pupils and ensuring adequate learning levels.

[2] The gross enrolment rate is the number of children enrolled in a certain education level as a percentage of the number of children who should be studying officially in that level. This indicator can be higher than 100% due to class repetition and early or late enrollment.

[3] The duration of primary education is 8 years (World Bank, 2022c).

5 Data

This study uses a panel dataset which covers three waves of the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) of Ethiopia, from 2011 to 2016[4]. Datasets of the different waves have the following sample sizes: Wave 1 (2011-2012), 3 969 households; Wave 2 (2013-2014), 5 262 households; Wave 3 (2015-2016), 4 954 households. Such individual level panel datasets are rare in the context of Sub-Saharan Africa (SSA) and are collected as part of a collaboration between the World Bank and national statistics offices in eight SSA countries. The choice to conduct the study with Ethiopian data is motivated by the fact that it best fits the requirement of this study with respect to main variables of interest (schooling and labor market indicators) and length of the panel (at least three waves).

Our analysis is based on information extracted from modules on demographic characteristics, education, health, time use and labor, food consumption and non-food expenditure. Since the datasets do not contain a measure of underemployment, this was calculated using information on education and occupation of individuals as follows. Following the normative definition of the International Labor Organization (ILO), an underemployed person, or an overeducated person, is defined as an individual whose highest level of education is above the educational requirements for their occupation. The educational requirement for an occupation refers to the correspondence between education and occupation based on the International Standard Classification of Occupations (ISCO), as provided by ILO (See Figure A2.1). Individuals' occupations were already coded in the datasets based on ISCO-08 (See Table 2.1) with the exception of individuals whose main activity is agriculture likely because of the difficulty of classifying individuals whose main occupation is in agriculture (ILO, ndb). For the latter, we classified people who spent at least 20 hours in the last 7 days on household agricultural activities in the ISCO category "9: Elementary Occupation", if they were not already employed in a job, including casual/part-time labor, for a wage, salary, commission or any payment in kind[5].

[4]A relatively recent 2018-2019 wave is not included in the panel because it is not a follow-up of the previous waves.

[5]We check for the sensitivity of the results with respect to the number of hours necessary for classifying

Table 2.1: Distribution of adults (>18) by occupation

	Year 1		Year 2		Year 3	
Main job over the last 12 months	**Freq.**	**Percent**	**Freq.**	**Percent**	**Freq.**	**Percent**
Managers, Legislators, Governement Officials	12	0.47	8	0.35	29	1.07
Professionals	21	0.83	33	1.45	111	4.11
Technicians and Associate Professionals	30	1.18	15	0.66	70	2.59
Clerical Support Workers	52	2.05	39	1.71	128	4.74
Service and Sales Workers	20	0.79	18	0.79	90	3.34
Skilled Agricultural, Forestry and Fishery Workers	4	0.16	6	0.26	20	0.74
Craft and Related Trades Workers	9	0.36	8	0.35	42	1.56
Plant and Machine Operators, and Assemblers	6	0.24	2	0.09	37	1.37
Elementary Occupations	2379	93.92	2154	94.35	2171	80.47
Total	**2533**	**100**	**2283**	**100**	**2698**	**100**

Note: This table shows the number and share of adults by professional category as coded is the first three waves of LSMS-ISA data for Ethiopia, with the exception of persons whose main occupation is agriculture. We included the latter in the "Elementary Occupations" category and test for the sensitivity of the results for including them in the category of "Skilled Agricultural, Forestry and Fishery Workers".

The underemployment variable is only constructed for individuals above the age of 18 and below 64[6], whom we call adults, while the outcome variables concern individuals from the age of 5 till 18 in primary school, whom we call children. The children retained in the analysis are children who were attending school during all the data collection waves.

A household is coded as treated (T=1) if there is one or more individuals in the household who are underemployed. The household is coded as untreated (T=0) if all adults in the household are matched. If there are individuals in the household who are undereducated, *i.e.* individuals who hold an occupation which is above their level of education, the household is taken out of the sample. Similarly, households with unemployed adults only are not included in the sample. Furthermore, our sample includes individuals whose information is available for all three waves. Table 2.2 shows the total number of children and households in the dataset used for analysis as well as the breakdown by cohort of treatment period.

Concerning the dependent variables of interest, the dataset contains a variable on extended school absenteeism which was asked as follows: "Were you absent from school last month

individuals as occupied in elementary occupations, removing from the sample those who do not reach the retained threshold. If no adult in the household is employed, the child does not appear in the database. In fact, to be classified as matched or mismatched, two pieces of information are required: level of education and occupation.

[6] Following the standard threshold for the working age population.

Table 2.2: Number of children and households in the dataset by cohort of treatment period

Type of cohort of children	Year 1	Year 2	Year 3	Number of children	Number of households
Cohort 1	0	1	1	79	48
Cohort 2	0	0	1	137	92
Cohort 3	0	0	0	914	645
Cohort 4	1	0	0	141	107
Cohort 5	1	1	0	99	70
Cohort 6	1	1	1	75	54
Cohort 7	0	1	0	134	94
Cohort 8	1	0	1	87	58
Number of children	1666	1666	1666	1666	
Number of households	1168	1168	1168		1168

Note: The numbers 0 and 1 indicate the treatment status of children. For instance, cohort 1 consists of children who lived with matched adults only in wave one and then with one or more underemployed adults in wave two and three. A child's treatment status may change for two reasons: either because an adult in the household has switched from a matched to a mismatched situation or because an adult in a certain professional situation has left or joined the household. Overall, 59% percentage of children do not change treatment status (Cohorts 3 and 6) while the remainder either go from living with matched individuals to living with one or more underemployed people (Cohorts 1 and 2), from living with one or more underemployed adults to living with matched adults only (Cohorts 4 and 5), or switch treatment status back and forth (Cohorts 7 and 8).

for more than a week?". As we show in the next section, this is not the ideal way to capture absenteeism in the context of this study as only a small percentage of children were absent from school for that long. It would have been preferable to use a less stringent variable to capture absenteeism, for instance, absence for one or two days in the past week, if such a variable were available. Other dependent variables of interest relate to out-of-school activities. These are: (1) "How many hours in the last seven days did you spend on household agricultural activities (including livestock and fishing-related activities) whether for sale or for household use?" ; (2) "How many hours did you spend yesterday collecting water and firewood (or other fuel materials)" - combined with - "How many hours in the last seven days did you spend on these other activities: running or helping with any kind of non-agricultural or non-fishing household business, big or small, for yourself or for the household; casual, part-time, or temporary labor; working for a wage, salary, commission, or any payment in kind, excluding temporary; working in an unpaid apprenticeship".

The remaining variables used in this study are time-varying covariates which are used in the regression analysis to control for income (proxied with food and non-food expenditure), age, grade, health and presence of biological mother or father in the household. Table 2.3 shows summary statistics of all variables used in the analysis.

Profiles of adults in the sample

The profiles of underemployed adults in the sample vary. As a result, children may be exposed to underemployed adults within their households with whom they have different relationships. Table 2.4 illustrates the relationship between underemployed individuals and the household head, revealing that a significant portion of the underemployed are the heads of households (nearly 50% annually), followed by their spouses, and then sons and daughters. Underemployment is less common among other categories, which include grandchildren, parents, siblings, nieces and nephews, in-laws, other relatives, domestic workers, and non-relatives.

The exposure of children to underemployed adults may vary due to two main factors: changes in the employment status of adults within the household or migration. The dataset does not specify the reasons for an individual's absence from the household wave after wave, for

Table 2.3: Summary statistics of variables used in the analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
Extended absenteeism	4711	0.089	0.285	0	1
Time spent on HH Ag Activities (Hours)	4548	9.905	14.991	0	85
Time spent on other activities (Hours)	4562	1.968	6.254	0	96
Health	4713	0.101	0.302	0	1
Age	4713	11.436	2.779	5	18
Mother Alive	4707	0.917	0.275	0	1
Father Alive	4710	0.791	0.407	0	1
Grade	4713	3.984	2.029	1	8
Household size	4713	7.079	2.167	2	17

Note: "Extended absenteeism" captures school absence of at least a week in the previous month. "Time spent on HH Ag Activities" is the number hours in the previous 7 days spent on household agricultural activities. "Time spent on other activities" encompasses the number of hours spent in the last 7 days on collecting water, collecting firewood, helping with any kind of non-agricultural or non-fishing household business (big or small), time spent on casual, part-time, or temporary labor, time spent on any work for a wage, salary, commission, or any payment in kind, excluding temporary, and time spent on unpaid apprenticeship. "Health" indicates whether the child had any health problems during the previous 2 months. Since there is no income variable in the dataset, We use principal components to capture food and non-food expenditure variables originally coded in 27 variables.

Table 2.4: HH Member Relationship with HH Head (Underemployed)

	Year 1		**Year 2**		**Year 3**	
	Freq.	**Percent**	**Freq.**	**Percent**	**Freq.**	**Percent**
Head	489	55.69	432	53.01	549	51.36
Spouse	131	14.92	111	13.62	144	13.47
Son/Daughter	208	23.69	235	28.83	295	27.6
Grandchild	10	1.14	8	0.98	8	0.75
Father/Mother	1	0.11	0	0	3	0.28
Sister/Brother	8	0.91	10	1.23	28	2.62
Niece/Nephew	5	0.57	2	0.25	7	0.65
Uncle/Aunt	0	0	1	0.12	2	0.19
Son/Daughter-in-Law	2	0.23	3	0.37	9	0.84
Brother/Sister-in-Law	1	0.11	3	0.37	3	0.28
Other Relative	8	0.91	3	0.37	8	0.75
Servant	8	0.91	5	0.61	5	0.47
Non Relative	7	0.8	2	0.25	8	0.75
Total	**878**	**100**	**815**	**100**	**1069**	**100**

Note: This table shows the different types of relationships of underemployed adults in the sample with the household head.

instance whether it is due to migration or absence during the interview period. It does, however, indicate when an individual joined the household in the past year, which helps identify recent movements into the household. According to Table 2.5, approximately 10% of adults joined the household at some point in the previous year.

Table 2.5: Number of months of absence from household during the previous 12 months

Year 1			Year 2			Year 3		
Num	**Freq.**	**Percent**	**Num**	**Freq.**	**Percent**	**Num**	**Freq.**	**Percent**
0	732	89.27	0	734	90.62	0	994	92.98
1	30	3.66	1	31	3.83	1	26	2.43
2	27	3.29	2	15	1.85	2	22	2.06
3	16	1.95	3	8	0.99	3	9	0.84
4	6	0.73	4	2	0.25	4	6	0.56
5	3	0.37	5	6	0.74	5	3	0.28
6	3	0.37	6	1	0.12	6	2	0.19
7	2	0.24	7	2	0.25	7	2	0.19
8	1	0.12	8	1	0.12	8	1	0.09
			9	4	0.49	9	1	0.09
			10	3	0.37	10	1	0.09
			11	1	0.12	11	2	0.19
			12	1	0.12			
Total	**820**	**100**		**809**	**99.87**	**Total**	**1069**	**100**

Note: Columns "Num" identify the number of months adults were absent from a household in the previous 12 months.

Adults experiencing changes in their employment status undergo various trajectories. Some transition from being matched to underemployed, as illustrated for instance by an individual with a 10th-grade education moving from an occupation in the "Service and Sales Workers" category to one in "Elementary Occupations." Conversely, some individuals move from underemployment to matched situations, while a few others switch treatment back and forth, for instance by switching back and forth from "Technicians and Associate Professionals" to "Skilled Agricultural, Forestry and Fishery Workers". Notably, a large number of adults are engaged in "Elementary Occupations," consisting mainly of agricultural activities but also of basic sales and services occupations. We analyze the robustness of results for categorizing individuals who work in agriculture in the professional category of “Skilled Agricultural, Forestry and Fishery Workers".

Table 2.6 reveals that about half of the adults in the sample lack formal education, with the next largest group having only primary education. This data, coupled with Table 2.1 on occupations, which indicates a significant number of individuals are employed in the agricultural sector, suggests that our analysis primarily examines the impact of studying and remaining in the agricultural sector on schooling outcomes of children in the household. In regions of rural Africa, where subsistence farming is the default occupation, education offers children the chance to pursue different careers from their parents'.[7]

Table 2.6: Education level of adults in the sample

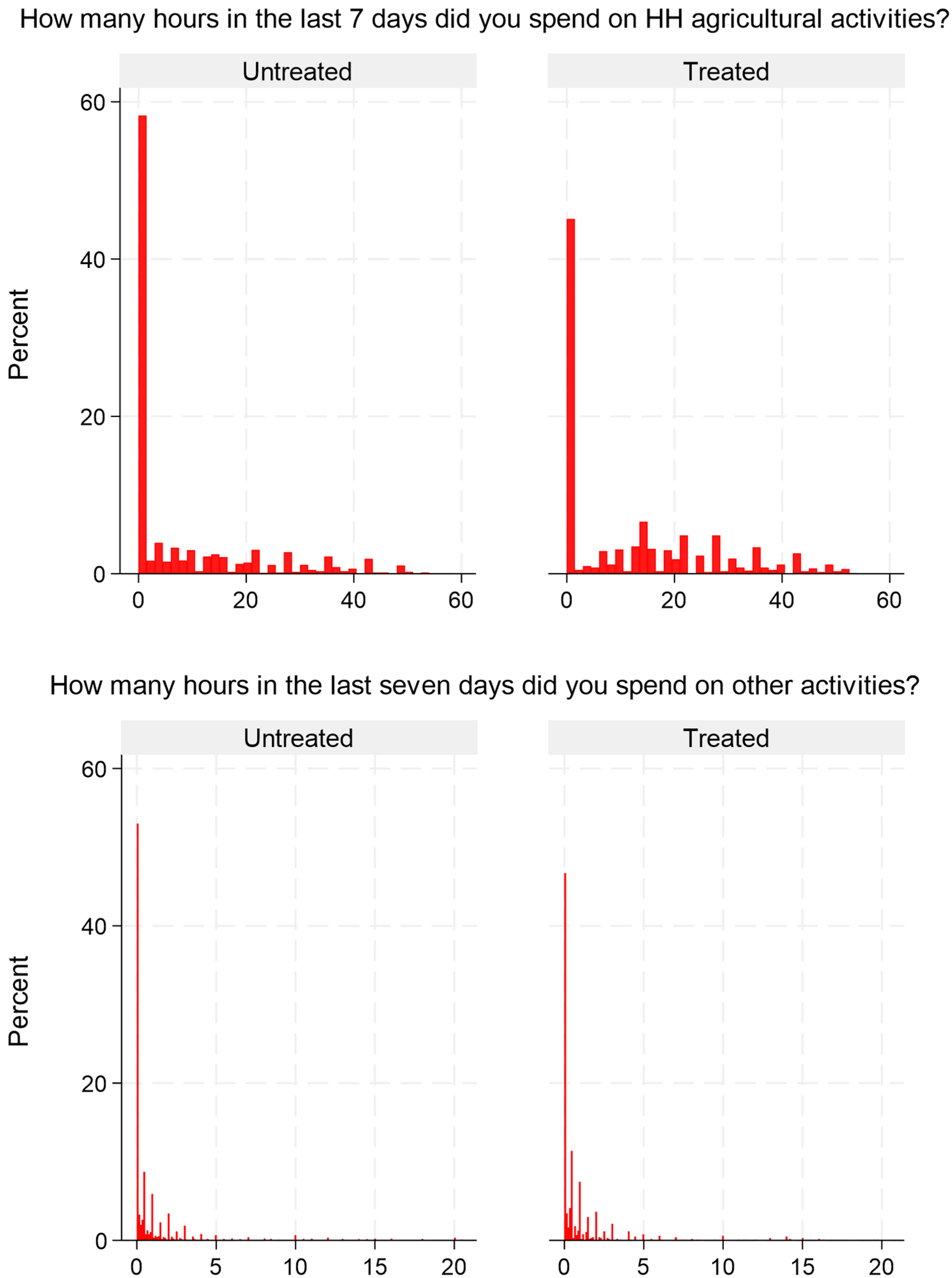
	Year 1		Year 2		Year 3	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
No education	1508	59.82	1361	59.69	1237	45.85
Pre-primary	10	0.4	2	0.09	8	0.3
Primary	741	29.39	656	28.77	715	26.52
Secondary	175	6.94	175	7.66	415	15.4
Post-secondary	87	3.46	82	3.6	322	11.94
Total	**2521**	**100**	**2280**	**100**	**2698**	**100**

6 Descriptive analysis

Table 2.7 shows statistics on the number of children who experienced extended absenteeism, *i.e.* who were absent from school for over a week during the previous month, by year of data collection. When examining untreated children, meaning children who live in a household of matched adults only, the rate of extended school absence is approximately 12% in the first year, and treated children, meaning those residing in households with at least one underemployed adult, exhibited a statistically similar absenteeism rate of 11%. The rate of school absence is also similar in the two groups for the second and third years.

[7] It should be noted that following ILO' normative classification of occupations (Figure A2.1), an individual is considered underemployed if possessing a secondary education or higher. This definition is not applicable using the dataset at hand because of the small proportion of individuals with a secondary education or above (See Table 2.6).

Figure 2.1: Children's participation is out-of-school activities



Note: For clarity, these figure exclude outliers defined as values that are more than three standard deviations away from the mean.

Table 2.7: School absence for more than a week

	(1)		(2)		
Treatment status	Untreated		Treated		p-value
	N	Mean	N	Mean	(1)-(2)
Year 1	1208	0.117	387	0.106	0.562
		[0.009]		[0.016]	
Year 2	1246	0.057	377	0.058	0.920
		[0.007]		[0.012]	
Year 3	1147	0.097	346	0.101	0.810
		[0.009]		[0.016]	

Note: "Untreated" refers to children living in a household with matched adults only. "Treated" refers to children living in a household with one or more underemployed adults. Columns (1) and (2) show the share of children who were absent from school for more than a week in the month prior to data collection. For instance, in the first year, approximately 12% of children living with matched adults were absent from school for more than a week compared to 11% among the group of children living with one or more underemployed adults. Standard errors are shown in brackets.

The contrast between treated and untreated children becomes apparent when comparing the hours dedicated to household agricultural activities and time spent collecting water, firewood and other activities. Figure 2.1 suggests that children who live with underemployed adults consistently dedicate more time to these activities compared to children from households with matched adults only.

Overall, these simple, descriptive results align with the theoretical mechanisms posited above, with the exception of school absenteeism. The rest of the analysis seeks to disentangle the income effect and the motivation effect, to account for other potential confounding variables, and to consider the treatment time of the children, among other refinements of the correlations observed in this section.

7 Identification strategy

To identify the impact of underemployment on children's outcomes, we exploit variations in the timing of when adults in the household are affected by underemployment. For the period from 2011 to 2016, we compare the outcomes of children living with underemployed adults to those of children living with matched adults, meaning adults whose education level corresponds to their occupation. More specifically, we group children by cohort of treatment. By cohort of treatment, we mean the year when children started living with one or more underemployed adults in the household. Table 2.2 shows the different cohorts of children in the dataset. To do this, we rely on the Extended Two-Way Fixed Effects (ETWFE) model, which is also our main specification[8]. The ETWFE model estimates the causal effect by restricting the comparison to children with a similar treatment timing over the period 2011 to 2016. Furthermore, the model subtracts the observed difference in outcome from the difference which is constant prior to treatment. We estimate parameters of the following equation:

$$Y_{it} = \sum \alpha_{ct}(C_c \times Year_t) + \boldsymbol{X}\beta_{it} + a_i + b_t + \epsilon_{it} \tag{2.1}$$

where Y_{it} represents different children outcomes related to school absenteeism and out-of-school work at time t (with $t = 1, 2, \tau = 3$) for child i. $(C_c \times Year_t)$ corresponds to interactions of indicators of the cohort C_c and the survey year t at which the effect is estimated. α_{ct} represents the ATT for cohort C at year t. $\boldsymbol{X}$ is a set of time-varying control variables that could potentially affect underemployment, children's outcomes or both : household expenditure, household size, child's health, child's age, an indicator of whether the mother is alive, an indicator of whether the father is alive and the child's grade level. The a_i represents individual fixed effects and b_t represents time fixed effects.

We focus initially on cohorts 1, 2 and 3, and estimate treatment effects, *i.e.* the effect of exposure to underemployed adults in the same household on children's schooling, with

[8] In fact, (Goodman-Bacon, 2021) show that a simple Two-Way Fixed Effects (TWFE) estimator with one treatment indicator, in the presence of variation in treatment timing, is usually biased because it uses already treated units as control units.

treated units in cohorts 1 and 2 and comparison units in cohort 3. We similarly apply the ETWFE on cohorts 4, 5 and 6, with cohort 6 the comparison group, but here, the logic is reversed, meaning that the treatment effect is interpreted as the effect of ending exposure to underemployed adults. The identifying assumption underlying the Difference-in-Differences specifications is that children's outcomes would have followed similar trends in the absence of exposure to underemployed adults. We therefore test for parallel trends conditional on the above covariates using a placebo test consisting in computing a treatment effect before the actual treatment took place (Wooldridge, 2021). We also assume no anticipation.

Our discussion of results leverages a non-parametric estimation approach developed by Callaway and Sant'Anna (2021). The CS estimator addresses the critique of Goodman-Bacon (2021) and offers several advantages. It combines Difference-in-Differences with Propensity Score Matching, and it easily produces an event study graph, which facilitates interpretation. However, a notable drawback is that it is a non-parametric estimator making it challenging to read and manipulate. On the other hand, the ETWFE estimator, as a parametric model, is relatively easy to interpret in addition to producing almost the same results as the CS estimator. Since the CS and the ETWFE methods require to exclude already treated units, data from cohorts 7 and 8, which include children whose treatment switches on and off (See Table 2.2), are omitted.

8 Results

Our findings are presented first for cohorts 1 to 3, and then for cohorts 4 to 6. This stratification ensures the comparison of individuals who receive a similar treatment: (1) children who go from living with matched adults to living with underemployed adults (Cohorts 1 et 2 in comparison to Cohort 3); (2) children who go from living with underemployed adults to living with matched adults (Cohorts 4 and 5 in comparison to Cohort 6). We also show the results obtained from the standard TWFE estimator in Table A2.1. These are slightly lower, but within confidence interval of the ETWFE results.

Our initial ETWFE results for cohorts 1 to 3 are presented in Table 2.8, showing the impact of underemployment on extended absenteeism, household agricultural activities and other out-of-school activities. Columns (1), (2), and (3) exclude income controls, while Columns (4), (5), and (6) incorporate them through nine principal components proxies representing household food and non-food expenditure. All specifications feature a parallel trends test whose results are shown in the first row, evaluating the impact of underemployment in Year 2 for Cohort 2, which is a pre-intervention period. Standard errors are clustered at the household level to account for intra-household correlation.

Overall, we obtain expected results for some of the treatment cohorts but not others. Significant results indicate that underemployment increases the amount children spend on household agricultural activities by approximately 5.1 hours per week ($p<0.05$) in the first year of treatment (For Cohort 2), and an estimated 5.7 hours per week ($p<0.01$) in the second year (For Cohort 1)[9]. This is measured against a sample mean of 8.8 hours per week that children who live in matched households spend on household agricultural activities. Similarly, underemployment augments the time allocated to other activities by about 1.3 hours ($p<0.10$) in the first year (For Cohort 1), and by 1.6 hours ($p<0.10$) in the second year (For Cohort 1), given a sample mean of 2 hours dedicated to these other activities for children in matched households. Once household income is controlled for, the magnitude of these results slightly decreases. This suggests an influence of income and motivation on children's engagement in out-of-school activities going in the same direction, and that motivation has a stronger effect.[10]

We point out that these results are weakened by the fact that the coefficient on the interaction of Cohort 1 and Year 2 is not significant in column (2) and similarly for the coefficient on the interaction of Cohort 2 and Year 3 in column (3). However, we show below that when we combine total year effects for both cohorts, using the CS estimator, we obtain significant results for the first and second year when the outcome is household agricultural activities, and for the first year only when the outcome is other activities. The influence of underemployment on extended school absenteeism is not significant across all specifications,

[9] Total year effects for both cohorts are shown below using the CS estimator.

[10] We show analogous results obtained using the TWFE estimator in Table A2.1. They suggest that underemployment increases children's participation in household agricultural activities by approximately 4.9 hours per week. The effects on other activities as well as school absenteeism is not significant.

which is potentially attributable to a small proportion of children in the sample being absent for over a week (See Table 2.7).

Table 2.8: ETWFE : Cohorts 1, 2 and 3

VARIABLES	(1) Extended Absenteism	(2) HH Ag Activities	(3) Other Activities	(4) Extended Absenteism	(5) HH Ag Activities	(6) Other Activities
Cohort2*Year2	0.014	-1.879	0.529	0.022	-2.331	0.590
	(0.033)	(1.849)	(0.803)	(0.034)	(1.898)	(0.815)
Cohort1*Year2	-0.085	2.152	1.309*	-0.069	1.024	1.206
	(0.059)	(2.242)	(0.693)	(0.058)	(2.399)	(0.762)
Cohort1*Year3	-0.061	5.725***	1.566*	-0.045	4.893**	1.502*
	(0.064)	(2.198)	(0.801)	(0.064)	(2.347)	(0.867)
Cohort2*Year3	-0.001	5.132**	0.764	-0.002	4.846**	0.844
	(0.040)	(2.415)	(0.915)	(0.040)	(2.385)	(0.928)
Observations	3,189	3,081	3,087	3,142	3,038	3,044
R-squared	0.036	0.028	0.058	0.045	0.036	0.067
Number of Children	1,129	1,129	1,129	1,129	1,129	1,129
Controls for Income	NO	NO	NO	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES	YES
Mean of Matched	0.0918	8.756	2.004	0.0918	8.756	2.004

Standard errors are clustered at the household level
*** p<0.01, ** p<0.05, * p<0.1
Note: The dependent variables are "Extended Absenteism", indicating school absence of more than a week in the previous month, "HH Ag Activities", capturing time spent by children on household agricultural activities in hours, and "Other Activities", indicating time spent by children on other activities such as collecting water and firewood, in hours. The coefficients on "Cohort2*Year2" are placebo treatment effects used to test for conditional parallel trends. The coefficients on "Cohort1*Year2" capture the treatment effects for Cohort 1 in Year 2 and similarly for other interaction terms. Income is controlled for using 9 principal components which capture household food and non-food expenditure.)

Table 2.9 presents estimates which combine the ETWFE and the Propensity Score Matching (PSM) method, which we use to compute a probability of being treated conditional on observable characteristics, *i.e.* a propensity score. The aim is to constrict the within-variation analysis of the ETWFE to relatively homogenous children[11]. Accordingly, children not falling within the common support are excluded (See Figure A2.2). This leads to a reduction in the number of children under analysis from 1 129 to 958.

Generally, the outcomes align closely with our previous findings, albeit with slight variations in magnitudes. As shown in the second column, underemployment results in an increase in children's involvement in agricultural activities by approximately 4.9 hours in the first year (For Cohort 2) and 5.0 hours in the second year (For Cohort 1). Column (3) also shows a significant impact of underemployment on the time children allocate to other activities in both the first and second years of treatment, increasing their involvement by approximately 1.5 hours in the first year and 1.5 hours in the second year (For Cohort 1).

[11] We apply a matching algorithm of one neighbor matching with a caliper equal to 0.2 times the standard deviation of the logit of the propensity score as is commonly done in practice.

As for our earlier results, the inclusion of income controls generally reduces the magnitude of estimated effects a little, suggesting the predominance of the motivational effect over the income effect. The influence of underemployment on extended absenteeism continues to lack significance even when the sample is restricted to relatively similar children. As mentionned above, this lack of significance could be attributed to the relatively small proportion of children in the sample who were absent from school for over a week. However, it could also suggest that children may not necessarily skip school but instead may experience diluted learning experiences due to their increased household responsibilities.

Table 2.9: ETWFE and PSM: Cohorts 1, 2 and 3

VARIABLES	(1) Extended Absenteism	(2) HH Ag Activities	(3) Other Activities	(4) Extended Absenteism	(5) HH Ag Activities	(6) Other Activities
Cohort2*Year2	-0.001	-1.305	0.636	0.011	-1.969	0.659
	(0.035)	(1.857)	(0.812)	(0.036)	(1.896)	(0.816)
Cohort1*Year2	-0.088	2.178	1.476**	-0.072	0.996	1.417*
	(0.062)	(2.429)	(0.712)	(0.060)	(2.592)	(0.778)
Cohort1*Year3	-0.050	4.961**	1.485*	-0.036	4.082*	1.402
	(0.069)	(2.171)	(0.845)	(0.069)	(2.294)	(0.924)
Cohort2*Year3	-0.006	4.887**	0.774	-0.003	4.447*	0.780
	(0.044)	(2.418)	(0.942)	(0.044)	(2.388)	(0.944)
Observations	2,738	2,734	2,737	2,711	2,707	2,710
R-squared	0.046	0.028	0.065	0.052	0.036	0.073
Number of Children	958	958	958	958	958	958
Controls for Income	NO	NO	NO	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES	YES
Mean of Matched	0.0949	8.634	2.096	0.0949	8.634	2.096

Standard errors are clustered at the household level
*** p<0.01, ** p<0.05, * p<0.1
Note: The dependent variables are "Extended Absenteism", indicating school absence of more than a week in the previous month, "HH Ag Activities", capturing time spent by children on household agricultural activities in hours, and "Other Activities", indicating time spent by children on other activities such as collecting water and firewood, in hours. The coefficients on "Cohort2*Year2" are placebo treatment effects used to test for conditional parallel trends. The coefficients on "Cohort1*Year2" capture the treatment effects for Cohort 1 in Year 2 and similarly for other interaction terms. Income is controlled for using 9 principal components which capture household food and non-food expenditure.)

From underemployment to a matched situation

We reverse the treatment logic to assess the impact of living in households comprised solely of matched adults, in comparison to previously living with one or more adults who were underemployed. Our conceptual framework suggests that this change of situation would likely decrease children's involvement in out-of-school activities and encourage greater participation in schooling. The few significant results in Table A2.2 are congruent with these expectations[12]. These results suggest that transitioning from a state of underemployment to a matched situation diminishes children's school absences (Column 4). However, these

[12]The results are based on ETWFE and PSM since the ETWFE alone does not pass the parallel trends test.

results are weaker than the previous ones as they are obtained for a substantially smaller sample of children (215 compared to 961 in Table 2.9) and do not generally pass the parallel trends test. Therefore, in what follows, we focus on cohorts 1 to 3 for which we have more degrees of freedom.

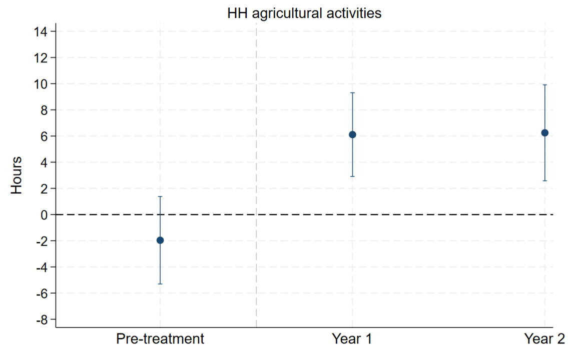
Year by year treatment: Callaway and Sant'Anna (CS) Estimator

We adopt an alternative approach introduced by Callaway and Sant'Anna (2021) to estimate the impact of underemployment. The CS estimator uses non-parametric estimation to compute group-time treatment effects. The estimator incorporates pre-treatment covariates by combining Inverse Probability Weighting (IPW) and outcome regression. Hence, the estimator is consistent if either the propensity score or the outcome regression is correctly specified, which implies that it is doubly robust.

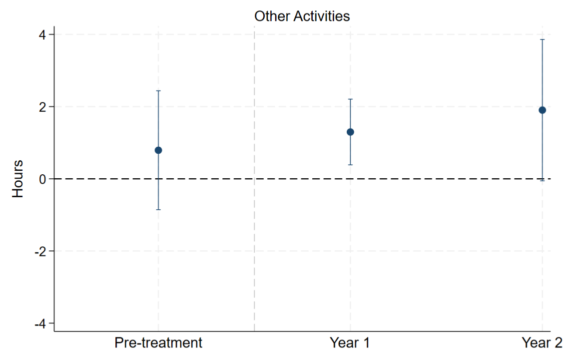
Despite employing a different methodology from the ETWFE, the CS estimator yields remarkably similar results. In Figure 2.2, we show a graphical representation of the results derived from the CS estimator where the impact from the first year of treatment is combined with the impact of the second year of treatment from Cohort 1 and Cohort 2, and all control variables are included[13]. Panel (a) indicates that when children transition from living with matched adults to living with underemployed adults, there is an increase in their involvement in household agricultural activities by approximately 6 hours in both the first and second years. Additionally, their participation in other activities rises by approximately 1 hour in the first year and nearly 2 hours in the second year (Panel (b)). However, this latter increase is not statistically significant at the 5% level (p-value = 0.057). Furthermore, there is no significant impact on school absenteeism in either the first or second year of treatment (Panel (c)). Figure A2.3 shows the results obtained when we dichotomize the dependent variables for the amount of time children spend on agricultural activities and other activities. These results suggest that underemployment not only increases children's involvement in agricultural work at the intensive margin (i.e. the number of hours worked) but also at the extensive margin, i.e. children begin to work in agriculture as a result of adult underemployment. Extensive margin results are not significant for other outcomes.

[13] We provide the corresponding regression results in Table A2.3

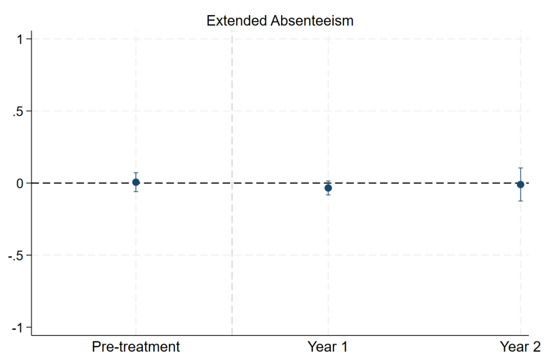
Figure 2.2: Impact of underemployment on schooling: CS (Cohorts 1 to 3)



Panel (a)



Panel (b)



Panel (c)

Notes: This figure shows the impact of exposure of children to underemployed adults on three different outcomes. Panel (a) indicates that when children transition from living with matched adults to living with underemployed adults, there is an increase in their involvement in household agricultural activities by approximately 6 hours in both the first and second years. Panel (b) indicates that their participation in other activities rises by approximately 1 hour in the first year and nearly 2 hours in the second year, but the latter effect is not significant at the 5% level. Panel (c) shows that there is no significant impact on school absenteeism in either the first or second year of treatment. Estimates are produced using the Callaway and Sant'Anna (2021) estimator.

Overall, the results above suggest that policies aimed at addressing underemployment could have a dual benefit, improving not only economic conditions but also educational outcomes. Furthermore, policies aimed at improving educational outcomes should consider the interplay between economic conditions and educational motivations at the household level.

Since the results relate to the influence of the state of the labor market on primary school level of education (and not the secondary or tertiary levels), the motivation for schooling is likely stemming mainly from adults rather than from children themselves. Hence, underemployment among adults could be leading to a diminished emphasis on the importance of schooling. This suggests that underemployment faced by adults not only affects income and job satisfaction as shown by the previous literature (For instance Pascual-Saez and Lanza-Leon (2023); Sam (2020) but may also affect educational priorities within households.

The results also provide a interesting perspective on the link between underemployment and educational outcomes in low-income setting. While previous research has established a connection between labor market conditions and education, this study's emphasis on underemployment, particularly in a low-income country setting, contributes to the previous literature that primarily focuses on the impact of unemployment on education in high-income countries (For example Clark (2011); Sievertsen (2016); Witteveen (2021)).

Heterogeneity by grade and by age

We examine the heterogeneity of the results by grade level of the child and by their age. It could be that the motivation channel is more effective as children get older and become more aware of the mismatch between adult occupations and their educational attainments. If this is the case, we should observe more pronounced treatment effects for older children or children in more advanced classes.

We analyze this dimension of heterogeneity by splitting the sample in two groups at the 50% percentile. For heterogeneity analysis with respect to grade, we split the sample between children in lower and higher grades, i.e. children in grades 1 to 4 on one hand and children in grades 5 to 8 on the other hand. For the heterogeneity with respect to age, the sample is divided between children aged 5 to 11 and children aged 12 to 18. The results, presented in Figure 2.3 for grade and Figure 2.4 for age, align with expectations to a certain extent. There is some evidence that as a child advances in their education level, the more they react to adult underemployment and engage more in HH agricultural activities. The evidence regarding age is less clear cut but also suggests that the older a child gets, the more they might engage in HH agricultural activities as a result of underemployment of adults in their household. However, results regarding other activities and extended absenteeism are not significant.

Heterogeneity by the type of relationship between the child and the underemployed person

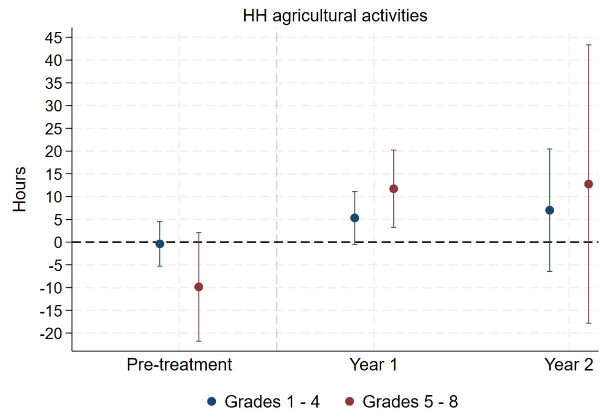
We consider the relationship of underemployed adults with the child whose education outcome we estimate. It could be that children react more to underemployment of parents more than that of other family members (See Table 2.4 for the full list of relationships in households). In our sample, heads of households, who are often the parents in the house, represent approximately 50% of the sample. Hence, we analyze the heterogeneity of the results with respect to heads of households and other household members[14]. Results are shown in Figure 2.6 and suggest that children react more strongly to underemployment of their parents more than other household members regarding engagement in household agricultural activities. The evidence for other household activities is weaker but points in the same direction, and the results of school absenteeism are not significant.

Taking into account migration

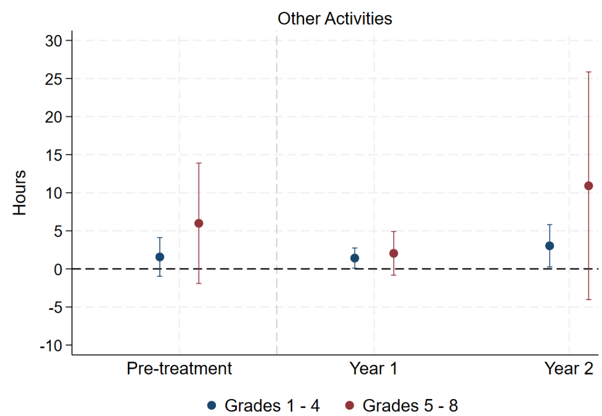
As stated earlier, part of the reason household treatment status changes is because a new member has joined the household or has left it. It could be that underemployment of new household members does not influence the education of children in the household as much as employment mismatch of adults who have been living in the household longer. We investigate this hypothesis by restricting the sample to individuals who have been part of the household

[14] It could also be that children are more influenced by employment mismatch of the first-degree family member more than other household members, however, the data at hand does not allow to analyze this dimension of heterogeneity.

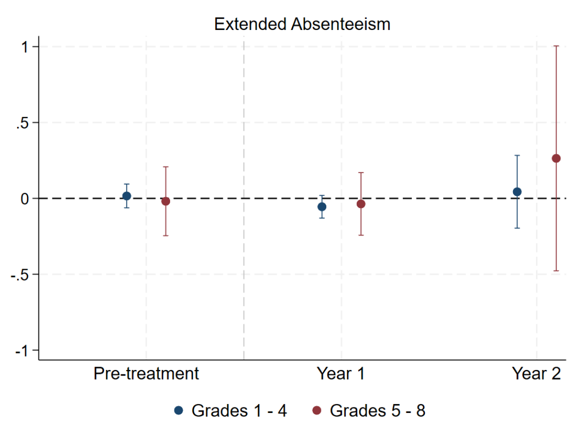
Figure 2.3: Impact of underemployment by grade of children



Panel (a)



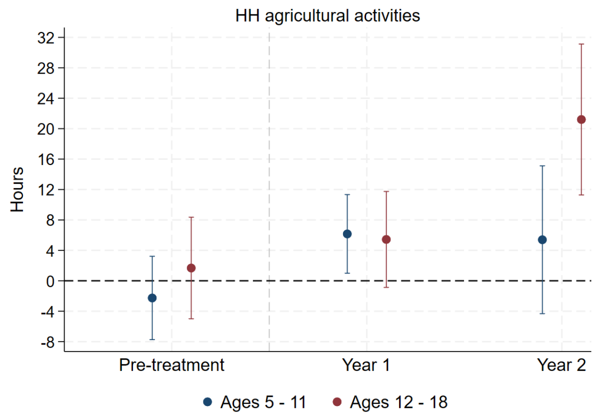
Panel (b)



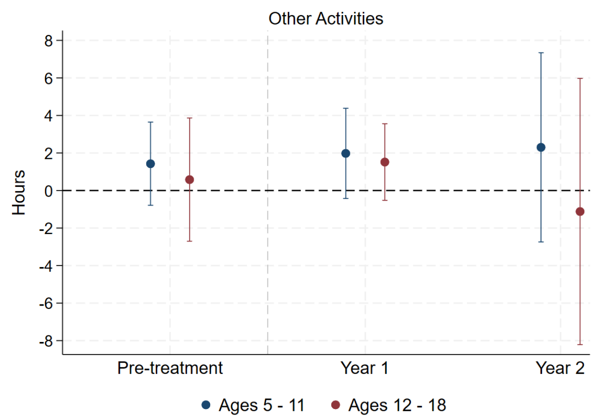
Panel (c)

Notes: These graphs show the impact of adult underemployment on children involvment in HH agricultural activities (Panel a), other household activities (Panel b) and extended absenteeism (Panel c). Point estimates in blue represent children in grade 1 to 4 and point estimates in red represent children in grade 5 to 8.

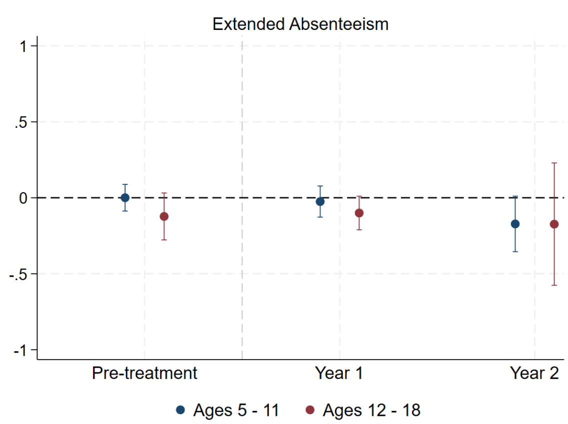
Figure 2.4: Impact of underemployment by age of children



Panel (a)



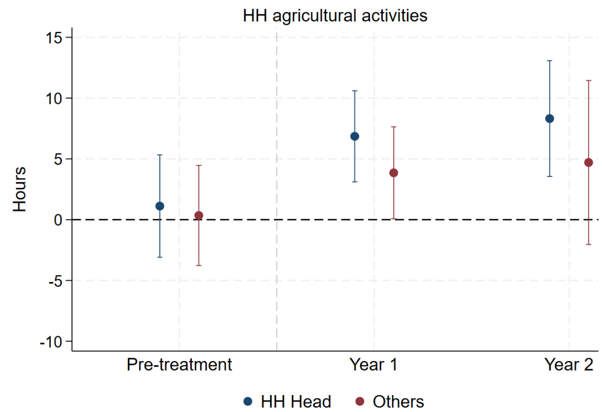
Panel (b)



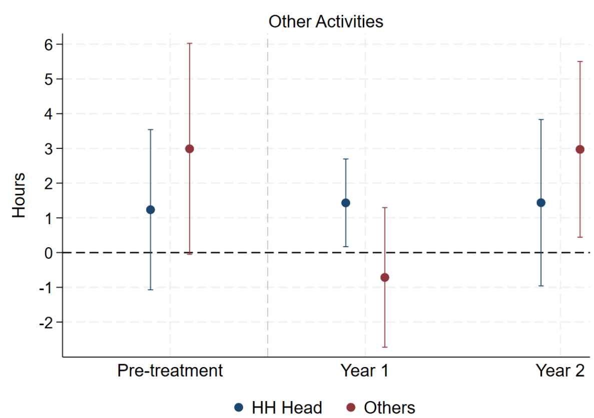
Panel (c)

Notes: These graphs show the impact of adult underemployment on children involvment in HH agricultural activities (Panel a), other household activities (Panel b) and extended absenteeism (Panel c). Point estimates in blue represent children aged 5 to 11 and point estimates in red represent children aged 12 to 18.

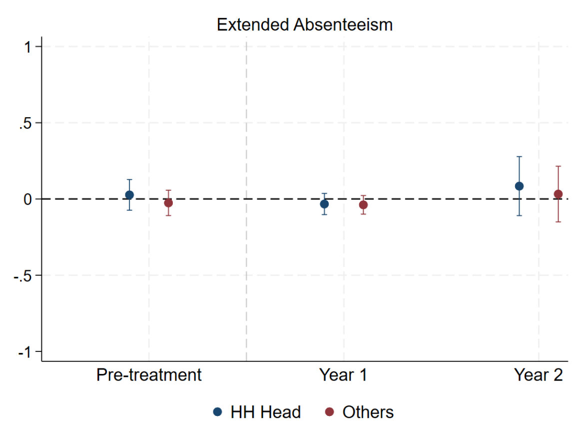
Figure 2.5: Impact of underemployment considering the relationship between the child and the underemployed person



Panel (a)



Panel (b)



Panel (c)

Notes: These graphs show the impact of adult underemployment on children involvment in HH agricultural activities (Panel a), other household activities (Panel b) and extended absenteeism (Panel c). Point estimates in blue represent children who live in households where one of the underemployed persons is the household head and point estimates in red represent children who live in households where underemployed persons exclude household heads.

for a minimum of one year. We then contrast the findings from this subgroup with those derived from a sample that includes all adults. Results, in Figure 2.6, indicate that results are mixed. It appears that children react more to underemployment of recent household members with respect to work in agriculture and react less with respect to other types of activities. Effects related to school absenteeism are not significant throughout.

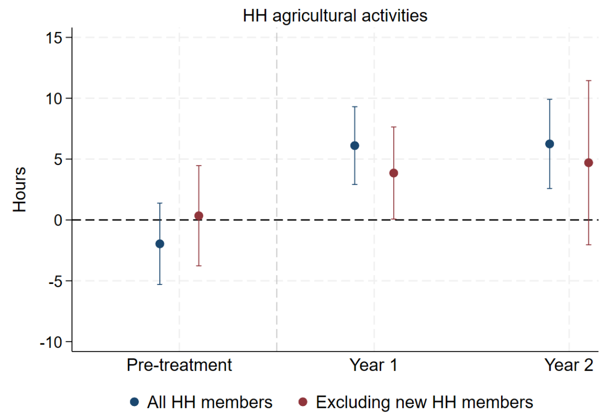
The effect of underemployment on excessive hours of work

It is reasonable to argue that not all forms of children's work have a detrimental effect on their education. If a child spends only a little time on such activities, it could even be beneficial, provided the work offers an opportunity to learn in different ways. For example, selling items in a shop could enhance mental calculation skills and develop soft skills. While there is a general consensus on the types of work children should not do, as codified under the Worst Forms of Child Labour Convention (ILO, 1999), including slavery, prostitution, illicit activities and dangerous work, there is less agreement on the acceptable amount of time children should spend on non-problematic work, referred to as "light work" under Article 7 of ILO Convention No. 138 (ILO, 2024).

For the specific case of children at the primary level, it is reasonable to assume that they should not work at all. However, one can also think that it may be good for them to work a little bit. In fact, research has investigated the threshold of work involvement for children, recognizing that this threshold may vary based on factors such as the child's age, the specific educational outcomes of interest (e.g., school attendance or learning outcomes), the structure of the school day and the type of work performed (Assaad et al., 2010). The latter study finds that child work negatively affects school attendance when it exceeds approximately 10 hours per week for girls and 14 hours for boys. For Dumas (2012), child work begins to detrimentally affect learning when more than 17 hours per week are spent on these activities. Having established standards on the matter of child labor, ILO defines work performed by "children aged 5-11 working at least 1 hour per week in economic activity and/or involved in unpaid household services for more than 21 hours per week" as child labor.

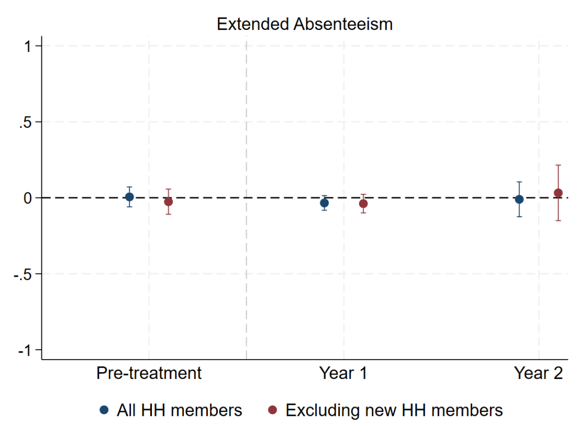
In this analysis, we use the ILO threshold, coding the number of excessive hours as 0 if the hours spent on household agricultural activities are below 22 hours and as 1 otherwise

Figure 2.6: Impact of underemployment considering migration



Panel (a)

Panel (b)

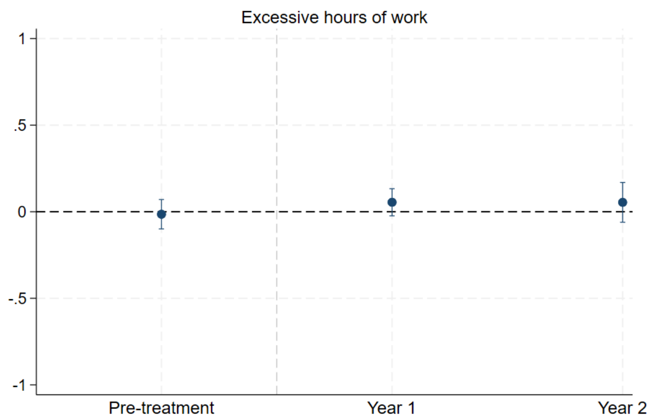


Panel (c)

Notes: These graphs show the impact of adult underemployment on children involvment in HH agricultural activities (Panel a), other household activities (Panel b) and extended absenteeism (Panel c). Point estimates in blue correspond to main results, which do not distinguish between new and existing household members, and point estimates in red represent children who live in households where underemployed persons exclude individuals who joined the household less than 12 months ago.

[15]. Figure 2.7 shows the results we obtained. We find that underemployment does not significantly affect excessive hours of work in household agricultural activities.

Figure 2.7: Impact of underemployment on excessive hours of work



Notes: This graph shows the impact of adult underemployment on children involvment in HH agricultural activities for more than 21 hours in the past week, the ILO threshold for determining child labor.

Sensitivity analysis of the main results

The primary findings reveal that children's transition from living with matched adults to residing with underemployed adults leads to an increased engagement in household agricultural activities of close to 6 hours per week in both the first and second years following the transition. Additionally, there is a noticeable rise in their participation in other activities, by approximately 1 hour in the first year and nearly 2 hours in the second year. The influence of underemployment on extended school absenteeism is not significant across all specifications.

We analyze the sensitivity of these main results to some working definitions adopted previously. We first analyze the sensitivity of the results with respect to the threshold for working in agriculture. As indicated in the data section, the main results are based on a threshold of 20 hours for classifying individuals as mainly working in agriculture. While this threshold may seem reasonable, it can also be viewed as arbitrary. Therefore, we present the

[15]We exclude other activities as they combine different types, some estimated for the past week and others for the past month

main coefficients of interest for thresholds between 1 and 40. Figure A2.4 shows the results we obtain. Results related to the number of hours children spend in agriculture suggest a positive correlation between the amount of time adults spend in agriculture and the amount of time children spend in related activities as a result of adult underemployment. However, this correlation is absent for other activities and school absenteeism.

Secondly, we analyze how the main results change when we consider a different classification of persons whose main activity is agriculture. In fact, in the International Standard Classification of Occupations (ISCO), occupations related to agriculture, forestry and fisheries can be found in groups 1, 2, 3, 6, 8 and 9 (ILO, ndb). While the distinction of different farming practices, such as subsistence farming and market-oriented farming, and different roles, such as managers and laborers, is useful, it is difficult to implement in practice. As a result, related national classifications vary around the world. Nonetheless, it could be argued that the distinction between skilled agricultural workers classified in group 6 and elementary agricultural workers in group 9 is important, if one views agriculture as a relatively complex activity. Having classified all agricultural workers thus far in group 9, given that we are in a developing country context, we analyze the sensitivity of the results to classifying them in group 6. Figure A2.5 compares results obtained when agricultural workers are classified in group 9 and results obtained when they are in group 6. Results for classifying agricultural workers in group 6 are not significant for all outcomes. This is not surprising given that to be classified as underemployed while your occupation is in group 6, one has to have at least a short cycle tertiary education, which is arguably too high in the context of this study. Table 2.6 shows that our sample comprises of less that 10% of adults with more than a secondary level of education. Therefore, the lack of significance shown in Figure A2.5 is probably due to the lack of degrees of freedom.

Limitations of the study

It would have been interesting to investigate the potential impact of underemployment on children's test scores. However, the absence of relevant indicators in our datasets limits this exploration. Furthermore, by influencing outcomes examined in this study, *i.e.* out-of-school activities and school absenteeism, underemployment could have more profound educational consequences, such as grade repetition and school dropout. To thoroughly examine these longer-term outcomes, more extensive data, encompassing more than the three waves currently available, would be required. Another limitation of this study is the potential influence of the employment status of adults outside the household, which our dataset does not account for. For instance, the underemployment of a sibling who migrated to the capital city for higher education but fails to find a job commensurate with their qualifications could affect the educational outcomes of their siblings who remained in the countryside. Such external influence is an aspect that could provide further insights into the labor market influence on education at the family level and not just the household level, but was not explored here due to data constraints. Finally, people may switch occupations due to seasonality. For example, a farmer might run a business outside of the agricultural season or take on a temporary job in a government project. Ideally, these temporary occupational changes should be excluded. One approach to address this is to use household information collected at nearly the same time each year. However, the dataset available does not include information on the timing of the interviews.

9 Conclusion

This paper investigates the impact of underemployment on children's schooling, in a low-income country setting: Ethiopia. The analysis shows that underemployment has significant repercussions on children's involvement in out-of-school activities, specifically household agricultural tasks and other activities like collecting water and firewood. These results suggest broad ramifications of underemployment in affecting the motivation of children for learning from school.

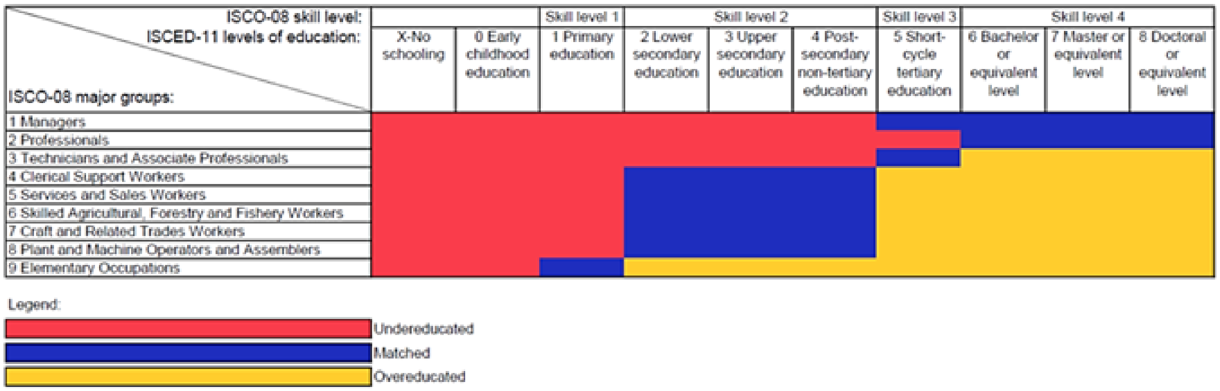
However, while underemployment was systematically linked with heightened participation in out-of-school activities, extended school absenteeism remained unaffected in most specifications. The absence of a significant impact of underemployment on prolonged school absenteeism might be due to the low number of children in the study who missed more than a week of school. However, it might also indicate a more complex relationship between underemployment and its effects. Instead of missing school, children might attend but with diminished learning experiences due to their increased household duties. The robustness of these findings across different estimators enhances the reliability of the results.

In highlighting the influence of underemployment on children's schooling in the context of low-income countries, this research diverges from previous studies which have focused on high-income countries in investigating the influence of the labor market on education. Considering the findings of this study, addressing underemployment could ameliorate educational outcomes in addition to improving economic conditions. Moreover, future interventions aimed at enhancing educational outcomes in developing nations should consider the challenges posed by underemployment. For instance, policymakers aiming to improve educational outcomes at the primary level often focus on interventions directly related to primary schools. However, the findings of this study suggest that efforts to enhance primary education should also consider the labor market outcomes of the adults living with these children, as the economic conditions of these adults may significantly impact children's educational achievements.

Future research avenues exploring the relationship between underemployment and education could include assessing the impact of underemployment on test scores as well as longer-term outcomes like grade repetition and school dropout rates. Furthermore, examining the external influence of household members who have migrated could yield interesting insights. Finally, investigating the effect of unemployment on education in high-income countries, by leveraging within household variation in schooling indicators, could be another interesting research direction.

10 Appendix

Figure A2.1: Correspondence between education and occupation based on ISCO-08 educational requirement



Source: ILO (nda).

Figure A2.2: Common support of PSM using cohorts 1 to 3

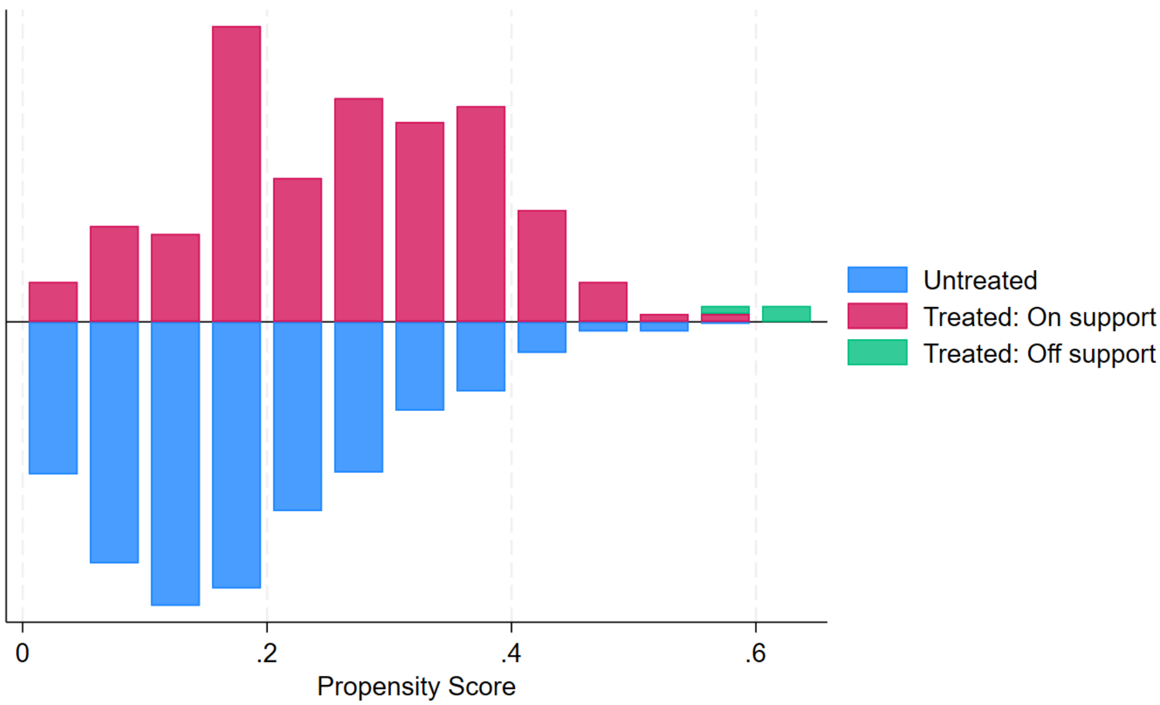


Table A2.1: Standard TWFE results: Cohorts 1, 2 and 3

VARIABLES	(1) HH Ag Activities	(2) Other Activities	(3) Extended Absenteism
Underemployment	4.864***	0.787	-0.031
	(1.664)	(0.490)	(0.028)
Observations	3,038	3,044	3,142
R-squared	0.033	0.066	0.044
Number of Children	1,129	1,129	1,129
Controls for Income	YES	YES	YES
Individual Fixed Effects	YES	YES	YES
Mean of Matched	8.756	2.004	0.0918

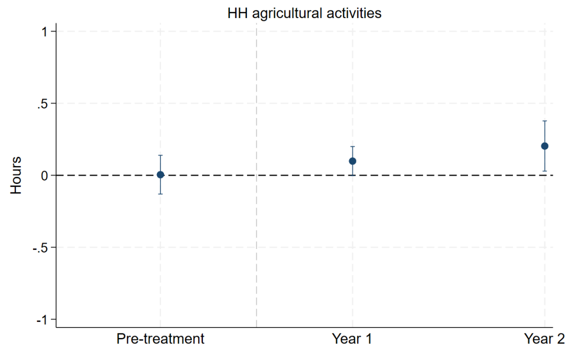
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The dependent variables are "HH Ag Activities", capturing time spent by children on household agricultural activities in hours, "Other Activities", indicating time spent by children on other activities such as collecting water and firewood, in hours and "Extended Absenteism", indicating school absence of more than a week in the previous month. Income is controlled for using 9 principal components which capture household food and non-food expenditure.)

Table A2.2: ETWFE and PSM: Cohorts 4, 5 and 6

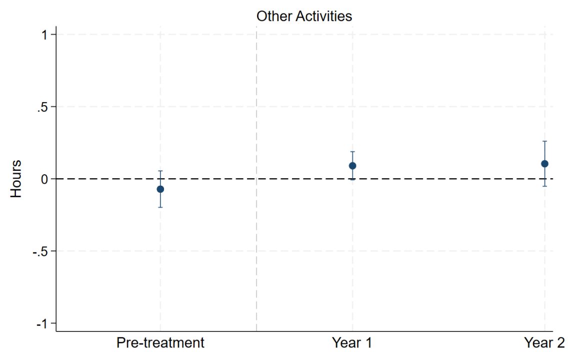
VARIABLES	(1) Extended Absenteism	(2) HH Ag Activities	(3) Other Activities	(4) Extended Absenteism	(5) HH Ag Activities	(6) Other Activities
Cohort2*Year2	-0.022	-6.379**	-2.748	-0.016	-7.276**	-3.233*
	(0.053)	(3.166)	(1.762)	(0.056)	(3.381)	(1.773)
Cohort1*Year2	-0.107*	-4.016	-2.807**	-0.109*	-4.977*	-2.992**
	(0.060)	(2.761)	(1.394)	(0.063)	(2.904)	(1.433)
Cohort1*Year3	-0.113*	-2.093	0.268	-0.118**	-2.078	0.503
	(0.058)	(3.179)	(1.628)	(0.059)	(3.063)	(1.602)
Cohort2*Year3	0.022	-9.410**	0.154	0.010	-7.929**	0.719
	(0.064)	(3.811)	(1.462)	(0.064)	(3.796)	(1.679)
Observations	617	617	617	609	609	609
R-squared	0.101	0.040	0.050	0.125	0.074	0.074
Number of Children	215	215	215	215	215	215
Controls for Income	NO	NO	NO	YES	YES	YES
Individual Fixed Effects	YES	YES	YES	YES	YES	YES
Mean of Matched	0.0476	9.043	1.153	0.0476	9.043	1.153

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The regressions in this table correspond to the impact of transitioning from living in a household with one or more underemployed adults to living with matched adults only. The dependent variables are "Extended Absenteism", indicating school absence of more than a week in the previous month, "HH Ag Activities", capturing time spent by children on household agricultural activities in hours, and "Other Activities", indicating time spent by children on other activities such as collecting water and firewood, in hours. The coefficients on "Cohort2*Year2" are placebo treatment effects used to test for conditional parallel trends. The coefficients on "Cohort1*Year2" capture the treatment effects for Cohort 1 in Year 2 and similarly for other interaction terms. Income is controlled for using 9 principal components which capture household food and non-food expenditure.)

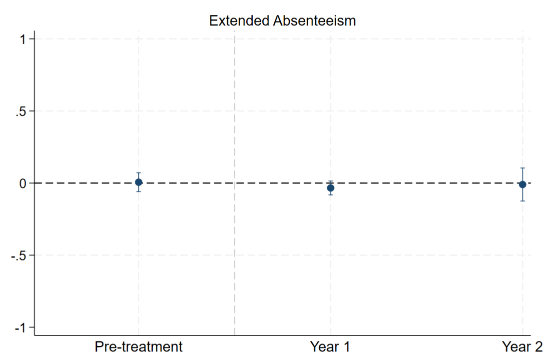
Figure A2.3: Impact of underemployment on schooling: binary dependent variables



Panel (a)



Panel (b)



Panel (c)

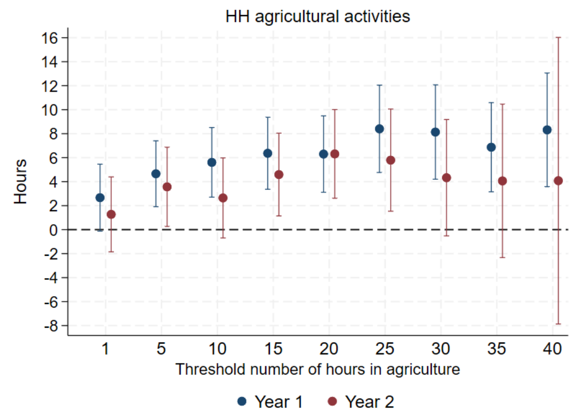
Notes: This figure shows the impact of exposure of children to underemployed adults on three different binary outcomes. Panel (a) indicates that when children transition from living with matched adults to living with underemployed adults, they tend to start working in agricultural. Panel (b) indicates that their participation in other activities is not affected. Panel (c) shows that there is no significant impact on school absenteeism. Estimates are produced using the Callaway and Sant'Anna (2021) estimator.

Table A2.3: Impact of underemployment on schooling: CS (Cohorts 1 to 3)

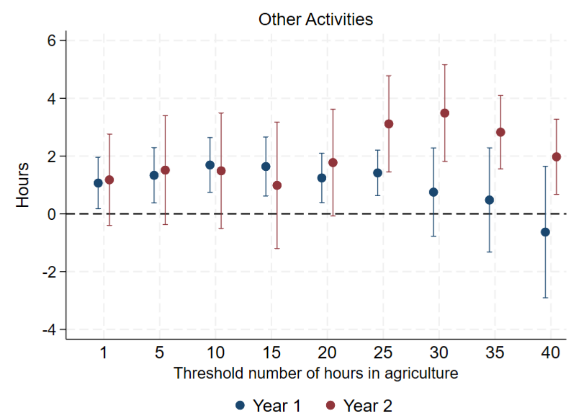
	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
Panel 1: Household Agricultural Activities						
Pre-average	-1.96178	1.704933	-1.15	0.25	-5.30339	1.379828
Post-average	6.178371	1.344971	4.59	0	3.542276	8.814465
Pre-treatment year	-1.96178	1.704933	-1.15	0.25	-5.30339	1.379828
First year of treatment	6.10865	1.630932	3.75	0	2.912082	9.305217
Second year of treatment	6.248092	1.869861	3.34	0.001	2.583232	9.912952
Panel 2: Other Activities						
Pre-average	0.791386	0.840158	0.94	0.346	-0.85529	2.438065
Post-average	1.600015	0.650713	2.46	0.014	0.324641	2.875388
Pre-treatment year	0.791386	0.840158	0.94	0.346	-0.85529	2.438065
First year of treatment	1.297053	0.464577	2.79	0.005	0.3865	2.207607
Second year of treatment	1.902976	0.999122	1.9	0.057	-0.05527	3.861219
Panel 3: Extended Absenteeism						
Pre-average	0.005821	0.033448	0.17	0.862	-0.05974	0.071377
Post-average	-0.02205	0.036358	-0.61	0.544	-0.09331	0.049211
Pre-treatment year	0.005821	0.033448	0.17	0.862	-0.05974	0.071377
First year of treatment	-0.03398	0.024701	-1.38	0.169	-0.0824	0.014428
Second year of treatment	-0.01011	0.058473	-0.17	0.863	-0.12472	0.104492

Note: This table shows CS results for cohorts 1, 2 and 3. In Panel 1, the outcome is Household Agricultural Activities. In Panel 2, the outcome is Other Activities and, in Panel 3, the outcome is Extended Absenteeism. The results include the full set of control variables.)

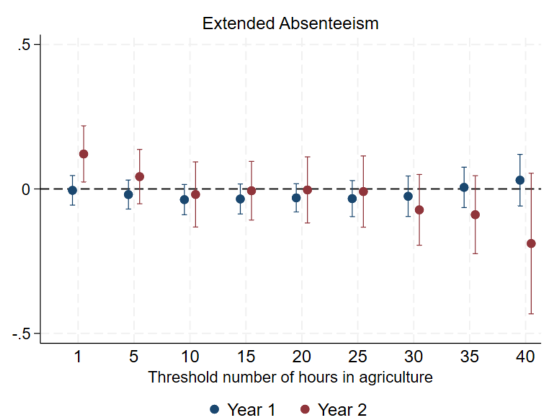
Figure A2.4: Sensitivity of the main results with respect to the threshold for classifying individuals as working in agriculture



Panel (a)



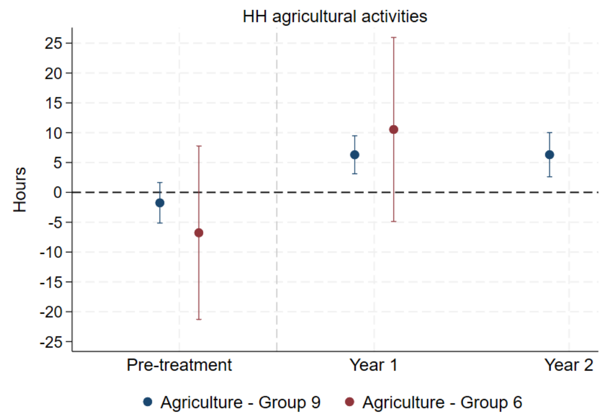
Panel (b)



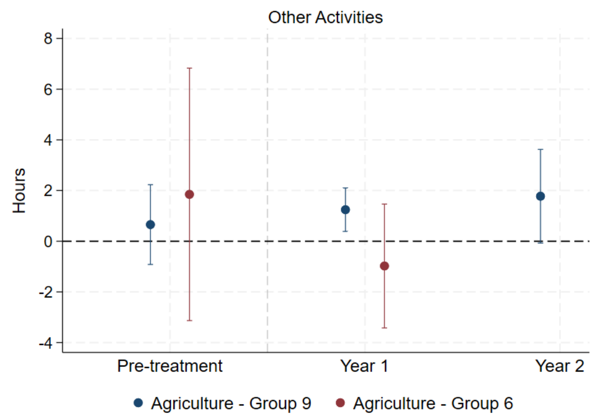
Panel (c)

Notes: These graphs show the impact of adult underemployment on children involvment in HH agricultural activities (Panel a), other household activities (Panel b) and extended absenteeism (Panel c). Point estimates in blue correspond to year 1 effects and point estimates in red represent year 2 effects. The x axis indicates the minimum number of hours required for classifying an individual as working in agriculture.

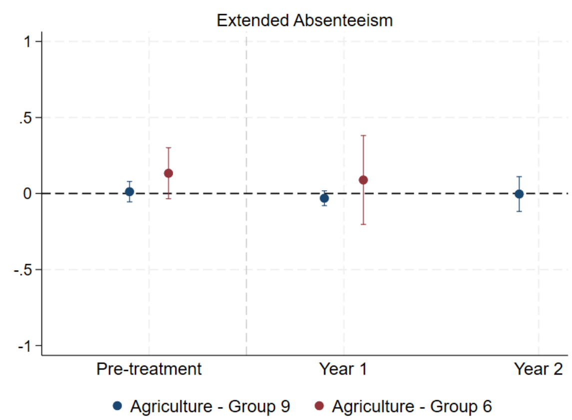
Figure A2.5: Sensitivity of the main results to an alternative classification of agriculture



Panel (a)



Panel (b)



Panel (c)

Notes: These graphs show the impact of adult underemployment on children involvment in HH agricultural activities (Panel a), other household activities (Panel b) and extended absenteism (Panel c). Point estimates in blue represent results obtained when agriculture is classified in group 9 (main results) and point estimates in red represent results obtained when agriculture is classified in group 6.

Chapter 3

Under-training by Employers in General Skills: Evidence from Spot Labor Markets in Burundi

With Nicholas Swanson, Luisa Cefala and Pedro Naso

1 Introduction

A defining feature of labor markets in low and middle-income countries is that they are often organized via short-term informal spot contracts. In many cases, contracts last only a few days and workers are frequently re-matched with different employers. Such spot markets are the primary source of employment for hundreds of millions of workers in LMICs (Kaur, 2019; ILO, 2018).[1] The lack of a longer-term relationship between worker and employer generates the scope for distortions: an employer may find it unprofitable to invest in training workers, since she would not capture the future returns of such training.[2] In these markets, this appropriability problem could have substantial consequences for the level of human capital in the workforce and, consequently, productivity.[3]

The idea that firms might limit training investments because they fail to capture the returns is a classic labor economics theory and has spawned a sizable theoretical literature (Pigou, 1912; Becker, 1964; Acemoglu, 1997; Acemoglu and Pischke, 1999a,b). However, there remains limited empirical evidence in rich or poor countries that under-investment in general human capital by employers generates meaningful distortions in the economy.

This paper tests whether there is under-investment in general skills training within agricultural labor markets in Burundi. In this and related agricultural settings, increased agricultural productivity requires training workers in improved, labor-intensive agricultural techniques.[4] We focus on one such technique, row planting, that has been shown to increase yields by 30-70% in a similar setting (Dusabumuremyi et al., 2014), and is widely promoted by international organizations and governments in Sub-Saharan Africa (Vandercasteelen et al., 2014). However, adoption remains limited in Burundi: few farmers use the technique on all of their fields at baseline and scarcity of skilled labor is mentioned by a majority of agricultural employers as a reason for limited adoption. Despite this, there is little training of local

[1] For example, 98% of agricultural employment in India is through casual labor contracts (Kaur, 2019).

[2] Because of the high level of turnover in these labor markets, the employer may not capture the returns from training even if the worker is not the full residual claimant of the returns.

[3] This may be exacerbated in LMICs, in which firms are an important source of human capital investments, due to lower levels of formal education (Lucas, 2015).

[4] Examples of such technologies include demi-lunes (Aker and Jack, 2021) and pit planting techniques (BenYishay and Mobarak, 2019; Beaman et al., 2021).

workers by agricultural employers. While 64% of agricultural employers in our sample state that they are capable of training workers in row planting, only 18% have done so (Figure A3.3), with the majority citing the appropriability problem as a rationale for not training (Figure A3.4).[5]

We hypothesize that agricultural employers (farmers) desire to adopt row planting and could do so if there was sufficient skilled labor in the village. However, agricultural employers do not train workers because they cannot capture the returns from the training, *i.e.* they cannot guarantee the ability to re-hire those workers during planting time in the future.[6]

We test this hypothesis through two field experiments in rural Burundi. In the first experiment, we test for the existence of the appropriability problem. In some local labor markets (here, villages), we induce some employers to train local workers in row planting and observe the general equilibrium response in the labor market. We then measure who captures the returns from training: the employer who provided the training, other employers (who may poach the trained worker), and the worker herself (whose wage might increase).

In the second experiment, we test whether solving the appropriability problem induces employers to invest in training. To do this, we use our partnership with an international NGO called One Acre Fund (1AF), operating in Burundi, to introduce a contract that makes it more likely that the employer can hire the worker in the future. We then measure whether this contract leads more employers to teach workers row planting techniques.

We conduct these field experiments among farming communities in Burundi, in collaboration with the country office 1AF. Within these communities, we can categorize farmers into two groups that align with the classical training framework: large farmers, who cultivate and regularly employ labor, and laborers, who are subsistence farmers that also work on other farmers' fields. These communities are well suited to documenting the spillovers from training, since doing so requires an environment consisting of small, isolated labor markets in

[5]Because planting occurs at short notice once the rains arrive, training would need to be done in advance of the agricultural season, and employers mention it is difficult to guarantee that a trained laborer would return once planting starts.

[6]This requires an inability to write and enforce intertemporal contracts. We see this in our setting. For example, more than half of employers report workers not showing up for work after being contracted in advance.

which, if firms train, the returns to training can be measured for training firms, workers, and non-training firms in the same market. We find these conditions in Burundi: each village in this context represents a local labor market, allowing us to assess both direct and spillover impacts of training.

In the first experiment, the "Spillover Experiment", we test for the presence of two features of a market featuring under-investment in general skills. We first show that when training happens, workers and non-training firms capture a large portion of the returns. We then show that the aggregated returns are greater than the cost of training, meaning that training is underprovided. We conduct the Spillover Experiment in 80 villages (locally called *sous-collines*) in rural Burundi and survey more than 3,600 farmers. The village-level treatment is implemented as follows. Within each village, we incentivize some employers (trainer-employers) to invite a laborer (trainee) to an event in a central location several months prior to the planting season. We randomize villages into one of two conditions that generate different incentives for trainer-employers to train the identified worker. In the control condition, we provide a short training on a non-relevant technique, and then enumerators suggest that the trainer-employer could also train the trainee in row planting,[7] before giving the trainer-employer an unconditional financial transfer. In the *T1-Financial incentives to Train* condition, we augment the control condition by making the payment that is given to trainer-employers in the control villages conditional on training the trainee for at least half a day. Several months after the training event, during the next planting season, we measure the hiring, employment, technology adoption, and farm profitability of trainer-employers, trainees, and *spillover-employers* –employers uninvolved in the training– to measure who captures the returns from training.

In the paper's first main finding, we demonstrate that when farmers train laborers, there are large returns, but a sizable proportion of these returns spillover to others. There is a strong first-stage in treated villages: trainer-employers in T1-Financial incentives to Train villages are almost 80 percentage points more likely to train their trainees than their counterparts in control villages. This training is effective and generates an increase in the amount of

[7] The training also involved fertilizer microdosage, a complementary agricultural practice.

skilled labor in these villages. Trainees in treated villages work on average 3.4 more days for employers doing row planting tasks (p<0.01) and earn 8.2% higher wages during the agricultural season (p=0.02) than trainees in control villages. Trainees also adopt row planting on their own farms, planting 1.3 more of their own fields using row planting in treated villages (p<0.01).

We then document that the increase in skilled labor generates sizable labor market spillovers to other employers in treated villages who are uninvolved in training. While trainer-employers in treated villages hire 46% more days of labor to do row planting (p<0.01), which enables them to adopt row planting on 19% more fields (p<0.01), spillover-employers in treated villages hire 55% more days of labor to do row planting (p<0.01), which enables them to adopt row planting on 24% more fields (p<0.01).[8]

After showing evidence of spillovers from training to workers and other employers, we quantify the returns to training by measuring the change in total agricultural earnings in treated villages.[9] Farm profitability increases by 10.8% (p=0.05) on average for those in treated villages in our sample. This effect is driven by all groups: profits of trainer-employers, spillover-employers and trainees increase by 9%, 9.6% and 14.2% respectively (p=0.08, 0.10 and 0.04).[10] We test whether there is under-investment in training by aggregating the increase in earnings in treatment villages and comparing it to the cost of training. We estimate a benefit-cost ratio of 3.2, suggesting that a dollar of training investment generates 3.2 dollars of returns. Almost half of this surplus, however, accrues to *spillover-employers*.[11]

What constrains employers' training investments in a market where employers' profits increase if they hire trained workers? Given the large spillover effects to other employers

[8]We augment survey measures with field visits to randomly audited fields and find they are consistent, suggesting that the results do not reflect demand effects or reporting biases.

[9]The increase in earnings includes both labor market earnings and farm profitability. We measure farm profitability directly using farm revenues and subtract all input costs and labor costs. More details are provided in the relevant sections of the paper.

[10]The effect for trainees is driven in part by increased on-farm labor supply. Total labor market earnings for trainees in treated villages also increase by 20% (p=0.02).

[11]This is driven by the fact that non-training employers increase farm profitability and are a large share of the sample.

in the Spillover Experiment, and our motivating evidence suggesting that employers believe that workers will not return after being trained, we hypothesize that employers do not train workers because of the high likelihood that workers do not return to employers after being trained.

We test this hypothesis in a second experiment, the "Contract Experiment". In this experiment, we create a contract that farmers might struggle to replicate, which makes it more likely that workers will work for particular employers during the planting season. To implement the Contract xperiment, we recruit a sample of trainer-employers and trainees in different villages using the same protocol as the Spillover Experiment. We then randomly assign farmers to one of two conditions. In a control group, trainer-employers are told that the trainee they identified will receive an unconditional cash transfer during the planting season. In the contract treatment group, trainer-employers and trainees are told that the trainee they identified will receive a cash transfer during the planting season only if the trainee returns to work for the farmer during the planting season for two days.[12] We then offer a training event in which trainer-employers in both conditions are invited to attend to train their workers, but we provide no other incentives to train.

In our next main result, we find that this contract, designed to allow farmers to capture more of the returns from training, substantially increases farmers' willingness to train. Trainer-employers in the contract treatment group are more than 50 percentage points more likely to attend the training event for half a day or more (a relevant benchmark as used to measure training in the Spillover Experiment). To show that this attendance translates into skill transfer, we document that 35% more trainees in the treatment group use the trained techniques either on their own fields or working for other employers (*i.e.*, beyond the contracted employer) during the following planting season. This result indicates that farmers believe there are positive returns to training but only train in circumstances when they know they can appropriate the returns.

We explore several alternative explanations for the findings in both experiments. We show

[12]The amount of money offered per day –a top-up of around 70% of the daily wage– is designed to be not so large that it distorts hiring decisions meaningfully but large enough to credibly increase the probability that a worker will work for a particular employer.

that the effects in the Spillover Experiment are unlikely to reflect salience or social learning, revelation of unobserved worker heterogeneity, or heightened signaling of the technology caused by the training event. Additionally, we find limited evidence that the treatment effects in the Contract Experiment can be attributed to demand effects, trainee investments in training due to eased liquidity constraints, or changes in wage bargaining dynamics.

Finally, we provide qualitative evidence for which features of the market limit worker investments in training and restrict employers and workers from writing contracts leading to efficient training investments. We find two contracting frictions in our setting that limit the scope for efficient training investments.[13] First, the majority of laborers state that they do not want to make upfront payments for training since employers might not train them well,[14] and are also limited in their ability to pay by liquidity constraints. While this could be partially overcome through a contract structure with backloaded payments for training,[15] the majority of trainer-employers perceive that once trained, trainees would likely renege on such an agreement.[16] These contracting frictions, coupled with the sizable surplus that is generated from training, suggest that relying on decentralized transmission of new skills may be infeasible in environments with weak contract enforcement and a lack of generalized trust, even when the returns are high. This points to a potentially important role for coordinated or centralized policies that lead to skill transmission, such as coordinated investments in training or, more generally, policies that incentivize individuals who have skills or the know-how to utilize new technologies to disseminate these among the population.

The remainder of the paper proceeds as follows. Section presents the related literature. Section 3 provides a simple conceptual framework for our treatments and describes the main

[13]These results are potentially surprising given that one generally expects such frictions to be overcome through relational contracts, particularly in a village setting. However, we document that there is limited social capital among employers and employees, a fact that is possibly due to their different positions in the social hierarchies in the village. Contracting frictions in village settings have been shown to lead to inefficient contracting in other settings (Anderson, 2011; Bubb et al., 2018).

[14]This problem is compounded by the fact that trainees do not know what it is they should learn and have limited recourse if they are not trained well. This problem could be overcome by employers developing a reputation for providing good training. This anecdotal evidence suggests that this has not happened yet in this environment.

[15]For instance, through lower future wages.

[16]These findings are consistent with related research in LMICs demonstrating that contracting frictions can generate meaningful distortions to decision-making and reductions in total surplus (Blouin, 2022; Bubb et al., 2018; Macchiavello and Morjaria, 2023).

empirical predictions we test. Section 4 discusses the geographic and economic context of our project and describes our sampling frame. Section 5 discusses the experimental design. Section 6 outlines the data and our empirical strategy. Sections 7 and 8 show the paper's core results for the Spillover and Contract experiments respectively. Section 9 discusses alternate explanations. Section 10 discusses the generalizability of the results, and Section 11 concludes.

2 Related Literature

This project speaks to several literatures. We contribute to a long theoretical and empirical literature on training investments in general skills and firm training impacts. While a substantial theoretical literature has long argued that firms are likely to underinvest in training their workers in general skills (Pigou, 1912; Becker, 1964; Acemoglu, 1997; Acemoglu and Pischke, 1998, 1999a,b), some empirical papers have shown that firms invest in general skills beyond a level that is offset by lower wages (Loewenstein and Spletzer, 1999; Autor, 2001).[17] Our paper contributes to this literature by documenting under-investment in training and suggesting that some of this is driven by "poaching externalities."

A related empirical literature documents the returns to training interventions and highlights the barriers to firm investments in training in these environments (Card et al., 2011, 2018; McKenzie, 2017). Recent contributions to this literature have documented that firms in numerous low-income country contexts appear unwilling to invest in training employees (Alfonsi et al., 2020; Caicedo et al., 2022), and two recent papers suggest that worker-firm separation may limit training investments (Brown et al., 2024; Adhvaryu et al., 2023).[18] We contribute to this literature by testing for spillovers to other firms from training and showing that if firms believe workers are less likely to leave, then they become more willing to train

[17] Another strand of literature has shown theoretically and empirically the distinct mechanism that firms may underinvest in hiring novices because there is worker heterogeneity in the type that is revealed through hiring (Pallais, 2014; Terviö, 2009).

[18] Brown et al. (2024) show that conditional financial incentives for firms can lead them to train more and generate large returns for trainees and suggests that worker separation from the firm may limit firm investments in training ex-ante. Adhvaryu et al. (2023) finds in an experiment that managers do not select to train employees with the highest returns and argues that this is because the employees with the largest returns are more likely to separate from the firm after training.

them.

This paper also contributes to a literature on labor markets in developing countries. A key feature of these markets is that they are often organized as spot markets. Past work has highlighted potential advantages of short-term contracts–for example, the ability of the labor market to flexibly respond in the face of shocks (Rosenzweig, 1988; Breza et al., 2021). However, there has been little empirical work studying possible distortions that may arise from short-term informal contracting.[19] We highlight that this feature of developing country labor markets could be consequential for contributing to low labor productivity through a mechanism of low on-the-job learning by workers.

This paper also speaks to a long literature on the barriers farmers face in adopting improved agricultural technologies (Duflo et al., 2011; Bridle et al., 2020). A vast amount of prior research has proposed that credit (Jack, 2013), risk (Karlan et al., 2014), behavioral frictions (Duflo et al., 2011) or information markets (Foster and Rosenzweig, 1995) might hinder the adoption of new technologies (see De Janvry et al., 2017, for a review). A well-documented literature has also explored the returns to training interventions of new technologies (Aker and Jack, 2021; Barrett et al., 2022; Islam and Beg, 2021; Kondylis et al., 2017). However, only nascent literature has suggested that frictions in the labor market may pose meaningful constraints to adoption (Jones et al., 2022).[20] We contribute to this literature by showing clean evidence for one particular labor market friction generating meaningful distortions in the decisions of farmers about whether to adopt new agricultural techniques.

Finally, we contribute to a literature on social learning and information diffusion in agriculture (Griliches, 1957; Conley and Udry, 2010; Foster and Rosenzweig, 1995). We also build on a recent strand of literature that has considered which types of farmers are best able to diffuse agricultural information and under which conditions this diffusion is successful (BenYishay and Mobarak, 2019; Behaghel et al., 2020; Beaman et al., 2021; Chandrasekhar et al., 2022). We contribute to this literature by proposing a novel mechanism

[19] There is a large literature on the costs associated with informality in general. For examples, see (Ulyssea, 2020; La Porta and Shleifer, 2014).

[20] In a non-agricultural setting, Atkin et al. (2017) suggests that misalignment of employers and employees' incentives is an important labor market constraint limiting the adoption of profitable technologies in manufacturing.

that might limit those who hold information related to new technologies from diffusing it more widely.

3 Conceptual Framework

This section provides a simple framework to illustrate that spillovers may arise from training to non-training firms, that this spillover may limit training and that training investments in such an environment maybe inefficient. The framework used is based on Acemoglu (1997) models of frictional labor market and general human capital investments. We first illustrate that the level of training in such an environment maybe lower than the first best. We then use this framework to illustrate the effects of two shocks that we use to motivate our experimental treatments. First, we show that a shock to the level of training changes returns for workers, training and non-training firms. Second, we show how a change to the separation rate in this environment changes firms' willingness to train.

3.1 A stylized model of General Skills Training

We use the model of general skills investments with labor market frictions, such as those in Acemoglu (1997); Acemoglu and Pischke (1998, 1999a,b). These models demonstrate that, because of a compressed wage structure, firms might invest in training their workers in general skills. However the level of training firms invest in may be less than the social optimum because some of the returns to training accrue to workers, or other firms. In the following section we use a stylized version of the model in Acemoglu and Pischke (1999b) to illustrate investments in training and surplus generated in the environment.

To match the stylized facts in this environment, we assume in this version of the model that only firms will make investments in general skills training. More generally, this assumption could be microfounded by assuming that the worker is severely liquidity constrained, or by assuming that in the environment contracts are incomplete and cannot enforce transfers from the worker to the firm in the event they leave the firm after being trained.

The model consists of two periods. We assume there are three actors: a firm i who trains, a firm j who does not train and a worker. We assume that the marginal product of the worker is $f(\tau)$, with $f'(\cdot) > 0$ and $f''(\cdot) < 0$. For firms, we assume there is a cost of training, where $c'(\cdot) > 0$ and $c''(\cdot) > 0$. In period 1, production is normalized to 0 and the worker earns wage W. Firms choose to invest in a worker training level τ at a cost $c(\tau)$.

We assume that in period 2, there is a probability q that the worker is separated from the firm. In period 2, the worker can also quit and search for another job. If the worker quits or is separated, they are able to match with another firm with probability p_w. If the worker does not match with another firm, we assume that they earn nothing.

Firms when matched with workers determine wages by nash bargaining. The parameter β captures the portion of rents that workers capture. Therefore the outside option of the worker in period 2 is $v(\tau) = p_w \beta f(\tau)$. There is wage compression if $p_w < 1$ or $\beta < 1$.

One can then show (See 14) that the level of training chosen by the firm and social planner respectively satisfy:

$$f'(\tau^1) = c'(\tau^1) \tag{3.1}$$

Social Planner

$$(1-q)(1-\beta)\left(f'(\tau^*) - \left(p_w \beta f'(\tau^*)\right)\right) = c'(\tau^*) \tag{3.2}$$

Firm

Specifically training is lower than the first best because: i) worker's capture some of the returns from training through an improved outside option $v(\tau)$, ii) worker's capture some returns from bargaining over rents β and iii) other firms may capture some returns when the worker is separated from the firm with probability q.

3.2 Spillovers from Training

We use the framework above to generate simple predictions regarding the incidence of a subsidy paid to firms to train workers on the returns from training in response to the offer.

Specifically, consider a subsidy S paid to a firm conditional on offering a level of training τ_1 that is (slightly) higher than the market equilibrium level τ^*. We introduce the notation $\Delta f(\tau_1) = f(\tau_1) - f(\tau^*)$ to simplify notation going forward.

Firms train if

$$(1-q)(1-\beta)(\Delta f(\tau_1) - \Delta v(\tau_1)) + S \geq \Delta c(\tau_1)$$

and the total returns from an increase in training can be written as

$$= \underbrace{(1-q)(1-\beta)\Big(\Delta f(\tau_1) - \Delta v(\tau_1))\Big) - \Delta c(\tau_1)}_{\text{A - Profits of training firm}} + \underbrace{qp_w(1-\beta)\Delta f(\tau_1)}_{\text{B - Profits of non-training firm}}$$
$$+ \underbrace{(1-q)\beta\Big(\Delta f(\tau_1) - \Delta v(\tau_1)\Big) + qp_w\beta\Delta f(\tau_1)}_{\text{C - Earnings of Trained Workers}}$$

Implying that the initial level of training was inefficient if:

$$= \underbrace{(1-q)(1-\beta)\Big(\Delta f(\tau_1) - \Delta v(\tau_1))\Big)}_{\text{A - Profits of training firm (excluding training cost)}} + \underbrace{qp_w(1-\beta)\Delta f(\tau_1)}_{\text{B - Profits of non-training firm}}$$
$$+ \underbrace{(1-q)\beta\Big(\Delta f(\tau_1) - \Delta v(\tau_1)\Big) + qp_w\beta\Delta f(\tau_1)}_{\text{C - Earnings of Trained Workers}} \geq \underbrace{\Delta c(\tau_1)}_{\text{D - Cost of Training}}$$

This leads to our first two predictions:

Prediction 1 *Training generates spillovers to those not incurring the training cost.*

Prediction 2 *Training is underprovided.*

Specifically, the earnings of trained workers rise as the wage rises, and the combination of a positive separation rate and wage compression entail that other firms capture some of the returns of a given firm's training when they hire these. Moreover if these returns, plus the returns of the training firm, are larger than the cost of training, then the level of training in the economy is inefficiently low.

Finally, differentiating the firm's first order condition (3.2) with respect to the separation rate q yields the following comparative static, and prediction:

$$\frac{\partial \pi(\tau)}{\partial q} = -(1-\beta)\left(f'(\tau^*) - \left(p_w \beta f'(\tau^*)\right)\right) - c'(\tau^*) < 0$$

Prediction 3 *An increase (reduction) in the separation rate decreases (increases) firm training investments.*

In a frictional labor market in which employers capture returns from training when matched with a skilled worker, reducing the probability of separation increases the expected surplus from training.

4 Context

In this section we provide a brief overview of the context of the experiment. Additional context is provided in Section 15 in the appendix.

4.1 Agriculture in Burundi

We conduct this experiment with farming households in Muramvya and Gitega provinces, Burundi. The vast majority of the Burundian agriculture is rain-fed and, although the climate is favourable for production, yields are low. In 2018, average maize and bean yields were equal to approximately 1.53 tonnes and 0.66 tonnes per hectare, which are among the lowest yields in the world for these two crops (Ritchie and Roser, 2013).[21]

This project follows the course of two agricultural seasons in Burundi. Farmers plant their fields at the onset of rains, in a short window –typically of around one to two weeks following

[21] The average yield production in the world in 2018 was equal to 5.92 tonnes and 0.88 tonnes per hectare, for maize and beans respectively (Ritchie and Roser, 2013).

the onset of rains– during which they must finish planting since the season is short.[22] Planting is also relatively time intensive as compared to other tasks required during the season, such as field preparation and weeding. Interviews with farmers and 1AF field officers suggest that they expect around 50% of total labor input for the season to be required during the relatively narrow window for this task.

This generates an environment with two key features. First, the demand for laborers to assist with planting is concentrated within a very narrow window after the onset of rains. Second, while this planting labor has potentially high returns, it is used only for a week or two each agricultural season after the onset of rains[23].

4.2 Row Planting and Fertilizer Microdosage

The training that is conducted in this paper consists of teaching two planting practices: row planting and fertilizer microdosage. Row planting requires farmers to till the land and construct well ordered seedbeds, and then sow in parallel lines spaced by the same distance throughout the field. By contrast, the traditional practice of broadcasting ("Jujuta" in the Burundian language) is characterized by the semi-random broadcasting of seeds on a farmer's field. The microdosage of fertilizer is a complementary technology that requires farmers to apply fertilizer in the appropriate quantities carefully in rows, ensuring to apply it in the right order (along with compost) rather than broadcasting the fertilizer (Vandercasteelen et al., 2016).

Adoption of row planting rather than the broadcasting of seed has been found to substantially increase farmers' yields in some cases. Agronomic studies for beans in Rwanda, a similar context, found yield increases of 30-70% from spacing alone (Dusabumuremyi et al., 2014), while agronomic studies in other contexts find yield increases of 70-100% for other crops

[22] The government sends "moniteurs agricoles" to villages to provide farmers with information on the planting windows.

[23] Traditionally, Burundi has two agricultural seasons per year that coincide with the two rainfalls that occur each year. Farmers plant for Season A in October and harvest in February, and the primary crop at this time is maize. Farmers plant for Season B in March and harvest in July, and the primary crop during this season is beans. Recently, a cultural season C has been introduced during the dry season by leveraging irrigation and wetland farming (See: https://burundi-eco.com, urldate = 2024-01-12)

(Vandercasteelen et al., 2014).[24] These yield gains derive from several sources: first, optimal density of seeding reduces plant competition for water and nutrients, increasing germination rates, chances of survival post-germination, and expected yields. Second, optimal spacing may reduce weeding requirements later in the season (Vandercasteelen et al., 2014; Mansingh J and Deressa Bayissa, 2018). In addition, row planting might also improve the yield response of a crop to other modern inputs (Vandercasteelen et al., 2020). Row planting has the potential to also reduce the costs associated with planting, by requiring less seed input, as well as less labor for weeding.

The primary additional cost associated with row planting is the additional labor input requirement while planting. Qualitative research indicates that the main constraint to increased adoption of these planting practices' adoption is lack of time: according to 1AF agronomic trials, they take at least twice the time of traditional planting methods.[25] This lack of time becomes binding given that farmers all want to plant their fields quickly after the onset of rains. Despite the increased time requirements, there is suggestive evidence that the uptake of these practices may be profitable: for instance Deutschmann et al. (2022) find that participation in 1AF programs increases maize profits for farmers in Western Kenya by 17%, and part of this effect maybe driven by changes in farmers' planting technqiues.

Adoption of row planting and fertilizer microdosage are limited in this sample at baseline. According to administrative data from 1AF, during season 2019B 40% of audited climbing bean fields were planted using row planting, while for 40-50% of fields, fertilizer was applied incorrectly. For other crops, non-adoption is even more acute, with only 15% of audited maize fields in 2020A being planted using row planting.[26] Moreover, for a subset of farmers, adoption appears constrained even when knowledge appears to not be a binding constraint. In the season we conducted our experiment, 20.8% of trainer-employers applied them in all

[24]Non-experimental estimates of yield returns vary but are generally positive. Monitoring, Evaluation and Learning (MEL) data from 1AF in Burundi finds that row planting increases bean yields by 40% without fertilizer, and when done perfectly in conjunction with fertilizer by around 50%, while MEL reports suggest that when done in conjunction with correct microdosage yields may increase 60% (1AF, 2016).

[25]Studies in other contexts found that the adoption of row planting was associated with significant increases in family labor input, and almost a doubling of hired labor input (Vandercasteelen et al., 2014).

[26]This sample includes both 1AF clients and non-clients, and it is representative at the agro-ecological zone level. These adoption rates are lower than in Rwanda, which has similar agroecological conditions: see Figures A4.1 and A4.2.

of their beans plots in the control group, while almost 80% planted using these techniques on at least one field.

4.3 Agricultural Labor Markets

Planting requires substantial labor input for the tasks of land-preparation, planting and fertilizer application, weeding and harvesting. Farmers rely primarily on family labor to supply this labor, but around 20% of total labor input is hired for larger farmers.[27]

The labor markets that we study are decentralized and informal, similar to spot markets in other LMICs (Breza et al., 2021). Given high transport costs and distances between villages, each village in our context comprises a local labor market, as has been found in other African contexts (Fink et al., 2020). Within each village, more than half of households engage in the agricultural labor market either as an employer, laborer or both, a proportion similar to other rural African contexts (Jeong, 2021). Contracting is arranged bilaterally between employers and laborers, often with the employers visiting the households of various laborers, or with laborers visiting employers requesting jobs.[28] In the vast majority of cases, employers attempt to contact laborers in person 1-2 days prior to requiring their labor, and contract labor for just a few days. In the majority of cases, employers report searching for employees in the areas that the worker lives. This style of search offers some scope for workers to signal their skills to employers, either by demonstrating their technique on their own fields near their house, or by showing how fields close to their households have been planted (if sufficient time since the onset of rains has passed and these fields were planted sufficiently quickly).

Similar to other African agricultural labor markets, wages appear to be bargained by laborers and employers, and depend on a variety of features including the task assigned and size of land required to prepare (Fink et al., 2020).

We measure a high rate of employer-employee turnover in these markets across seasons:

[27] Farmers in the spillover-employer control group in the experiment utilize on average 50 person-days of labor over the course of the agricultural season, see Table A4.10.

[28] This nature of contracting is the same as found in Jeong (2021).

laborers in the control group report only supplying 30% of the days of labor that they provided in a given year to the same employer they provided labor to the prior year. Employers also report limited commitment by workers when contracting: among the sample of employers in control villages, around half report contracting a worker to engage them in work, only for the laborer not to show up.

4.4 Evidence for Missing Training Markets

1AF data suggest that a lack of skilled labor for hire is a constraint to the adoption of the improved planting techniques: 47% of 1AF farmers report that it is difficult to find workers who know modern practices; and 49% state that, if they were to hire workers, they would need to train them, which is time-consuming. At baseline, we document a low level of training by farmers of casual laborers: despite more than 60% of farmers stating that they are capable of training workers, only a small fraction of farmers report ever having done so.

Farmers report that it is infeasible to train workers during the planting season, due to time constraints associated with planting quickly after the onset of rains (see Figure A3.4). Training workers *before* the planting season, however, appears to be limited by labor market frictions. In a sample of 321 farmers who said they knew a casual laborer that they would be willing to hire, more than half said that the reasons they did not train that worker was because the worker would not return, because they would work for another employer or would spend more time working on their own fields (see Figure A3.4). These contracting frictions are salient for farmers in our sample. Around half of farmers who hire labor state that workers they contacted to work did not show up, and almost 75% of these employers believe the worker did not show up because they went to work for another employer, or worked on their own farm.

While farmers who employ laborers may have insufficient incentives to train them, the standard solution to this problem is for unskilled laborers to finance investments in training themselves (Becker, 1964). At baseline, we document three reasons that limit worker training investments. First, liquidity constraints for this group mean that investments in training are not the marginal investment during the planting season time of the year. Second, unskilled laborers in general perceive the returns to training to be positive but not large. In a survey of 289 unskilled laborers, we find that 90% believe that using the techniques on their own field would be unprofitable.[29] While the majority do believe that there are positive labor market returns, these are perceived to be relatively small (a 15% wage increase on average) and temporary: the majority of laborers believe they would need to be retrained after an agricultural season in order to be employable the following season. Finally, half of laborers cite trust and contracting frictions as a barrier to financing ex-ante training investments: these laborers stated they were unable to screen which farmers were effective at training these techniques and therefore could not guarantee that learning these techniques would lead them to be trained well. These constraints and their generalizability are discussed in more detail in Section 10.

5 Design and Implementation

5.1 Design Overview

The hypothesis of this paper is that farmers do not train workers in techniques with positive social returns, because they do not capture a large enough share of the returns from training. We use two experiments to document two facts consistent with this hypothesis. First, following Prediction 1 in Section 3 we show that, if farmers train laborers in these agricultural technologies, the returns from the training spill over to others who do not incur the cost of training. Second, following Prediction 3 in Section 3 we show that, if farmers know that workers are less likely to separate from them after training, therefore allowing the farmer to capture a greater share of the returns from training, then the farmer will become more willing to train the worker. To conduct these tests, we utilize two separate experiments: a Spillover Experiment and a Contract Experiment.

[29] This belief appears to stem from a perception that using a small amount of seed on a small field must result in a lower harvest (laborers on average own less land than others in the village). In addition, laborers also tended to report that row planting and fertilizer microdosage may not be profitable because they would require relatively expensive complementary inputs.

Spillover Experiment

To test whether farmers capture the returns from training if they train a laborer, we randomize at the village level a subset of farmers in the village to one of the following conditions:

- **Control** - Employers in control villages receive an unconditional financial transfer of around 1.5 days wage. Field staff suggests to these farmers that they could train a laborer in row-planting and micro-dosage techniques.
- **Treatment 1—Financial Incentive to Train Treatment** - Employers in treatment villages receive the same information as in the control group. They are then told that they will receive a financial incentive of around 1.5 days wage conditional on training a laborers in row-planting and micro-dosage techniques.[30]

Contract Experiment

To test whether farmers become willing to train in an environment in which workers are less likely to leave them after training, and they are therefore more likely to capture the returns from training, we use the two following treatments, randomized at the individual level:

- **Control**: A selection of farmers identify a laborer who meets certain criteria (See next section). This farmer and their laborer are then told that the laborer will receive an unconditional financial transfer at planting time.
- **Separation Contract**: A selection of farmers identify a laborer. This farmer and their laborer are then told that the laborer will receive the same financial incentive as the laborers in the control group, but *only* conditional on returning to work for the farmer for two days during the planting season.

Interpretation

Both treatments potentially increase the returns to training. In the Spillover Experiment, this is achieved by offering farmers financial incentives to train workers. This then creates a

[30] Specifically, farmers are told that the financial incentives is conditional on the farmer spending at least half a day with the laborer, at our training location. Because of the timing of the event, this generally required the farmers to return for a second day to finish training the laborer.

natural mechanism to measure who captures the returns from training in an environment in which other features of the labor market are left unchanged. In the Contract Experiment, the returns to training are potentially increased by increasing the returns to the laborer to returning to work for the employer. This contract then allows us to test how changes to the perceived probability of workers' separation from employers after being trained changes farmers' willingness to train.

5.2 Implementation

Sampling

We conduct the two experiments described above in villages ("*sous-collines*") selected in two provinces in Burundi. We use villages as our unit of randomization because each village defines a local labor-market within each of these provinces.

Village selection

We used 1AF administrative data to enumerate the villages in two provinces near its headquarters.[31] We then screened out villages that were unreachable by vehicle during the planting season, villages where 1AF had fewer than 20 clients or villages deemed to be particularly small, and villages where individuals did not primarily derive their livelihood from farming in general or from farming of beans in season B in particular.[32] As a result, a total sample of 120 villages was deemed suitable for the study. We randomly ordered these 120 villages and visited the first 92 of the randomized list. Within each village, we sampled four groups of individuals: i) trainer-employers, ii) trainees, iii) spillover-employers and iv) spillover non-employers. We provide details on the recruitment of each group below. The Spillover Experiment was conducted in 80 villages. For the Contract Experiment, we selected an additional 6 villages.

Recruitment of trainer-employers

Trainer-employers were initially recruited for the study by 1AF Field Officers (FOs), and

[31] These provinces are Muramvya and Gitega.
[32] This last criteria ruled out a number of villages close to towns.

consisted of clients of 1AF in the village. At the time of this screening, the 1AF Field Officer was not aware of the treatment status of the village they were working in. Within each village, the FO was trained on a recruiting protocol for 1AF clients to serve as trainer-employers. Specifically, 1AF clients were screened on: i) whether they knew the modern planting practices and ii) whether they regularly hired casual labor in the labor market. Each FO was instructed to bring 20-30 of these employers to the training event.[33]

Recruitment of laborers

Eligible trainer-employers were then asked to bring a laborer to the training event. The laborer had to meet several criteria. First, the individual had to be someone who regularly supplied daily labor during the planting season. Second, the laborer had to be an individual that the trainer-employer would themselves be interested in hiring. Third, the laborer had to not know row planting and fertilizer microdosage. Fourth, the laborer could not be an individual from the trainer employer's household.

Eligibility of Trainer-Employers and Laborers

At the training event, we conducted a second screening of trainer-employers and laborers based on these criteria and pairs where the trainee was found ineligible were screened out of the project. A list of trainers and trainees was provided to the team prior to the event and this list was randomized. We then sampled approximately the first 18 of the eligible trainer-employers at the training event and first 12 of the eligible laborers to take surveys, for each village.

Recruitement of spillover households

In addition, in the Spillover Experiment, we randomly sampled three sets of households in each village. We randomly sample around 25 households who regularly hire labor during the planting season and around 10 households who do not hire labor during the planting

[33] See categorization of village households in Figure A3.2.

season–five that engage primarily in family labor and five that primarily supply labor. These proportions do not reflect the proportion of each type in the village. Instead, we oversample employers to have power to detect spillover effects on hiring and adoption, while sampling non-spillover-employers gives us some ability to examine mechanisms.

Randomization

Randomization in the Spillover Experiment was conducted at the village level. Details on balance of the sample is provided in Section 6.3. Randomization in the Contract Experiment was conducted at the individual level.

5.3 Spillover Experiment – Implementation

After trainer-employers and laborers were recruited, we held a training event in each village. The training event was held at a location in the village, which consisted of a large parcel of land, equipped to train these planting techniques (e.g. string and sticks to build stakes). On average, 19 trainer-employers and 19 laborers attended each training event.

Training event protocol

For all villages, each trainer-trainee pair received a small plot of land (away from all other training pairs) and was told that they would be surveyed. Trainer-employers and trainees were told that the training event would last up to two days, although the second day would be optional. Each trainee-employer was asked to give a short description of methods and demonstrate to their trainee how to correctly store grains post harvest to decrease spoilage. After this time, farmers were explained the conditions in their group (Control, T1), as outlined above. Afterwards, farmers were free to continue training or leave. Staff did not explain how to train and did not train themselves. However, they monitored the training to ensure that i) each pair remained separate from others ii) that farmers did appear to be doing something on their land with the trainee.[34]

[34] Farmers were told they would not receive payment for just standing around, for instance.

5.4 Contract Experiment – Implementation

Within each village, farmers and laborers were asked to come to a central location to be surveyed. At this location, screening was conducted according to the criteria described in Section 5.2 above. During the survey, trainer-employers and trainees (laborers) were explained their treatment conditions. After this, farmers were told that a training event would be held the next week for several days. They were told that the training event would consist of the provision of land and equipment that could be used to teach trainees planting techniques. They were told that we would not provide any training ourselves and therefore that if trainers and trainees wanted to do training they would need to come as a pair. They were also told that each pair would be separated from others (*i.e.* there would be no group training). Finally, trainer and trainee pairs were told that there were no other benefits of attending the training event and that not attending the training event would not influence the participant's participation in the study. Therefore, participants were encouraged to decide for themselves if the benefits of attending the training event were worth their time.

5.5 Treatment Design Decisions

In both experiments, we made two design decisions that might have consequences for interpreting the results.

First, in order to measure spillover effects from training, we knew that we needed to have a strong first stage. Because of this, we did not randomly sample agricultural employers to invite them to the event since we knew that i) some did not know row planting and fertilizer microdosage themselves, ii) some employers have high opportunity costs of attending the event and would not respond to our incentives to attend the event/train workers. Because of this, we conducted the screening described above. However, this means that the trainer-employers in our sample may not be representative of agricultural employers as a whole.

Second, we held our training events in a central location. This ensured that we were able to monitor training and ensure it occurred. This, however, does potentially alleviate some constraints associated with training (e.g. preparing land and finding equipment).

We discuss the implications of both design decisions later in the paper.

6 Data and Empirical Strategy

6.1 Data Collection

We measured the core outcomes for this project in three ways: enumerators' direct observation of the training event, self-reported survey data and audits of farmers' fields. We measured hiring, employment and technology adoption through surveys during the planting season, at harvest, and during the planting season one year following the intervention.

Spillover Experiment

Training outcomes

During the training event, enumerators measured the amount of time farmers spent with their trainee on a plot of land for each of the two days of the training event. In addition, to measure whether training translates into better skills in these techniques, we asked laborers to perform an incentivized practice test of the seeding technologies after the first day of the training event.

Hiring outcomes

To construct measures of hiring, we asked each farmer for each worker hired i) the days that the worker worked, ii) the tasks completed in these days and the days spent completing the row planting or fertilizer microdosage during those days and, iii) payments made. In addition, questions about days worked and tasks completed were also asked for each family member that worked during the planting season.

Technology adoption outcomes

We measured adoption during the planting survey, *i.e.* approximately one month after the training events. Before the beginning of the survey, enumerators demonstrated to participants what correct spacing of fields consists of using tape measures and verbal descriptions, and then told them that, at the end of the survey, one of their fields will be audited randomly to test whether their description of the field lines up with how it is planted. Enumerators then elicited for each field, i) whether it is planted using row planting or broadcasting, and whether microdosage was adopted, and ii) for which proportion of the field. The core outcome is then the number of fields in which the majority of the field is planted using these techniques – however, we show robustness to any part of the field being planted this way, or to whether the field utilizes broadcasting or not.

Employment outcomes

To measure changes in employment, we asked each farmer the number of employers that they worked for during the planting season. We then asked for each employer, i) the number of days they worked for this employer, ii) the payment received and iii) the tasks completed. Finally, individuals were also asked whether they did any other work during Season B, and total earnings from such work.

Harvest and profit outcomes

To measure harvest outcomes, for each crop, we asked each farmer the quantities harvested and its price, and the overall harvest value. We construct crop revenues by multiplying quantities of crops harvested by the price of the crop at the nearest market.[35] To measure profits, we subtract from this measure all other non-labor input costs, and subtract these and labor input costs.

Additional surveys

Finally, one planting season after our intervention, we conducted a second set of planting surveys, measuring adoption, hiring and agricultural employment one year on, as well as the quantities harvested of crops planted during season B that were not harvested yet at the time of the original harvest survey.

Field audits

Finally to validate the survey responses, survey staff visited at least one field per farmer.

[35] Because crops come in different varieties with different prices, we multiply the quantity harvested by the average reported price in that village. We also show robustness to using the median price of respondents in the same area.

Plots were selected randomly for each visit, and in each visit the survey team measured i) whether the field was seeded using row planting or traditional seeding practices and ii) conditional on using row planting the distances between rows and pockets at three randomly located points on the field. This piece of information is used to construct non-self reported measures of how farmers planted their fields and this second visit is also used to incentivize truthful reporting of how farmers plant their fields during the plot roster described above.

Contract Experiment

Training outcomes

During the training event, enumerators measured the amount of time farmers spend with their trainee on a plot land for each of the two days of the training event.

Contract Takeup

When the contract is implemented, enumerators visited farmers/households' fields to observe laborers working.

Hiring, Employment and Technology Adoption Outcomes

At the end of the agricultural season, we surveyed trainer-employers and laborers .

6.2 Timeline

The Spillover experiment followed the Burundian Agricultural Season B, which runs from February to July —with most of the planting activities concentrated early in the season (see Section 4.1 and Figure A4.4 for details). We conducted training events during December 2021 and January 2022. We measured hiring of daily laborers, adoption (self reported and field visits) and agricultural employment in a first visit between March and May 2022. We surveyed farmers on harvest outcomes and family labor during a second visit between July and September 2022. We conducted a follow up survey between June and August 2023 that measured planting outcomes one year on, as well as harvest of crops that were not ready for harvest in the initial harvest survey. For more details, see Figure A3.1.

The Contract Experiment followed the Burundian Agricultural Season A, which runs from September to December. We conducted baseline surveys and described contracts to farmers in July 2023. Training events were offered in July and August 2023. Contracts were implemented in September and outcomes for the Agricultural Season were measured in October 2023.

6.3 Summary Statistics

Table A3.1 presents descriptive statistics and a test for balance in the Spillover Experiment. Columns 1-3 show the means, standard deviations and a test of equality for treatment and control trainer-employers, while columns 4-6 and 7-9 present the same summary statistics for spillover-employers and trainee workers. The sample appears balanced with 3 of 60 tests exhibiting $p<0.1$, and balance is achieved on many important outcome variables, including wages, labor market and farm earnings. Spillover-employers do adopt the planting techniques on slightly more fields at baseline, hence we control for this in regressions.

The table also provides informative descriptive statistics. First, as has been found in other contexts, households of laborers are considerably poorer than those that employ laborers, having less land (15.7 ares versus 40-50) and savings.[36] They are on average 34 years old and are almost equally likely to be a man or woman. By construction, they are less knowledgeable of the agricultural technology, being less likely to have planted in lines in the past season, or in the past 5 years, and show low knowledge scores on a quiz about the techniques. Finally, almost all supplied labor the past season, of which they supplied on average of 11 days.

Selection into training is not random, which leads to some important differences among the trainer-employers and spillover-employers. One difference arises from the screening criteria - trainer-employers exhibit high scores on the knowledge quiz of the technology and have all used the technology previously. By contrast, only 80% of spillover-employers previously used the technology, and they exhibit generally lower scores on the knowledge quiz.

Several other important distinctions emerge. While both trainer-employers and spillover-

[36] Fink et al. (2020) find workers more likely to provide ganyu (labor during the planting season) if they are liquidity constrained or among the lowest asset quintile.

farmers are substantially larger farmers than laborers, spillover-farmers are on average larger than trainer-employers, having 50 ares of land and 6.5 fields as opposed to trainer-employers, who have 40 ares of land and 6 fields. Finally, while both groups are equally likely to hire, spillover-employers generally hire more days of labor than trainer-employers, hiring 29 days of labor as opposed to 20 days.

Table A4.1 shows a similar table for trainer-employers and trainees in the Contract Experiment. The table shows generally the same pattern across the two groups: trainer-employers are substantially larger farmers, hire more labor and are more knowledgeable of the planting techniques than trainees.

6.4 Empirical Strategy

We use the following empirical specification to measure Intent-to-treat (ITT) effects in the Spillover Experiment:

$$y_i \;=\; \beta T_{v(i)} + \gamma X_i + \varepsilon_i \tag{3.3}$$

where y_i is the outcome of individual i, $T_v(i)$ is a dummy for the treatment status of village v (a function of the individual whose outcome is being measured), and X_i is a vector of baseline controls for individual i. Standard errors in all regressions are clustered at the village level. In this specification, β measures the average treatment effect of being an individual in a treatment village on outcome y_i.

We run unweighted regressions for the specification above for each group: 1) trainer-employers, 2) trainees and 3) spillover employers. We also use inverse probability weighting to estimate the total impact of the intervention across the three groups.

When running heterogeneity analyses, we use the following specification:

$$y_i \;=\; \beta_1 T_{v(i)} + \beta_2 Het_i + \beta_3 T_{v(i)} \times Het_i + \gamma X_i + \varepsilon_i \tag{3.4}$$

where Het_i is a measure of heterogeneity.

In the Contract Experiment, we run simple regressions of outcomes on a treatment dummy to measure intent-to-treat effects of the contract. We use robust standard errors.

Discussion. To the extent that training successfully increases the stock of skilled labor, our specification estimates the return to living in a village in which the stock of skilled labor increases. Because we intended to measure both the spillovers from training as well as the returns from adoption, we purposefully engineered the potential for quite sizable shocks to the stock of skilled labor by inviting many laborers to our training event.

This feature of our design, however, means that in some cases, for trainer-employers our empirical estimate may not equal their return to training a worker outside of the experiment. This is because training employers in treated villages may capture returns through general equilibrium effects that run through the event, such as being more likely to be able to hire a skilled worker they didn't train (because the stock of skilled workers has increased) or by having it less likely that their worker is poached (since there are many other workers to hire). We discuss further how to interpret these returns in the following section.

7 Spillover Experiment: Measuring who Captures Returns

In this section we present the results of the Spillover Experiment, which speaks to Prediction 1: that training generates spillovers to other actors uninvolved in training themselves. First, we show that financial incentives in treatment villages substantially increase trainer-employers' willingness to train. We then show how this changes the employment and adoption of row-planting of trainees, before turning to how this changes the hiring and adoption of row-planting of trainer-employers and spillover-employers.

7.1 Willingness to Train and the Stock of Skilled Labor (First-Stage)

In response to the offer of financial incentives, trainer-employers in treatment villages become more likely to train their paired trainee in T1-Financial Incentives villages, as compared to control villages.[37] Almost 80% of trainer-employers in the T1-Financial Incentives villages train the laborer they brought to the training event, as compared to less than 1% of trainer-employers in the control group (see Figure A3.7).[38] Spending time training may not translate into a meaningful change in the skills of workers if farmers engage in training in limited ways, are incapable of teaching or laborers are unwilling or unable to learn. To test whether training translates into meaningful changes in the skills of trainees, we ask trainees in treatment and control groups to perform a timed, incentivized row-planting task, which measured laborers' ability to complete well spaced row planting under time pressure, the skill that employers in these villages primarily hire.[39] As Figure A4.6 shows, trainees in T1-Financial incentives villages perform better in this task post training: we reject the null hypothesis that the treatment and control score is the same at the 1% significance level. Taken together, these results are suggest that training results in an immediate increase in the skills of some laborers in row planting and microdosage.

7.2 Changes to Trainee employment and farming decisions

Prediction 1 states that training generates returns for those not bearing the cost of training. This requires that workers use the skills they are trained in, and may capture some of the returns of training through higher wages. Table A3.2 provides evidence consistent with this hypothesis, by documenting the treatment effect of being in a T1-Financial incentives village on trainees' employment, earnings and wages. Trainees use the skills they are trained in: column 1 shows that trainees in treated villages are employed for 3.43 days more days doing row-planting or microdosage than trainees in control villages (p-value<0.01). This is a sizable change, with trainees substituting toward row planting work for almost half of the days that they work during the planting period (which totals around $\sim$ 8 days, Column 3). Trainees primarily substitute away from other work tasks rather than increase the number

[37] We measure whether the employee is trained by whether the trainer-employer spends at least half a day training the trainee at our event

[38] This does not imply that no training occurred in these villages, rather that few farmers passed the threshold of training required from farmers in treatment villages to qualify for incentives. Moreover, this does not rule out that in control villages farmers may have trained these laborers at times/places not observed by enumerators.

[39] Laborers were scored on the number of rows and pockets planted at correct distances within a short period of time.

of days worked, as total days of employment for trainees in treated villages increases by 0.8 overall (an increase of 13%), an increase is not significant at conventional levels. There is no impact of training on the *extensive* margin of employment during the planting season: around 84% of the trainees do any agricultural work during the planting period in both treatment and control villages (Column 5, p=0.98).

Prediction 1 states that returns to training are captured by those not bearing the cost, and these returns might include increased wages for workers trained. We find evidence consistent with this hypothesis: among the sample of trainees supplying *any* agricultural labor–, wages increase by 8.2% in treatment villages (p=0.02). This wage increase, coupled with a slight change in employment, leads however to a total earnings increase by almost 20% (p=0.02). Finally, column 7 documents an additional channel though which trainees might capture the returns from training: adoption of row-planting on their own fields. Specifically, we find that trainees in treatment villages plant 1.3 more fields using the correct row planting techniques as compared to only 0.23 among trainees in control villages (p-value <0.01).

These results provide evidence consistent with trainers failing to fully capture the returns to training, due to workers' wages rising, and potentially through them using row-planting on their own fields. These results are robust to the selection of alternate controls, winsorization, and the use of randomization inference p-values (see Appendix Table A4.13).

The effectiveness of the training appears to be due to changing the beliefs of workers, providing them with technical information about how to row plant, as well as allowing them to practice and receive feedback on row-planting, lowering the cost of effort of doing so.[40] Survey evidence from a sample of laborers in other villages suggests that many laborers do not perceive that there are returns to the adoption of row-planting on their own fields (see Figures A4.11 and A4.12). The substantial increase in the likelihood that trainees adopted row planting on their own fields (Column 7 of Table A3.2) suggests trainer-employers during training may have changed trainees' beliefs about the technology and about its profitability on their own farms. Additional evidence, however, suggests that the training transmitted

[40] Prior literature has found mixed results on the effectiveness of agricultural training interventions. See for instance, Kondylis et al. (2017); Udry (2010); Aker and Jack (2021)

meaningful changes in knowledge and skills, rather than simply changing the beliefs of trainees. We find that trainees in treatment villages have better technical awareness of details of the row planting process, as measured by a knowledge quiz that we administered during subsequent surveys, with this greater awareness persisting for almost a year after training, suggesting that training also transmitted technical information to trainees. Finally, the fact that there is a change in the performance of trainees in the incentivized planting task after training, suggests that during the training their ability to do row-planting under time pressure improved. Anecdotally, it seems that trainees found most helpful the process of practicing row-planting while receiving feedback from trainer-employers.

7.3 Who Hires Newly Skilled Labor? Measuring Hiring Spillovers Following Training

Trainer-employers' Hiring and Technology Adoption

Prediction 1 states that trainer-employers may not capture returns from training because other employers hire newly trained workers. We find that trainer-employers in treatment villages may not hire as much of their trainee's labor as they desire following training. Column 1 of Table A3.3 measures the likelihood that a trainer-employer attempted to hire the trainee that they invited to the training event.[41] While 57% of employers in the control group attempt to hire the trainee that they invited to train, 72% of employers in the treatment group do the same. This increase likely reflects the fact that unskilled labor is easier to find and more interchangeable than skilled labor. Column 2, however, shows that trainer-employers in treatment villages are *less* likely to successfully hire their trainee, suggesting that after being trained, it becomes harder to hire these workers. Trainer-employers in treatment villages are 16 percentage points more likely to state they were unable to hire their paired trainee ($p<0.01$). Columns 1 and 2 combined suggest that trainer-employers are unable to hire trainees 41% of the time conditional on trying to hire them, as compared to 55% of the time in treatment villages.

Trainer-employers hiring of labor for row-planting does increase in treatment villages,

[41] This data was collected in a follow up survey with a random subsample of trainer-employers.

however. Column 5 shows that in total, trainer-employers increase by 46% the number of days that they hire to do skilled tasks (an increase of 0.81 days on a base of 1.76 days, $p<0.01$). Partially this increase reflects more days of hiring the paired trainee (0.52 days increase (Column 3)) while partially it reflects a spillover involving hiring trainees of other trainer-employers at the training event (Column 4, which shows that there is a 0.84 day increase in hiring any trainee at the training event to do the skilled labor task). This increase suggests that trainer-employers do capture some of the benefits of their own training, while also benefiting from the spillover created by living in a treatment village. Moreover, this hiring leads to an increase in total labor used for row-planting, rather than substituting for family labor (see Appendix Table A4.3). Increased hiring facilitates more adoption of row-planting: trainer-employers in treatment villages plant 18.6% more fields using improved row spacing practices than in control villages (an increase of 0.46 fields from a base of 2.47 fields, Column 6, $p<0.01$). These results are robust to the selection of alternate controls, winsorization, and the use of randomization inference p-values (see Appendix Table A4.11).

Spillover-Employers' Hiring and Technology Adoption

The fact that trainees report supplying more than 3 days of labor for trained techniques during the planting season, but trainer-employers only report hiring 0.8 days of labor for such techniques, suggests that a sizable proportion of this employment is captured by other employers. To check for this, Table A3.4 shows treatment effects on hiring and adoption of the agricultural technology for Spillover-Employers uninvolved in training workers themselves.

Columns 1 and 2 measure for spillover-employers the days hired of 1) trainees to do work involving the trained techniques and 2) any worker to conduct work involving the trained techniques. Days hired overall for this task increase by 60% over the control group mean (*i.e.* 1.29 days, $p<0.01$). All of this increase in hiring for this task is driven specifically by the hiring of trainees invited to the training event. The fact that the hiring effect for spillover farmers is larger than for trainer-employers probably reflects the non-random nature of sorting into training, with spillover farmers having more land and hiring more days of work, on average. Again, Table A4.3 confirms that this increase in hired labor for the skilled task does not substitute for family labor, and therefore skilled task labor input rises among spillover-employer farmers in treated villages.

These large hiring effects for non-spillover-employers demonstrate that training generates returns captured either by other employers or workers, consistent with theories of general skills training. This could reflect a labor market that generally features high levels of turnover. Alternatively, the appropriability problem for trainer-employers may be exacerbated by trainees being *more* likely to work for other employers once trained, either because there is "poaching" or a higher skilled labor separation rate. Figure A4.10 provides some suggestive evidence for whether the spillover magnitude reflects high labor market churn, or additional sorting/poaching in response to treatment. The blue bar in the figure shows that trainees in the current season work on average only 30% of the days for an employer they worked for in the previous season. The red bar in the figure instead represents the treatment effect on the number of days of skilled labor supplied by treatment trainees (about 3 days, as we saw in Column 1 of Table A3.2). The green bar then shows the proportion of these days one would predict to be supplied to a previous employer based on the probability from the blue bar on the left, which is slightly more than a day. By contrast, Column 1 shows the actual number of days hired by trainer-employers of their trainees, which is around half a day. This, coupled with the fact that trainer-employers report being less able to hire their own trainee once trained, provides some evidence that the sorting to the spillover group may not be purely reflective of regular labor market churn, and may partly also reflect additional sorting/poaching in response to training.[42]

The changes in hiring by spillover-employers suggest the possibility of returns from training accruing to employers who do not themselves train employees. In this environment, this is most likely to occur if increases in hiring of skilled labor lead farmers to adopt more row-planting and fertilizer microdosage on their own fields. Column 3 in Table A3.4 shows that

[42]One caveat related to this result is that we did not ask laborers the number of days that they worked for an employer of the previous year in the first season of the project– therefore the blue bar is constructed from data from year 2 of the project. Therefore an alternative interpretation of this figure is that there was not excess churn in response to treatment, and instead the churn rate in the control group was much higher in year 1.

this increased labor input facilitates an increase in the adoption of better planted fields by 0.45 fields, an increase of 23.7% ($p<0.01$). Results in this section are robust to the selection of alternate controls, winsorization, and the use of randomization inference p-values (see Appendix Table A4.12).

Generally, one would expect the magnitude of spillovers to be smaller than the direct effects on treated participants. Why do we find such large effects? We explore whether this is driven partially by the self selection of trainer-employers into the sample. As noted previously, trainer-employers and spillover-employers differ along a number of key characteristics: spillover-employers have more land, hire more days of labor, and are less likely to know and use the trained techniques.

We explore whether these imbalanced characteristics drive the treatment effects and find some evidence that they do. Appendix Table A4.5 shows treatment effect heterogeneity for the cross section of employers by land size and prior hiring. We find that the treatment effects are larger for both hiring and adoption among larger employers, and some evidence that they are also larger for employers who hire more days of labor. Therefore, it seems plausible that the magnitude of the treatment effects in the spillover group is driven partially by the fact that this group comprises larger farmers.

7.4 Spillovers to Farm Profitability from Training

In the previous section we demonstrated that training generates returns for those who do not incur the training cost: trainees in T1 - Financial Incentives villages work for other employers after being trained, generating surplus not captured by the training employer. Moreover, the wage of trainees rises, ensuring that they capture some returns even when they remain with their employer.

In this section, we attempt to quantify the total returns to training for each subgroup. Specifically this includes i) farm profitability and ii) total labor market earnings during the season. To measure farm profits, we complete crop rosters of harvest sizes for all crops planted during the season, and multiply these quantities by local prices for these crops.[43] We

[43]We see no effect of treatment on local prices, see Appendix Table A4.9.

then subtract from this the cost of all labor and non-labor farm inputs during the season.[44] Given the challenges associated with valuing family labor, we compute farm profits with two bounds: i) a bound that values any family labor at a wage of 0 and ii) a bound that values family labor either at the individual's own wage, if observed, or at the average wage observed in the village. We show treatment effects on these outcomes for each subgroup, as well as regressions weighted by the inverse sampling probability for each group, to obtain the average treatment effect for those in the sample.[45]

Table A3.5 presents estimates of the treatment effect on farm revenues and profitability. Farm revenues increase by 8% on average (Panel A, p=0.08), including 10.6% for trainees (Panel B, p=0.06), 7% for trainer-employers (Panel C, p=0.09) and 8% for Spillover-Employers (Panel D, p=.11). These results are consistent with the technology, which should increase yields if applied correctly.

Are these technological changes profitable for farmers? We find evidence that they are as in general we do not find meaningful changes in input costs for these groups, which leads profits in all three groups to rise (see Appendix Figures A4.7-A4.9 for CDFs showing raw effects). Assuming a shadow value for family labor of 0, we find that farm profits increase by 10.8% on average for the sample (Panel A, Column 2, p=0.05). This average effect is made up of a 14.2% increase in profits for trainees (Panel B, Column 2, p=0.04), 9.2% increase in profits for trainer-employers (Panel C, Column 2, p=0.09) and 9.6% increase in profits for spillover-employers (Panel D, Column 2, p=0.10). This result is only sensitive to the assumed shadow family value of labor for trainees: while the profit magnitudes are largely the same when applying a positive wage rate to family labor for the other groups, estimate of farm profitability for trainees becomes statistically insignificant, reflecting the increased time that they spend on their own farm post training. Column 4 shows that trainer-employers and spillover-employers do not earn additional money from the labor market at this time,

[44]Non-labor farm inputs include spending on fertilizer, seed, compost, pesticides, land rental payments and other input costs. Given thin land markets and the likely noisy measures of land acreage measured at baseline, we do not measure the implicit rental value of land used as an input cost.

[45]Note that this is not the same as village level effects since these regressions leave out individuals in the village who are uninvolved in the labor market, as well as other laborers. To the extent that there are negative or null effects on these individuals, ATE for the village as a whole will be lower.

whereas trainees increase their labor market earnings as shown in Section 7.2.

These estimates suggest that there are farm level returns to training. However, as with most papers, we are only able to obtain a noisy measure of farm profitability. Moreover, farming is notoriously subject to annual aggregate shocks: suggesting that a single year estimate of farm profitability even if measured well maybe a poor approximation of the expected returns to adoption (Rosenzweig and Udry, 2020).

To test whether farmer's themselves perceive that these changes to behavior generate positive returns, we therefore rely on a second, revealed-preference approach, that measures the persistence of the behavioral changes one season later, and we suggest that, if we see persistence in this behavior, this suggests that farmers perceived that the actions generated surplus. Figures A3.8-A3.13 display the core treatment effects for each group over two agricultural seasons: the season immediately following training, and the season 12 months later.

We see enduring behavioral changes across all three samples, although there is some evidence of weaker treatment effects a year after the training. Trainees in Financial Incentive villages continue supplying more days of labor utilizing the technologies and applying the trained techniques on their own fields, although the magnitudes of these treatment effects are lower than in the first agricultural season. Similarly, Figures A3.10 to A3.13 show that trainer-employers and spillover-employers adopt the techniques on 0.23 and 0.28 more fields than their control counterparts (p=0.01 and p=0.02) and hire 0.98 and 1.28 more days of labor to conduct the trained techniques, respectively. These enduring changes to behavior suggest that the training generates surplus, at least for some members of the population.

7.5 Training Underinvestment and the Incidence of Returns

The prior sections demonstrate that there is meaningful surplus generated by training, and that a reasonable proportion of this surplus is captured by those not bearing the training cost. We now turn to two additional questions. The first is whether there is underinvestment in training as suggested by Prediction 2 in Section 3, since an important feature of models of general skills is that the equilibrium level of training maybe lower than the first best. The second question is what is the incidence of the returns from training, which is a function both of the treatment effects on returns (documented in Section 7.4) as well as the size of each group in the village. To answer these questions, we conduct cost-benefit analyses of training, and present estimates of the benefit-cost ratio.

Ideally, we would measure the benefits of the training as the aggregated willingness to pay of individuals in the village for the training to occur. Papers in the development literature that have computed similar ratios have used consumption changes as a stand in for this value (Bandiera et al., 2017). Since we do not have a measure of consumption, we use a measure of the change in earnings as found in Section 7.4, which maybe a reasonable proxy for consumption given that we find no changes in output prices. Two further assumptions are required for this assumption to be reasonable: first it should be that the increase in earnings is not driven by a large change in days worked (which would lead to an additional disutility of labor) and that the training does not yield another direct utility benefit or cost for some subpopulations (Hendren and Sprung-Keyser, 2020). We discuss the sensitivity of the estimate to these assumptions later in the section.

To aggregate the returns from training, we compute the benefits of training as the treatment effects on total income (farm profits and labor market earnings) for each subgroup (trainer-employers, trainees, spillover-employers). In our base case, we assume a discount rate of 10%. In line with the two year treatment effects on adoption, we assume that the earnings benefits that we measure lasts for two seasons. However, in line with the treatment effect that we measure on adoption, we assume that this change in earnings but depreciates at a rate of 50%. We then aggregate these benefits according to the proportion of each group in the village: which corresponds to weights of approximately 25% for trainees, 25% for trainer-employers and 50% weights for spillover employers.

We compute the total costs of training by summing the cost of incentives for participants, the cost of materials and the opportunity costs of time for participants in the training. In terms of equipment, we include the cost of land and equipment rental (25% of training costs). We include financial incentives paid to trainers to train the trainees (11% of total training costs). We also include an opportunity cost of time for the trainee (conservatively assuming

1 day of time) as well as the opportunity cost of time for the trainer to find the trainee (again, conservatively assuming that this takes 1 day). However, to avoid double counting, we only assign an opportunity cost to one day of the trainers time (as the second day they were financially compensated for their time). We value the time of each trainer and trainee at the average wage we see in the control group. Together these account for 14% of the training costs. Finally, we include the cost of staff time that was required to advertise the event, provide invitations, prepare and monitor the training (50% of total training costs). Finally, we assume that there are no fiscal externalities as a result of training.

Table A3.6 Panel E shows the Benefit-Cost ratio, aggregating the returns across these populations. In the first column, as is common in many training programs, it is assumed that the returns to training accrue only to the trainee - *i.e.* only the earnings accrued by trainees on their own fields and while working for others, are counted as benefits. In Column 2, added to these benefits are the additional farm earnings that the training generates for the trainer-employer as well. Finally, Column 3 adds to this total the additional farm earnings accrued by Spillover Employers in the same village.

Incorporating the returns to training for the trainee delivers a benefit cost ratio of 0.7, and we can't reject the null that returns to training are less than or equal to oneA benefit-cost ratio larger than one is a reasonable proxy for welfare improvements. (p=0.86). Incorporating the returns for the trainer as well increases the Benefit-Cost ratio to 1.6 (p=0.18). Including the returns to spillover-employers, however, increases the Benefit-Cost ratio to 3.2, suggesting that a dollar of training investment returns 3.2 dollars of returns, and we can reject the null of a ratio less than or equal to one at the 10% level (p=0.08). This large increase in the returns between column 2 and 3 is driven by the fact that trainer-employers and spillover-employers accrue similar returns to training, but there are a larger number of spillover-employers in the village population.

The returns to training remain large even if we assume there are no returns to trainees, and if we assume the earnings benefits only last one year. Therefore, while noisy, these estimates suggest that training was underprovided, and investments in training can increase total surplus.

This benefit-cost ratio may not correctly measure the welfare impact of the training program if the training generated a labor supply response. If this were the case, then the willingness to pay for the human capital generated by the training would equal the change in wage generated from the training multiplied by the individual's days worked pre-training, i.e. the welfare metric nets out the portion of additional earnings arising from changes in days worked (Kline and Walters, 2016). While we do not observe statistically significant changes in days worked in response to training, Table A3.2 and Appendix Table A4.3 do offer some suggestive evidence that there maybe an increase in labor supplied on and off farm for the trainee sample respectively. In Panel F, we repeat the 1 year calculation for trainees, and show that the benefit-cost ratio drops from 0.4 to 0.25, suggesting that trainees would be willing to pay for only 62.5% of the additional earnings they capture. While this doesn't change the general point that the social returns to the technology appear high, it does suggest that trainees maybe capturing only a small proportion of returns.

Taken together, these results suggest that there is underinvestment in training general skills, and moreover that the returns to training are large for employers, but diffuse across employers as a group. In the next section we turn to whether the fact that the returns to training are diffuse limits training investments.

8 Contract Experiment: Turnover as a Limitation to Training Investments

In the previous section, we provide evidence that training generates positive, but diffuse returns with a large proportion of the training surplus captured by trainees and, especially, other employers. The fact that training generates spillovers, however, might not contribute to underinvestment in training. For instance, employers might also have biased beliefs about the returns to the training or to the adoption of row planting. In this section, we provide evidence that farmers perceive the returns to training as positive, conditional on capturing sufficient returns.

To demonstrate this, we turn to the results of the contract experiment, in which employers were offered a contract that increased the probability that a worker might work for them in the future, and then offered an event at which they could train the worker. We begin by measuring the probability that employers attended the event for more than half a day, the amount of time that we determined was sufficient to train the worker in these techniques. Figure A3.14 shows that farmers become far more likely to attend the training event for this amount of time after being offered the contract. Half spend more than three hours at the training event, the amount of time suggested to become somewhat familiar with the practices. This suggests that in response to a higher likelihood of capturing training returns, employers perceive a positive return to training.

While this figure demonstrates attendance, no training was prescribed at the event: while it was suggested to trainer-employers that they could use the training event to train their worker, they were also free to use the event for other possibilities. For instance, employers may have used the event as a low-cost way to observe the skills or ability of the worker, to determine whether they wanted to hire the individual. Moreover, in order to not suggest or lead trainer-employers to train the worker in these techniques, we did not conduct an incentivized skills test with laborers after the training event.

Therefore to understand the extent to which the contract translated into skill upgrading, we surveyed control and treatment trainees and measured the extent to which they used row-planting or fertilizer microdosage either i) on their own fields, or ii) on the fields working for others. Figure A3.15 shows that this was the case - trainees chosen by trainer-employers in the Contract Treatment are 33 percentage points more likely to report that they use these techniques during the season than counterfactual trainees in the control group. Moreover this a lower bound on the extent of training, to the extent that laborers may have been trained but skills were not transferred, or the laborer decided not to use the skills that season. Taken together, this evidence suggests that, at least for a subset of farmers, training would be more likely to occur if the labor market was structured so that employers perceived they could capture more returns from training.

9 Alternative Explanations

In the preceding sections, we interpret the results as showing that inducing employers in some villages to train generates large returns captured by those in the labor market not incurring the cost of training, that this leads to overall welfare gains and that part of the reason employers do not train is because of weak attachment to laborers, meaning that after training they don't expect the laborer to work for them. In this section we consider alternate interpretations of this story.

9.1 Spillover Experiment: Learning/Social learning

Was there social learning of row planting and microdosage that enabled others in the village to increase adoption of these techniques without hiring skilled labor? This might have occured because the training event signalled the importance of these skills to the trainer-employers, trainees, or others in the village, who then shared or sought this information from others. While there almost certainly must have been some knowledge spillovers, several pieces of evidence point against this being the primary mechanism through which the treatment effects on adoption were generated. First, Panel B of Appendix Table A4.4 shows that there was no change in adoption or hiring for spillover non-employers, suggesting that such spillovers only appear to be impactful for those engaged in the labor market. Second Appendix Table A4.6 shows that while spillover-employers who had not previously row planted drove some of the adoption treatment effects for this group as a whole, we see similar magnitude of effects also for spillover-employers *who previously used the techniques*, and where knowledge spillovers would be expected to have more muted impacts. Finally Panel A of Appendix Table A4.4 shows heterogeneity in extensive margin adoption decisions for spillover-employers by several proxies for whether they previously used the techniques. This test is useful as one might expect if knowledge spillovers made this set of users begin adopting without additional labor input. By contrast, we see instead that these farmers only adopt these techniques if they also hire labor (columns 4 versus 5 and 6 versus 7) suggesting that the hiring enabled the adoption.

9.2 Spillover Experiment: Revelation of Trainee Type

A second explanation for these results could be that the training event served not to transfer human capital from trainer to trainee, but instead gave trainees a chance to reveal their type to employers. In this story, the training event still generates externalities, but through a mechanism of learning similar to Pallais (2014) or Terviö (2009). Three pieces of evidence suggest this is not the primary explanation for these findings. First, this requires this information to be shared with the spillover group by trainer-employers, which seems puzzling given that they then appear to be unable to hire desirable workers. Second, something must be transmitted to laborers, given that laborers in treatment villages perform better in the incentivized planting task, and change their planting decisions on their own farm. Finally, this concern might be more prominent among trainees who did not previously work for their employer, as presumably this would create more scope for employer learning about worker type. Appendix Tables A4.7 and A4.8 show treatment effect heterogeneity for the core labor market outcomes by whether the employer and employee previously worked together, and we do not see meaningful evidence that the treatment effects are driven by trainees who did not previously work with their employer.

9.3 Spillover Experiment: Signalling

When designing the spillover experiment, to ensure a first stage we decided that it was crucial for us to be able to monitor the training to ensure there was no gaming of the training for the financial incentive. Monitoring the training was not feasible at the individual farms of each farmer, and therefore we used the training event as a way to ensure that we could monitor training at scale.

While this achieved our goal of ensuring that training occurred, it does introduce some concerns with respect to signalling, that one might believe could impact the magnitudes of the effects we estimate. First, the fact that a large training event was held in the village might signal to the farmers invited, or the workers themselves, that the techniques being trained are useful, making them more likely to adopt. Second, the fact that a large training event was held in the village might have made it easier for trainees in the treatment to credibly signal to others that they had acquired the skills they were trained in. Both of these factors might accentuate the magnitude of the spillovers that we find relative to a situation in which a farmer individually trains a worker on their own land.

While these may have had some effect, we do not believe these concerns have first order impacts on these results, for the following reasons. First, the NGO 1AF and the Burundian Government have promoted the adoption of these techniques in villages for at least ten years. Farmers were familiar with these techniques prior to our training event and it is unlikely that our training event highlighted the importance of the technology more than any regular 1AF activities. Moreover the fact that we do not see increased technology takeup for individuals in the village not engaged in hiring in the labor market suggests that this signalling was not important to a large portion of the village (Panel B of Appendix Table A4.4). In addition, motivating Figures A3.3 and A3.4 suggest that farmers perceive outside of our experiment that if a worker is trained they are likely to go work for others, indicating that outside of our experiment workers are able to signal their skills to others.[46]

9.4 Contract Experiment: Demand Effects

Our interpretation of the training response to contracts offered in the T2 treatment arm is that this demonstrates farmers are willing to train once guaranteed a higher share of the returns from training. One concern is that the willingness to train in this treatment may simply reflect experimenter demand. To alleviate this concern, as discussed in more detail in the preceding paragraphs, we did extensive audits of whether workers worked *and whether farmers themselves paid these workers* and found that they did so. Specifically, 90% of farmers that we classified as having trained the worker hired them as part of the contract, suggesting that the training was a meaningful decision.

[46] This is generally done by workers demonstrating how to apply the techniques when search for the worker is conducted. Moreover, in subsequent seasons, farmers report learning from workers' fields if they are able to use the techniques.

9.5 Contract Experiment: Trainee Liquidity Constraints

Since the Contract Experiment involves a payment (conditional or unconditional) to the worker, an alternate interpretation of the results is that as a result of the treatment, workers paid trainer-employers to train them. This seems unlikely given that, a) the money was paid to the worker later in the planting season, b) money was paid unconditionally to control laborers, meaning that they could replicate the contract. This would mean that somehow this contract was only feasible for workers who received a contract to return to the farmer.

While this seems unlikely, we measure this directly by asking whether side payments were made from the worker to the trainer, and do not find any evidence for this. Specifically, at the time of contract implementation we asked workers if they made direct payments to the trainer to train them and zero said that they did.

9.6 Contract Experiment: Changes to Bargaining as a Result of the Subsidy

It is possible that the subsidy paid to employers changed bargaining dynamics - for instance employers may have appropriated a share of the subsidy paid to employees via pass-through. Given that the subsidy was paid unconditional on training, it is unclear why this would lead to training, if the pass through of the subsidy is just a level shift in the profits of the trainer-employer. To induce training, it would need to be that the pass through of the subsidy to the employer was increasing in the level of training of the worker. It is unclear why one would expect this to occur, unless the subsidy was being passed through to the employer by the worker as an implicit form of payment.

Do we see large changes to the wage paid by the employer as a result of the subsidy? During the planting season, the average wage paid by an employer to a laborer is $\sim$ 2900 FBU. We observe slightly lower payments made to workers during the contract: the average payment made to a worker is 2625 FBU. This suggests the possibility of a subsidy pass-through rate of 10%. However, it is unlikely that this pass through is an implicit form of payment by trainees in return for training. The magnitude of the pass-through appears to be small, and would suggest that in return for training employers are willing to forgo a minimum of a half a day of a wage today to obtain 20% of the wage several months in the future.

9.7 Spillover/Contract Experiment Interpretation: Importance of Other Frictions Resolved in Bundle

An important consideration when interpreting these results is that the treatment was bundled. For example, the T1-Financial Incentives treatment not only provided financial incentives to train: it also provided incentives for trainer-employers to find unskilled workers, and provided land, training equipment and some oversight of the training. These features, part of the treatment bundle, may have overcome additional frictions associated with providing training, including hassle costs, contracting and search frictions. The fact that these provided also to participants in the control group rule out that these features alone or in combination once provided are sufficient to induce training. By the same token, the interpretation of these results should be that the provision of monetary incentives or a contract, are necessary, but may not be sufficient, to induce training.[47]

Similarly, the contract that we offer in the T2-Contract Treatment may be a contract that employers and employees find it hard to replicate themselves. For example, the T2-contract may change the incentives of workers to provide effort on the job, because of the threat of employer complaints that might lead them to lose their wage. Moreover, the T2 contract also provided much of the same bundle of training components as the Spillover experiment.

How important are these other features of the treatment bundle? To shed more light on this, we conduct a short survey with farmers who received the T2 contract to ask them which aspects of the treatment bundle were valuable to the impact of the experiments.

We find no evidence that the training package mattered for farmers capability to train. Employers unanimously disagreed that the training event somehow enabled them to train workers, or that the provision of land and equipment were important.

[47]For example, the provision of a contract to trainer-employers for a worker to return, without the additional bundle of the treatment, may or may not induce training.

We find stronger evidence that the training event did resolve contracting frictions associated with training. Two frictions in particular seemed important. First, laborers agreed that the training event reduced the costs of requesting training - this suggests that at least for some laborers, self or social image maybe an important cost that deters asking for training (Chandrasekhar et al., 2018). Second, while employers overwhelming agreed that the contract was helpful because it increased the probability that the worker would return, they also mentioned that they believed it would make it easier to ensure the laborer worked well on the job. Therefore, to the extent that laborer effort and training investments are complementary, the contract may have increased the returns to training investments relative to what farmers might have achieved through informal contracts.

Taken together, qualitative evidence suggests that the treatment may have operated by reducing contracting frictions. In the next section, we discuss further the importance of these contracting frictions for understanding the equilibrium in this economy. As a final point, while these contracting frictions may make it difficult for farmers to replicate these effects, the benefit-cost ratio that we find in section 7.5 suggests that these costs are not insurmountable, which suggests that NGOs or the government through coordinated training investments like those we use in this study could generate large returns that overcome multiple frictions.

10 What Limits Training Investments in Equilibrium

These findings suggest that employers invest too little in training because they do not capture its returns, and that this leads to meaningful underinvestment in training. The generalizability of these findings depends on why alternate mechanisms that might generate training investments - such as payments made by workers or relational contracts - fail in this environment.

10.1 Limitations to Worker Investments in Training

Classic models of training suggest that workers should invest in training (Becker, 1964). Though in this setting workers do not appear to be the full residual claimant of the returns to training, they do appear to capture some returns and therefore presumably should be investing if these returns are larger than the training cost.

One reason that they may not invest in training is because the private returns to training for trainees is smaller than the cost of training, as suggested by Table A3.6. However, this table assumes that the return depreciates entirely after two years, and that the trainees would have to bear the full training cost incurred by the program. It is possible that these assumptions are overly conservative. If the returns to training for trainees are larger than the cost, then it suggests there are other market failures that limit their training investments.

From qualitative interviews with laborers and employers, two particular constraints to training in the environment arise that the training event may have helped to overcome. First, workers generally report not wanting to make upfront payments for training, for two reasons. The first are liquidity constraints: as shown in Table A3.1 workers are generally among the poorest in the village. This limits their willingness to make sizable direct investments in training or take large wage cuts ex-ante. The second feature of the market that limits trainee investments is that it involves contracting over an action - training - that is hard to define, and that the trainee themselves cannot ensure is being provided correctly. Because of these features of the contract, many laborers report mistrusting that employers will train them well if they are paid to do so. These contracting frictions, associated with worker financed training investments, have been discussed previously by a sizable literature (Acemoglu, 1997; Acemoglu and Pischke, 1999b).

A contract that employers might be able to offer that could overcome these frictions would be to offer to train workers today in return for labor in the future at lower wages, or the promise of a payment made to the employer in the event that the worker does not return after being trained. By moving the cost of training to the employer's side, this might credibly signal to laborers that the employer will train them well. However, employers state that such backloading of the contract then makes it tempting for the worker to renege on, and that such side payments would be infeasible to collect or enforce. Because of this, such a contract is not offered.

These contracting frictions in this market suggest a low level of generalizable trust among members of the village population. While this is may be surprising, since one might expect members of villages in low-income countries to be able to utilize relational contracts to overcome these contracting barriers, the lack of generalizable trust is consistent with the data we collected suggesting that there is limited social capital among employers and workers in this population, potentially due to their different ranks in village income hierarchies (see Appendix Table A4.2). This lack of social capital, coupled with the fact that we do observe farmers training their relatives and family members, suggests that relational contracts do exist, but that they may not extend between important segments of the population with real implications for total output.

Finally, another constraint that was also mentioned by laborers as a barrier to investment outside of the training event were stigma and social image costs that would have been endured in requesting to be trained outside of the experiment. While it may be surprising that these costs maybe so large, this evidence is consistent with a behavioral economics literature describing social image costs of seeking information, or sharing information outside of one's peer group (Chandrasekhar et al., 2018; Bandiera et al., 2020). In this context, the fact that the employers and employees clearly differ along measures of social status may exacerbate this effect.

Are these considerations generalizable? Certainly, research in other low-income countries has suggested that there maybe strong social norms or reputational effects that limit the scope for pareto improving contracts (Breza et al., 2019). The failure to write relational contracts is perhaps more surprising, given long literatures in development economics demonstrating how relationships and social capital can be leveraged in informal contracts (MacLeod, 2007; Macchiavello and Morjaria, 2023), but is consistent with studies showing meaningful surplus being left on the table by a failure to write formal contracts (Bubb et al., 2018). The fact that we do not see such contracts form in this context suggests either that there are large returns to defecting on contracts, or that there are limited returns to developing a reputation for trustworthiness/limited ability to be sanctioned by network members. In this context, this maybe true because of limited social capital that we measure between employers and labor market employees (see Appendix Table A4.2). This difference in social capital may also explain the differential propensity that we see of employers in this environment to train their family, as opposed to laborers. The general finding that trust is low in in LMIC, and particularly in Sub-Saharan Africa, suggests that this may make pareto improving contracts infeasible in a range of environments (Ashraf et al., 2019).

10.2 Limitations to Employer Contracts

In the second experiment, we show large training investments conditional on a contract that we implement that increases the wage paid to employees. This suggests that many employers perceive training to be profitable conditional on this contract. A general question then, is why employers don't increase wage offers (either to trained or untrained workers) to make it more likely that these workers return and work for the employer during the planting season.

While we consider this question beyond the scope of this study, we conducted qualitative interviews with employers and several themes emerged related to barriers to offering higher wages. The first was that employers did not want to develop a reputation for offering much higher wages than competitors in the market, as they stated that this could erode their bargaining power with other workers, while some also mentioned the possibility of being sanctioned by other employers for increasing wages substantially. Second, some employers stated that they did not perceive such a contract was profitable or that they would have the liquidity to offer such high wages at that time of the year.

11 Conclusion

Facilitating the uptake of better agricultural technologies is a key policy objective in low income countries, and particularly in Sub-Saharan Africa, where yields have remained relatively low despite technologies existing that could conceivably increase farm returns (Bank, 2007). In this paper, we suggest that one mechanism that might contribute to underadoption are labor market frictions that lead farmers to underinvest in training workers in these new technologies. We provide evidence that the failure of employers to appropriate the returns to training may lead to meaningful underinvestment in new technologies.

In this paper, we show three facts consistent with a model where there is underinvestment in general skills training. First, we show that when farmers train workers, this generates returns for other employers, and that there may be underinvestment in training general skills. To show this, we conduct a village-level RCT that provides monetary incentives to farmers to train workers. We show that these incentives are effective in this context at generating skill transfer: workers trained in this sample work for other employers using these techniques and adopt the techniques on their own fields. We show that the returns to this training however, accrue not only to employers who train workers: while training employers employ more trained labor, other employers in the same labor market also hire this labor. Profits increase for both training employers and spillover employers. These training investments generate an increase in total social surplus but only one quarter of this surplus is captured by the employers who train workers themselves. Of the surplus not captured by employers who train, two-thirds is captured by other employers, and one-third by trainees.

We then show that a shift of the training surplus to training farmers induces farmers to train. To show this, we design a contract that increases the perceived probability that workers will return to work for farmers after being trained. We then show that this induces training and skill transfer: farmers are fifty percentage points more likely to train workers after receiving this contract.

This paper provides a complementary policy lever that can be used to facilitate the transmission of this information. Many models of social learning implicitly model the flow of information as happening passively, as farmers observe neighbors' fields and experiments with new technologies (Griliches, 1957) and has spawned a literature that has considered the optimal network members to diffuse information to. However, many costly policies such as agricultural extension, have had somewhat muted impacts in diffusing new technologies

(Udry, 2010; Krishnan and Patnam, 2014). This paper, in the spirit of BenYishay and Mobarak (2019) and Chandrasekhar et al. (2022) assumes that information flow is not frictionless, and the transmission of information require effort on the part of those that hold it. Similar to their paper, we find that farmers may have insufficient incentives to transmit knowledge, and that policies that facilitate the diffusion of this information may have large multiplier effects.

Finally, this paper provides some evidence for "poaching externalities", or returns to training captured by other employers who do not incur the cost of training themselves. As discussed in a sizable theoretical literature, the existence of these returns could make standard contracting solutions to general skills investment decisions less likely to lead to first-best training investments (Acemoglu, 1997; Stevens, 1994). This fact, coupled with mounting evidence suggesting that those who seek information may face large costs in acquiring information, could justify more aggressive interventions in training markets.

Many important questions remain, including which policy prescription, changes to contract structure, subsidies to training investments or otherwise, is optimal in such situations. Moreover, additional evidence is needed on how experience with new technologies interacts with incentives to diffuse information, and the effectiveness of farmer led training.

12 Appendix

12.1 Tables and Figures

Experiment timeline, design, and sampling frame

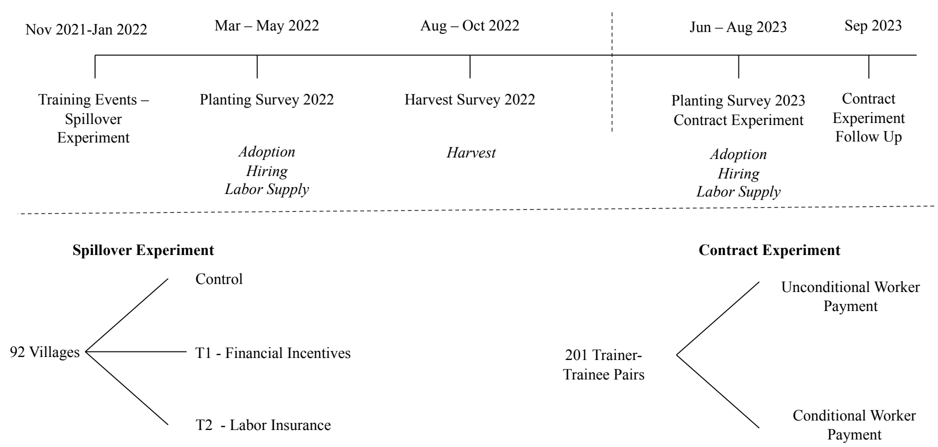


Figure A3.1: Timeline of field operations and data collection, and sampling for each experiment

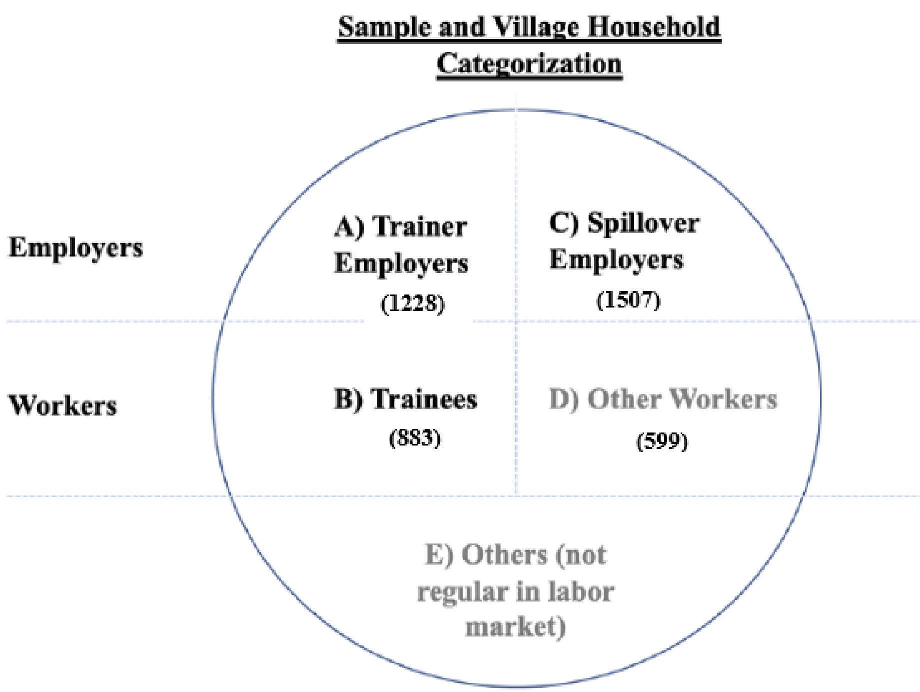


Figure A3.2: Categorization of village households

Notes: The top figure shows the experimental design and timeline of the intervention and surveys, as well as the primary outcomes measured in each survey. The bottom image shows different types of households in villages, and which households in particular we sampled for our project. We have the following samples: trainer-employers (1228), trainees (883), spillover-employers (1507), spillover non-employers (599).

Motivating evidence: agricultural employers' beliefs about their ability to train, and reasons for not training

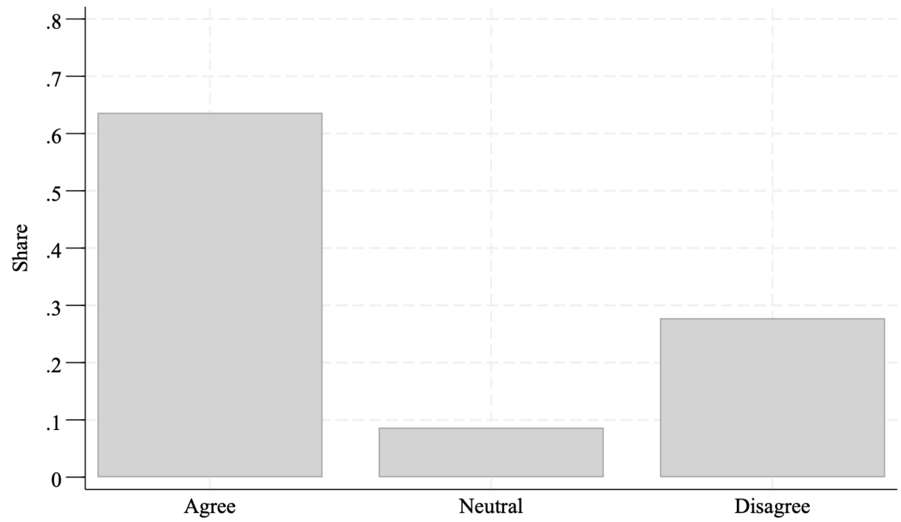


Figure A3.3: Proportion of employers agreeing that they are capable of training

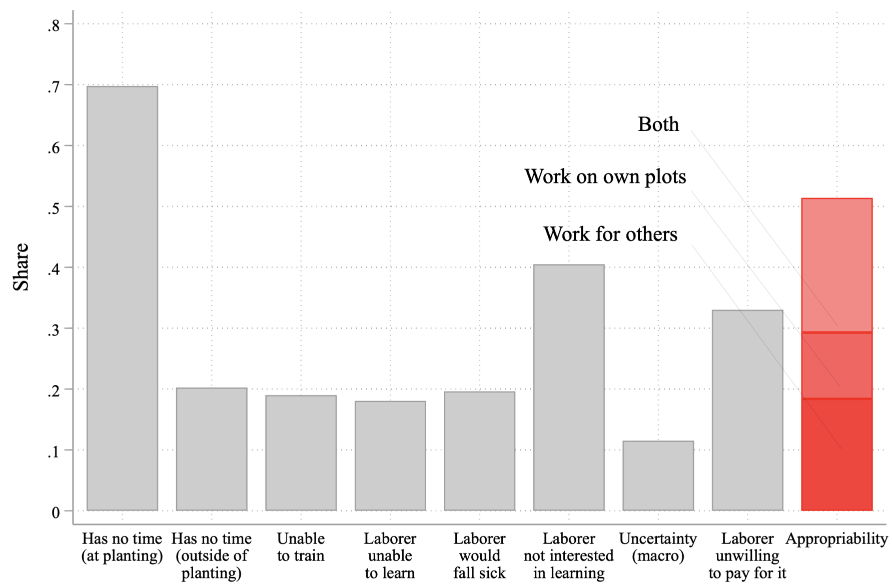


Figure A3.4: Proportion of employers stating reason for not training laborers

Notes: The first figure shows the share of agricultural employers who agree or disagree that they are capable of training workers. The second figure shows the stated reasons by farmers for not having trained workers previously. The "Appropriability" bar in the second figure indicates the share of farmers stating that if they train the worker, he or she would go and work for others, would spend more time on their own fields and so not return, or both. In the second figure, farmers could state multiple reasons. The sample comprises a random sample of farmers regularly employing laborers who do not belong to the villages in the main experiment.

Motivating evidence: share of agricultural employers reporting contracting failures, and reported reasons for why a contracted laborer did not show up to work

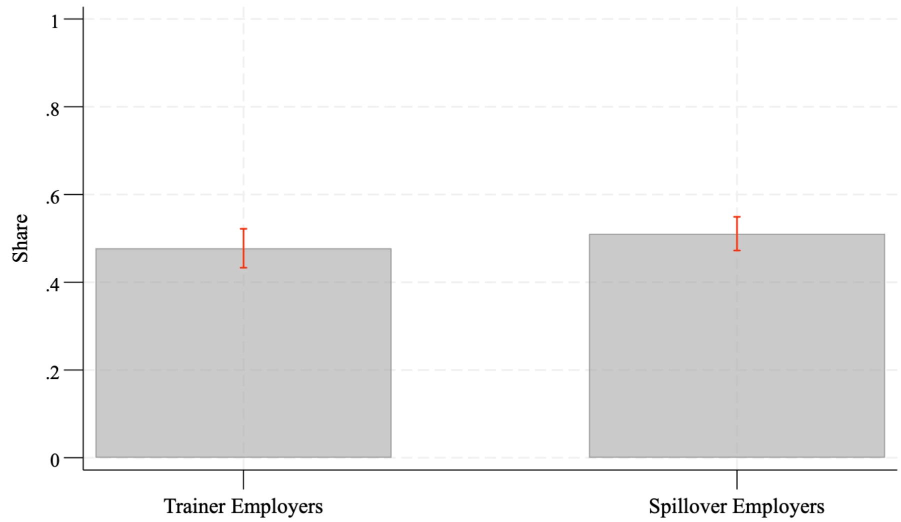


Figure A3.5: Share of employers reporting that a worker they contracted to work did not show up when expected.

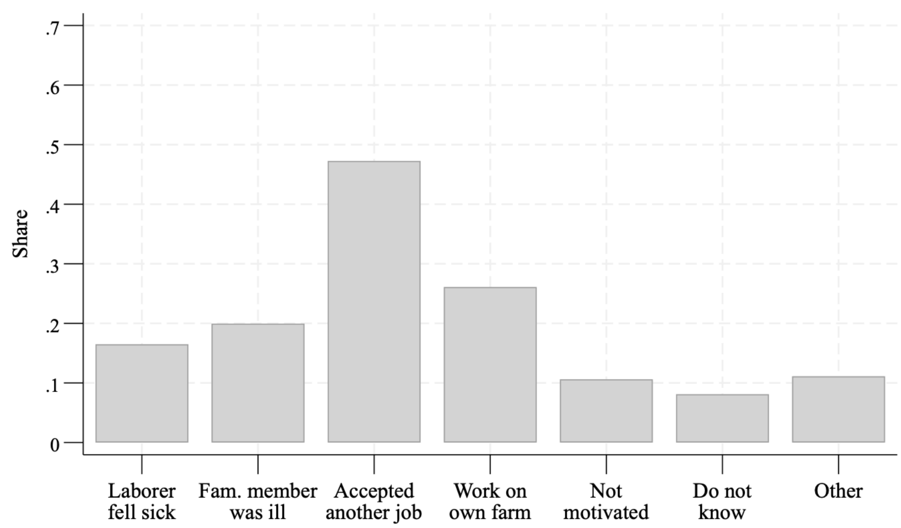
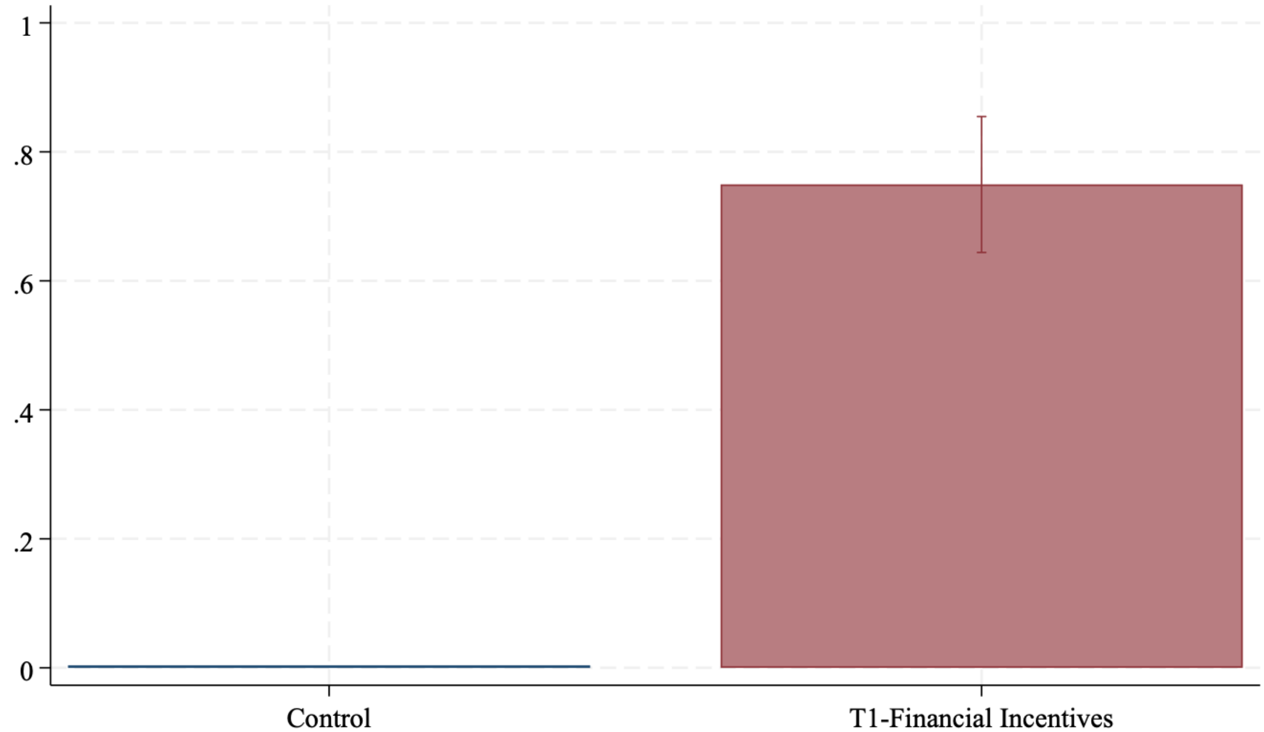


Figure A3.6: Reported reasons for why the worker did not show up for an agreed-upon job.

Notes: These figures show i) the prevalence of contracting frictions in the control group and ii) the reasons reported by farmers for why they think that a laborer whom they contacted to work did not show up to work for them. The first figure shows the proportion of control group employers (trainer-employers and spillover-employers) who stated they contacted a worker to work for them, but she did not show up. This data is taken from the first planting season following the intervention. The second question asks the reason that employers believe the worker did not show up. This question was asked during the harvest survey to all the respondents who reported trying to hire at least one laborer during the previous Season B (regardless of whether they managed to hire one or not), but had at least one laborer who agreed to work for them yet did not show up to work. The options for the answers come from open-ended questions asked during focus groups conducted with farmers not belonging to the main sample. The option "Others" contains also the options "Attended a funeral" and "Had an accident" that were selected by less than 10% of respondents (2.65% and 5.31% respectively).

Figure A3.7: Spillover Experiment: proportion of trainer-employers training the paired worker in the Control and T1-Financial Incentives to Train villages



Notes: This figure shows willingness of trainer-employers to train their train in the different treatment arms of the Spillover Experiment. We plot the share of trainer-employers who trained according to our definition of spending at least 180 minutes supervised with the laborer. In the Control group, trainer-employers received an unconditional financial incentive. In T1-Financial Incentive to Train villages farmers received a financial incentive conditional on this definition of training. Standard errors clustered at the village level are displayed.

Spillover Experiment: Trainees two season treatment effects on the adoption of row planting on own fields, and days worked in tasks involving trained techniques

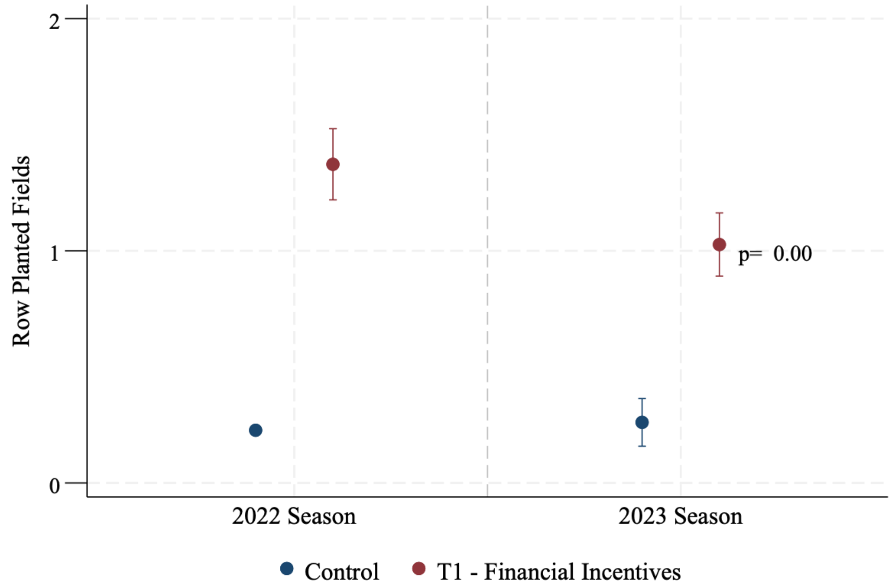


Figure A3.8: Adoption of trained techniques (fields)

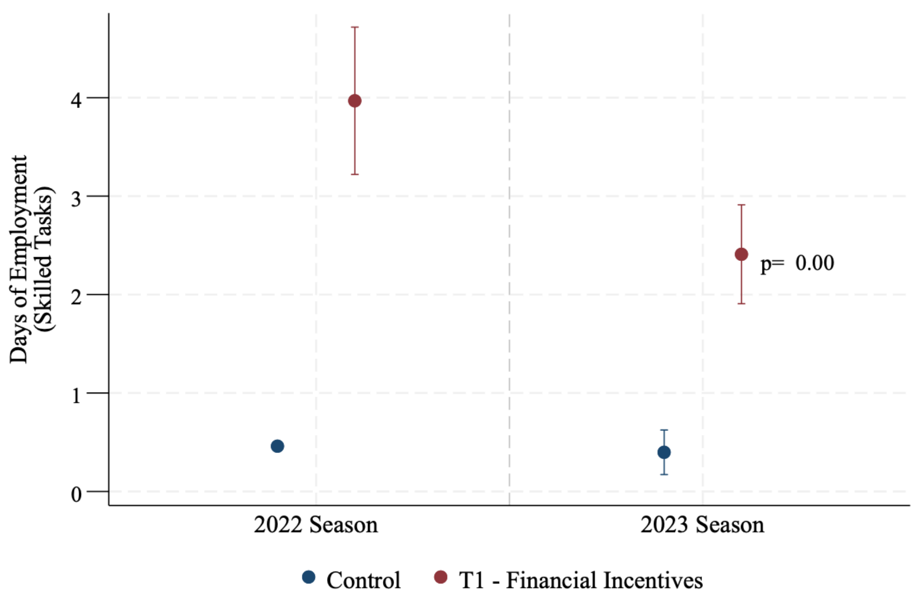


Figure A3.9: Days of employment in trained techniques

Notes: This figure shows the number of fields on which row planting was adopted and the number of days employed for tasks involving the trained techniques for trainees in the T1- Financial Incentives to Train and Control Villages. Data is shown for two seasons: the 2022 season (collected 1-2 months after training) and the 2023 season (12-13 months months after training). The outcome variable in the first panel is the number of trainees' fields planted using row planting. The outcome variable in the second panel is the number of days that the trainee was employed by others to do row planting or fertilizer microdosage. The 95% confidence intervals are displayed. P-values for a test of equality of control and treatment coefficients in the second season are displayed.

Spillover Experiment: Trainer-employer two season treatment effects on adoption of trained techniques and skilled labor hiring

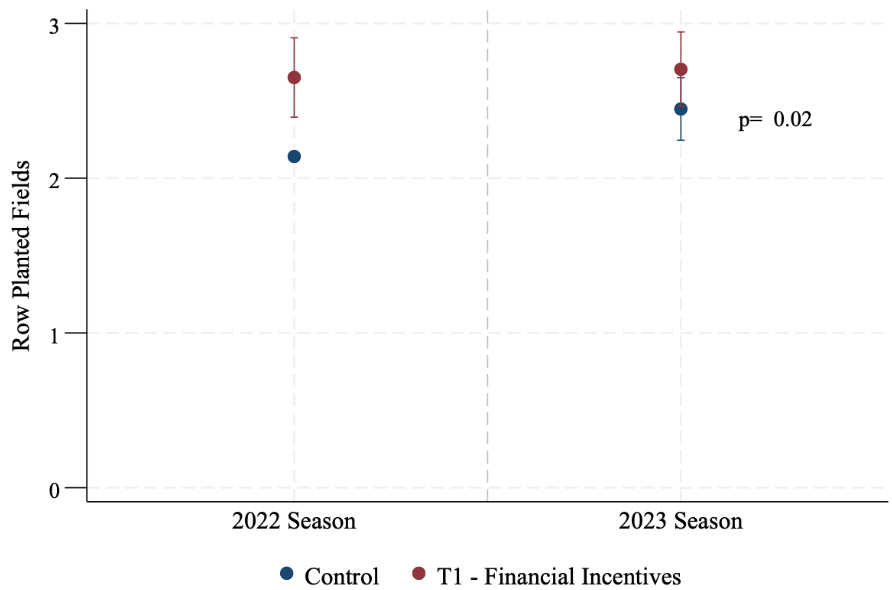


Figure A3.10: Adoption of row planting (fields)

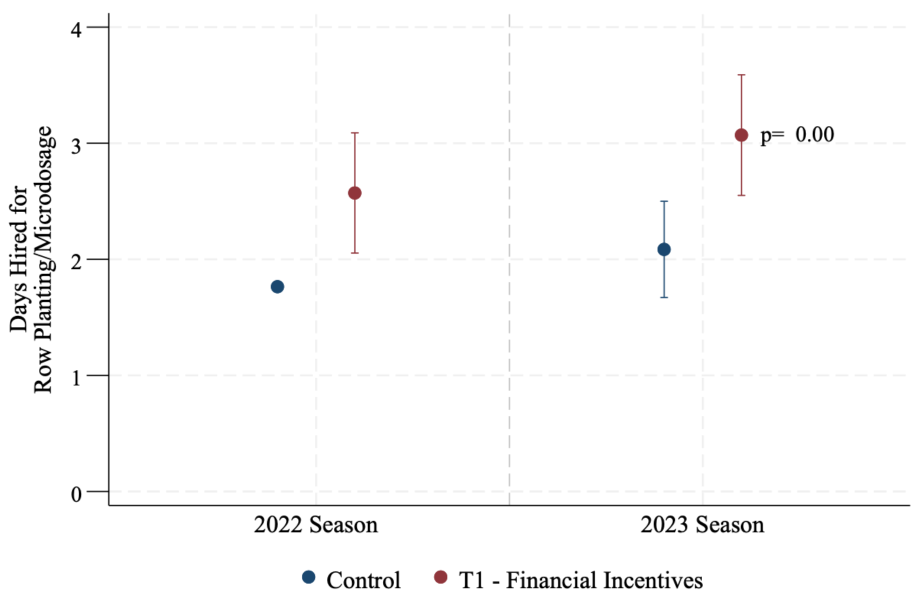


Figure A3.11: Days of labor hired to do row planting/microdosage

Notes: This figure shows the number of fields on which row planting was adopted and the number of days that labor was employed to do row planting/fertilizer microdosage, for trainer-employers in the T1-Financial Incentives to Train and Control Villages. Data is shown for two seasons: the 2022 season (collected 1-2 months after training) and the 2023 season (12-13 months months after training). The outcome variable in the first panel is the number of trainer-employers' fields planted using row planting. The outcome variable in the second panel is the number of days that the trainer-employers hired labor to perform the trained techniques. 95% confidence intervals are displayed. P-values for a test of equality of control and treatment coefficients in the second season are displayed.

Spillover Experiment: Spillover-employer two season treatment effects on adoption of trained techniques and skilled labor hiring

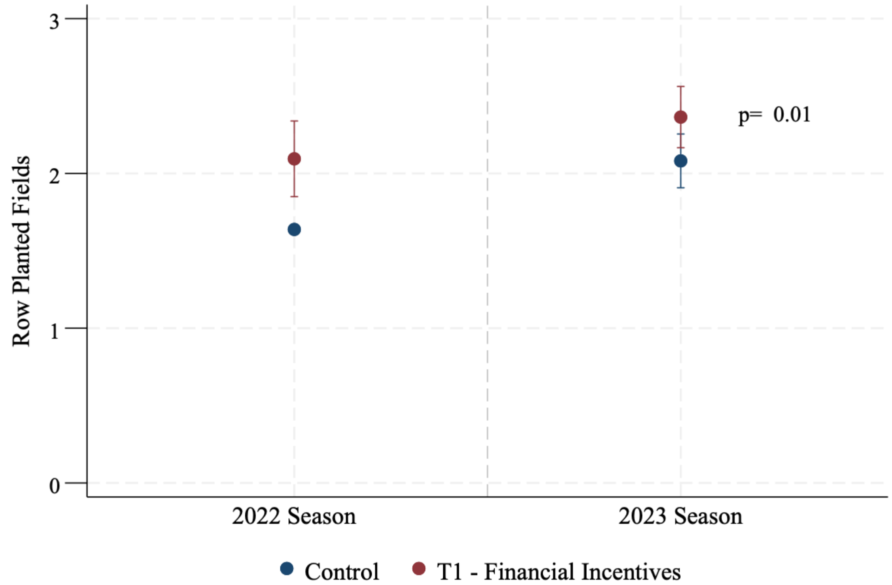


Figure A3.12: Adoption of row planting (fields)

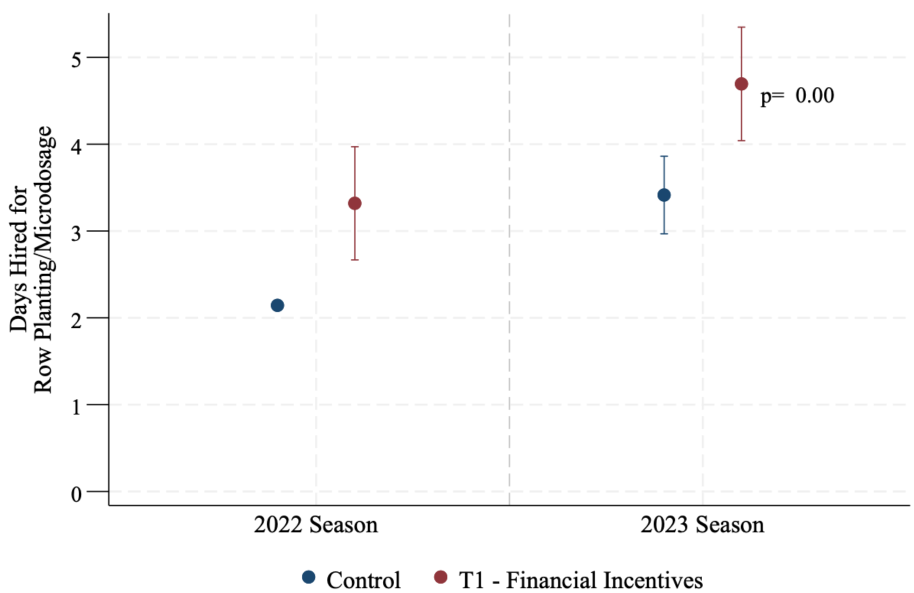


Figure A3.13: Days of labor hired to do row planting/microdosage

Notes: This figure shows the number of fields on which row planting was adopted and the number of days that labor was employed to do row planting/fertilizer microdosage, for spillover-employers in the T1-Financial Incentives to Train and Control Villages. Data is shown for two seasons: the 2022 season (collected 1-2 months after training) and the 2023 season (12-13 months months after training). The outcome variable in the first panel is the number of spillover-employers' fields planted using the trained techniques. The outcome variable in the second panel is the number of days that the spillover-employers hired labor to perform the trained techniques. 95% confidence intervals are displayed. P-values for a test of equality of control and treatment coefficients in the second season are displayed.

Contract Experiment: Impact of the contract on the trainer-employers' willingness to train and trainees' skill upgrade

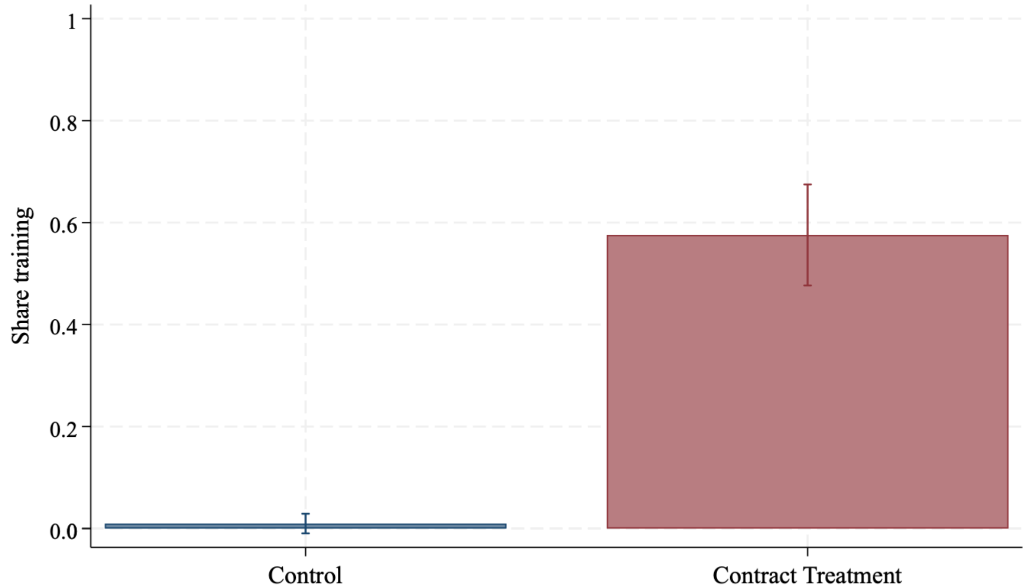


Figure A3.14: Share of trainer-employers attending the training event for at least half a day

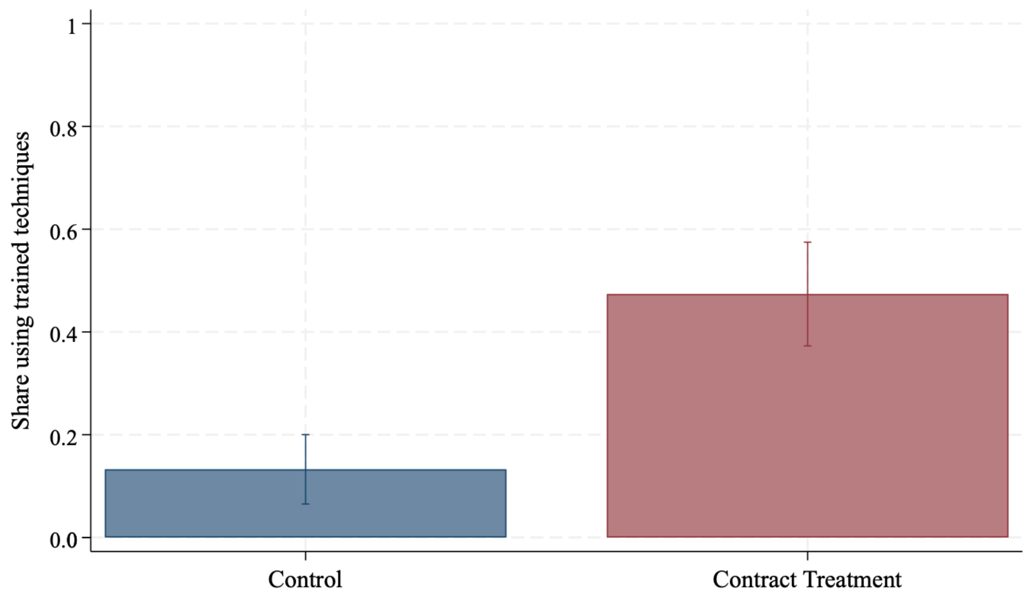


Figure A3.15: Share of trainees using trained skills

Notes: The top figure shows the proportion of farmers in the Contract Experiment who attend the training event that we held for at least 3 hours. Farmers in the Contract Experiment were previously randomly assigned to receive the contract that offered them a greater likelihood that the worker returned to work for them. 3 hours was the cutoff used to define training in the Spillover Experiment, and is generally considered the minimum amount of time to teach row planting and fertilizer microdosage. The bottom figure shows the proportion of trainees in the treatment or control group who adopted row planting on their own fields, or who worked for another employer (*i.e.* not their contracted employer) to do row planting or fertilizer microdosage. Robust standard errors are shown.

Table A3.1: Spillover Experiment - Balance table

	Trainer-Employers			Spillover-Employers			Trainees			Spillover non-employers (Non-engaged)			Spillover non-employers (Extra Laborers)		
Variable	Control Mean (1)	Treatment Mean (2)	P-value Δ (3)	Control Mean (4)	Treatment Mean (5)	P-value Δ (6)	Control Mean (7)	Treatment Mean (8)	P-value Δ (9)	Control Mean (10)	Treatment Mean (11)	P-value Δ (12)	Control Mean (13)	Treatment Mean (14)	P-value Δ (15)
Demographics															
Age	43.7	43.6	0.89	47.0	47.6	0.58	34.0	34.8	0.36	48.1	46.6	0.53	39.4	38.6	0.58
	(11.1)	(11.5)		(13.9)	(14.1)		(11.0)	(11.3)		(15.2)	(15.8)		(11.8)	(13.3)	
No Education (binary)	0.3	0.3	0.34	0.3	0.4	0.23	0.3	0.4	0.39	0.4	0.5	0.53	0.4	0.4	0.54
	(0.5)	(0.5)		(0.5)	(0.5)		(0.5)	(0.5)		(0.5)	(0.5)		(0.5)	(0.5)	
Primary (binary)	0.6	0.6	0.30	0.6	0.5	0.40	0.6	0.5	0.68	0.5	0.5	0.51	0.6	0.6	0.45
	(0.5)	(0.5)		(0.5)	(0.5)		(0.5)	(0.5)		(0.5)	(0.5)		(0.5)	(0.5)	
Household Size	5.0	4.9	0.23	4.5	4.5	0.97	3.8	3.9	0.48	3.4	3.5	0.73	3.8	3.8	0.90
	(1.9)	(2.0)		(2.1)	(2.2)		(1.9)	(1.9)		(2.1)	(2.0)		(1.9)	(1.8)	
Unmarried	0.0	0.0	0.68	0.0	0.0	0.68	0.2	0.2	0.32	0.0	0.0	0.44	0.0	0.1	0.18
	(0.1)	(0.1)		(0.2)	(0.2)		(0.4)	(0.4)		(0.2)	(0.2)		(0.2)	(0.3)	
Male	0.6	0.6	0.44	0.5	0.5	0.10	0.4	0.4	0.87	0.4	0.4	0.81	0.3	0.3	0.93
	(0.5)	(0.5)		(0.5)	(0.5)		(0.5)	(0.5)		(0.5)	(0.5)		(0.4)	(0.4)	
Savings (log)	9.9	10.0	0.31	10.2	10.3	0.74	7.6	7.8	0.31	8.9	8.8	0.84	8.4	8.6	0.70
	(2.3)	(2.1)		(2.3)	(2.2)		(3.1)	(3.1)		(3.6)	(3.2)		(3.2)	(3.1)	
Baseline farm and knowledge															
Land (plots)	6.6	7.1	0.09	7.4	7.6	0.57	3.5	3.7	0.31	3.7	3.6	0.84	3.2	3.3	0.68
	(3.3)	(3.7)		(3.9)	(3.9)		(1.6)	(1.9)		(1.8)	(1.9)		(2.2)	(2.1)	
Land (ares)	43.0	45.2	0.46	51.9	55.0	0.47	15.7	17.0	0.53	14.1	13.9	0.93	13.1	13.7	0.79
	(38.8)	(37.5)		(46.8)	(51.2)		(21.9)	(19.5)		(12.0)	(14.2)		(15.7)	(16.2)	
Staples value (Past B)	142045.8	133083.8	0.31	148776.7	145203.1	0.69	34549.1	38635.1	0.26	52797.4	45603.6	0.29	40248.7	39400.6	0.85
	(94817.2)	(89028.2)		(100787.3)	(98655.2)		(28110.4)	(44164.8)		(37745.7)	(37966.2)		(42290.4)	(35008.7)	
Fields (Past B)	6.1	6.3	0.33	6.6	6.6	0.94	3.5	3.7	0.38	3.8	3.4	0.10	3.2	3.3	0.94
	(2.7)	(2.8)		(3.4)	(3.3)		(1.7)	(2.0)		(1.6)	(1.6)		(2.1)	(1.8)	
Row Planted Fields (Past B)	3.6	3.4	0.24	3.0	2.6	0.03	0.2	0.2	0.76	1.2	1.0	0.48	0.9	0.7	0.34
	(2.0)	(1.8)		(2.6)	(2.0)		(0.8)	(0.8)		(1.2)	(1.3)		(1.4)	(1.0)	
Planted in lines (Past season)	1.0	1.0	0.34	0.8	0.8	0.31	0.1	0.1	0.90	0.6	0.5	0.40	0.4	0.4	1.00
	(0.1)	(0.1)		(0.4)	(0.4)		(0.3)	(0.3)		(0.5)	(0.5)		(0.5)	(0.5)	
Previously used improved technology	1.0	1.0	.	0.8	0.8	0.28	0.1	0.1	0.91	0.5	0.5	0.52	0.4	0.4	0.82
	(0.0)	(0.0)		(0.4)	(0.4)		(0.2)	(0.2)		(0.5)	(0.5)		(0.5)	(0.5)	
Practice usage (past 5 years)	3.0	2.9	0.79	2.2	2.0	0.26				0.9	0.8	0.59	0.7	0.4	0.15
	(1.8)	(1.8)		(2.0)	(1.9)					(1.6)	(1.3)		(1.3)	(1.0)	
Z Score Knowledge	0.7	0.8	0.18	0.3	0.3	0.81	-1.1	-1.2	0.13	-0.4	-0.5	0.37	-0.6	-0.5	0.29
	(0.6)	(0.6)		(0.9)	(0.9)		(0.4)	(0.4)		(0.6)	(0.7)		(0.8)	(0.8)	
Labor Market															
Past supply	0.2	0.2	0.38	0.2	0.2	0.27	1.0	0.9	0.27	0.0	0.0	.	1.0	1.0	0.79
	(0.4)	(0.4)		(0.3)	(0.3)		(0.2)	(0.2)		(0.0)	(0.0)		(0.2)	(0.2)	
Mandays supplied	2.0	1.7	0.45	0.6	0.7	0.80	11.7	11.1	0.56	0.0	0.0	.	11.1	10.2	0.31
	(4.3)	(4.3)		(2.5)	(2.8)		(9.0)	(10.1)		(0.0)	(0.0)		(9.4)	(7.2)	
Wage Past Season							2454.2	2355.1	0.16						
							(544.7)	(483.5)							
Labor Market Earnings							28934.3	26484.5	0.37						
							(23969.2)	(26333.3)							
Past demand	0.9	0.9	0.60	1.0	1.0	0.77	0.2	0.2	0.07	0.0	0.0	0.51	0.2	0.2	0.67
	(0.3)	(0.3)		(0.2)	(0.2)		(0.4)	(0.4)		(0.2)	(0.2)		(0.4)	(0.4)	
Mandays demand	20.0	20.6	0.71	29.0	33.0	0.12				0.3	0.4	0.62	3.0	3.3	0.79
	(22.6)	(18.7)		(27.5)	(30.0)					(1.7)	(2.9)		(8.8)	(10.8)	
Observations	590	638		718	789		432	451		95	124		198	172	

Notes: This table shows the balance between all groups of farmers in the Spillover experiment. Variables were collected at baseline and correspond to the entire sample. In columns (1) (4) (7) (10) and (13), we show the mean and standard deviation for the variable of interest among the Control group. In columns (2) (5) (8) (11) and (14), we show the same for the Treatment group. Finally, in columns (3) (6) (9) (12) and (15) we show the p-value for a T-test of equality of means. The p-values of the difference in the means test come from SEs clustered at the village level.

Table A3.2: Spillover Experiment: Trainee employment, earnings and technology adoption

	Trained Techniques		Agricultural Work				Own Fields
	Total Days	Total Earnings	Total Days	Total Earnings	Worked	Wage	Modern Fields
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T1 - Financial Incentives	3.45	8555.15	0.86	3612.24	0.00	191.20	1.33
Train	(0.37)	(945.19)	(0.53)	(1441.92)	(0.03)	(77.31)	(0.09)
	[0.00]	[0.00]	[0.11]	[0.01]	[0.96]	[0.02]	[0.00]
Control mean	0.46	983.61	7.33	16852.41	0.84	2303.99	0.23
Obs.	848	848	848	848	848	710	848

Notes: This table shows the effect of the T1-Financial Incentive to Train treatment on the employment and earnings of trainees –laborers selected by trainer-employers and invited to attend the training event. The dependent variable in Column 1 is the total number of days the laborer worked during the agricultural season doing work that involved the techniques taught during the training (row-planting and fertilizer microdosage). The dependent in Column 2 are the earnings from work that involved techniques taught in the training. Columns 3 and 4 are days worked and earnings from any kind of agricultural work during the agricultural season. Column 5 is an indicator variable for whether the laborer did any agricultural work during the agricultural season. Column 6 is the average wage earned by the trainee. Column 7 is the number of fields that the trainee planted using row planting. Standard errors are clustered at the village level.

Table A3.3: Spillover Experiment: Hiring and technology adoption among trainer-employers

	Tried Hire Paired Trainee (1)	Unable Hire Paired Trainee (2)	Paired Trainee Skilled Task (3)	Trainees Skilled Task (4)	Hired Skilled Task (5)	Adoption Total (6)
T1 - Financial Incentives Train	0.15	0.16	0.52	0.84	0.81	0.46
	(0.04)	(0.04)	(0.15)	(0.20)	(0.26)	(0.13)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Dependent Variable Unit	Binary	Binary	Days	Days	Days	Fields
Control mean	0.56	0.23	0.43	0.67	1.76	2.47
Obs.	555	555	1216	1216	1216	1216

Notes: This table shows the effect of the T1 - Financial Incentives to Train Treatment on hiring of laborers for different agricultural tasks during the planting season, as well as the adoption of row planting on own farmer's fields. The sample is comprised of trainer-employers (farmers who were invited to train laborers at the training event). Columns 1 and 2 are comprised of a randomly selected subsample of these individuals who we revisited one year after the initial survey. The dependent variable in column 1 is a binary variable equal to one if the farmer reported trying to hire the laborer they identified to bring to the training event during the planting season. The dependent variable in column 2 is a binary variable equal to one if the farmer reported trying to hire the laborer they identified to bring to the training event, and being unsuccessful in doing so. The dependent variable in column 3 is the number of days an employer hired the trainee who they invited to the training event to do skilled tasks on their fields (row planting and fertilizer microdosage). The dependent variable in column 4 is the number of days an employer hired any laborer who was invited to the training events to do skilled tasks on their fields (row planting and fertilizer microdosage). The dependent variable in column 6 is the number of fields in the farmer's household that were planted using row planting. Standard errors are in parentheses and p-values are in brackets. Standard errors are clustered at the village level.

Table A3.4: Spillover Experiment: Hiring and technology adoption among spillover-employers

	Trainees Skilled Task (1)	Hired Skilled Task (2)	Adoption Total (3)
T1 - Financial Incentives Train	1.25	1.29	0.45
	(0.19)	(0.32)	(0.13)
	[0.00]	[0.00]	[0.00]
Control mean	0.23	2.14	1.90
Dependent Variable Unit	Days	Days	Fields
Obs.	1466	1466	1466

Notes: This table shows the effect of the T1 - Financial Incentives to Train Treatment on hiring of laborers for different agricultural work during the planting season, as well as the adoption of row planting on own farmer's fieds. The sample is comprised of spillover farmers uninvolved in the village training even. The dependent variable in column 1 is the number of days an employer hired a laborer who was invited to the training event to do trained techniques (row-planting and fertilizer microdosage). The dependent variable in column 2 is the number of days hired for these tasks in total. The dependent variable in column 3 is the number of fields in the farmer's household where row planting was used. Standard errors are in parentheses and p-values are in brackets. Standard errors are clustered at the village level.

Table A3.5: Spillover Experiment: Incidence of training returns (farm profitability and total earnings)

	Farm Revenues	Farm Profits		Labor Market Earnings
		Wage = Own/Average	Wage = 0	
Panel A: Pooled	(1)	(2)	(3)	(4)
T1 - Financial Incentives	27,996	25,497	26,243	-598
Train	(15,023)	(12,949)	(12,737)	(783)
	[0.07]	[0.05]	[0.04]	[0.45]
Control mean	334,230	234,869	129,284	6,502
Obs.	3491	3491	3491	4060
Panel B: Trainees	(1)	(2)	(3)	(4)
T1 - Financial Incentives	16,551	16,408	12,084	3,382
Train	(8,558)	(7,786)	(7,634)	(1,409)
	[0.06]	[0.04]	[0.12]	[0.02]
Control mean	155,385	115,491	33,610	16,775
Obs.	839	839	839	839
Panel C: Trainer (Employers)	(1)	(2)	(3)	(4)
T1 - Financial Incentives	24,869	24,175	23,719	-732
Train	(14,690)	(13,507)	(13,281)	(635)
	[0.09]	[0.08]	[0.08]	[0.25]
Control mean	368,729	260,090	140,052	3,441
Obs.	1204	1204	1204	1204
Panel D: Spillover (Employers)	(1)	(2)	(3)	(4)
T1 - Financial Incentives	31,135	27,349	31,212	483
Train	(19,035)	(16,375)	(16,462)	(323)
	[0.11]	[0.10]	[0.06]	[0.14]
Control mean	409,011	282,978	175,626	859
Obs.	1448	1448	1448	1448

Notes: This table shows the effect of the T1 - Financial Incentives to Train Treatment on the profits of farmers in treatment villages. Panel A shows regression results for the pooled sample (Trainers, Trainees, Spillover). Panel B shows regressions results for the sample of trainees only. Panel C shows regression results for the sample of trainer (employers). Panel D shows the regression results for the sample of spillover (employers). The dependent variable in column 1 is farm revenues. The dependent variable in column 2 is farm profitability, as total crop revenues less labor and non-labor input costs, valuing family labor at a wage of 0. The dependent variable in column 3 is the same as column 2 except that it assumes that any family labor is valued at the wage of either the individual themselves, or the average wage in the village. The dependent variable in column 4 is labor market earnings. Standard errors are in parentheses and p-values are in brackets. Robust standard errors are clustered at the village level.

Table A3.6: Spillover Experiment: Cost-benefit ratio of training

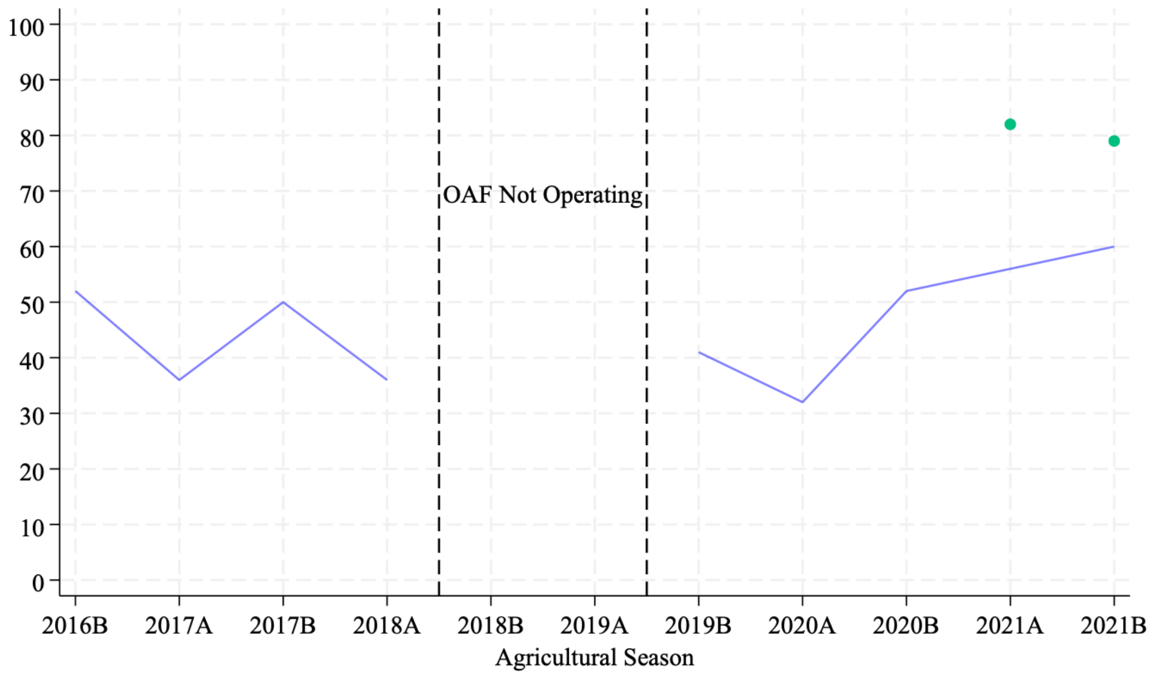
Panel A: Assumptions			
Seasons of Returns	2		
Depreciation of Returns	0.5		
Panel B: Parameters			
Discount Rate	0.1		
Panel C: Benefits			
Profits and Labor Market Earnings (Pooled)			
Proportion of Sample:			
	Trainee	Trainer	Spillover
	25%	25%	50%
Panel D: Cost			
Land/Equipment rental, Training Incentives, Staff time			
Opportunity cost of time (Trainee and Trainer Search)			
No Fiscal Externalities			
Panel E: Benefit/Cost			
	Trainee Only	Trainer/Trainee	Trainee/Trainer/Spillover
2 season	0.7	1.6	3.2
p ($H_0 : B/C \leq 1$)	0.86	0.18	0.08
1 season	0.4	1.0	2.2
p ($H_0 : B/C \leq 1$)	1.00	0.47	0.14
Panel F: Benefit/Cost adjustment for Labor Supply Response			
Benefit = Compensating Variation			
1 season	0.25		

Notes: This table shows estimates of the benefit cost ratio associated with the training. Panel A shows the assumptions associated with the length of time the benefits last. Panel B presents other parameters. Panels C and D describe the Benefit and cost estimates. Panel E shows estimated benefit cost ratios and p-values for the test of the null that the ratio is less than or equal to 1. The first column in Panel E includes only the earnings benefits for trainees (increase in own field profitability and labor market earnings), the second column adds to this also the increase in farm profitability for trainer-employers, and the third column includes also the increase in farm profitability for spillover-employers. Panel F adjusts the one season Benefit-Cost ratio for trainees netting out the portion of earnings that is due to an increase in days worked.

13 Supplementary Appendix

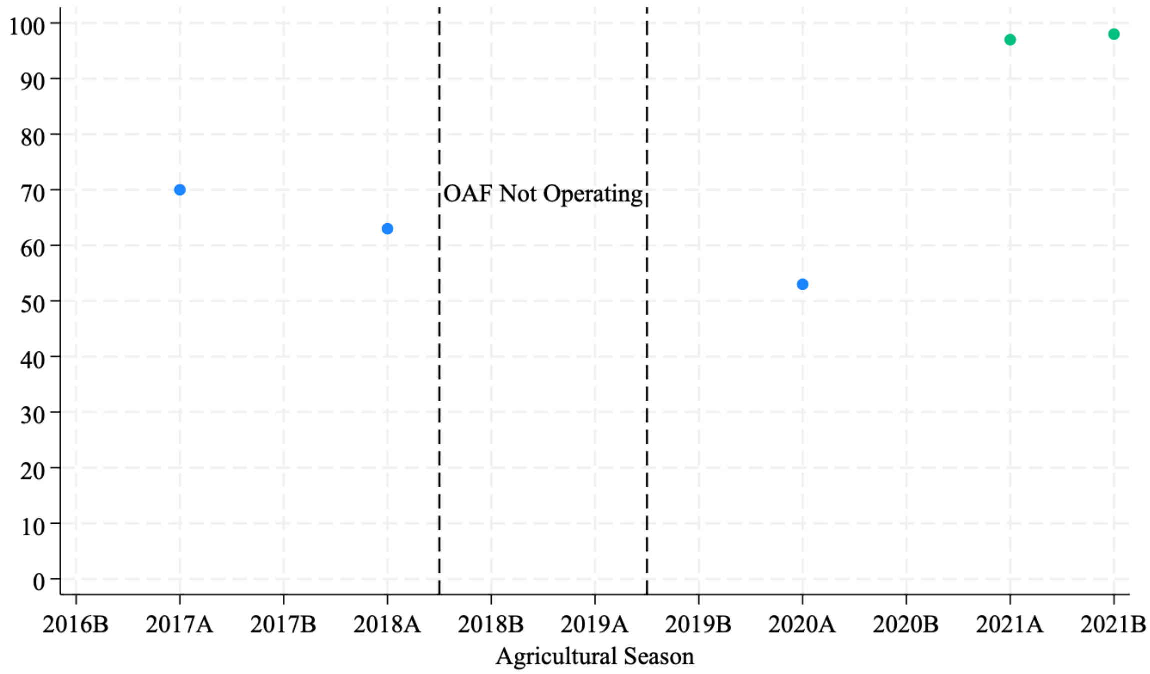
13.1 Appendix Figures

Figure A4.1: Adoption of planting practices over time - Beans



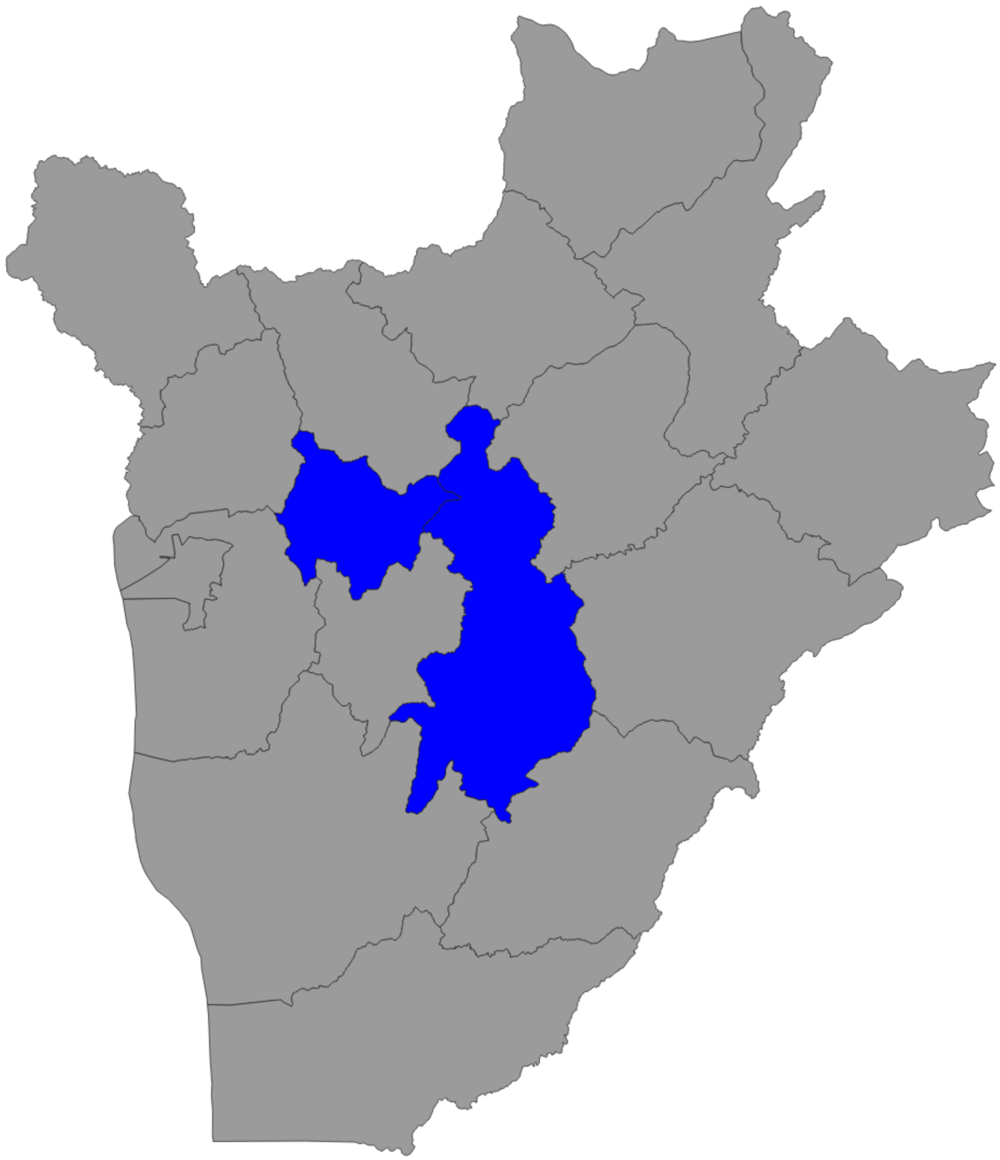
Notes: This figure shows the proportion of 1AF clients that planted randomly audited bean fields using row planting (*i.e.* the trained planting technique) each season. The solid line shows the proportion of Burundian 1AF clients that planted randomly audited fields using this technique. The green dots shows the proportion of Rwanda 1AF clients that planted randomly audited fields using this technique. 1AF was not operating in Burundi in the period between the dashed lines. Data comes from 1AF Monitoring and Evaluation reports.

Figure A4.2: Adoption of planting practices over time- Maize



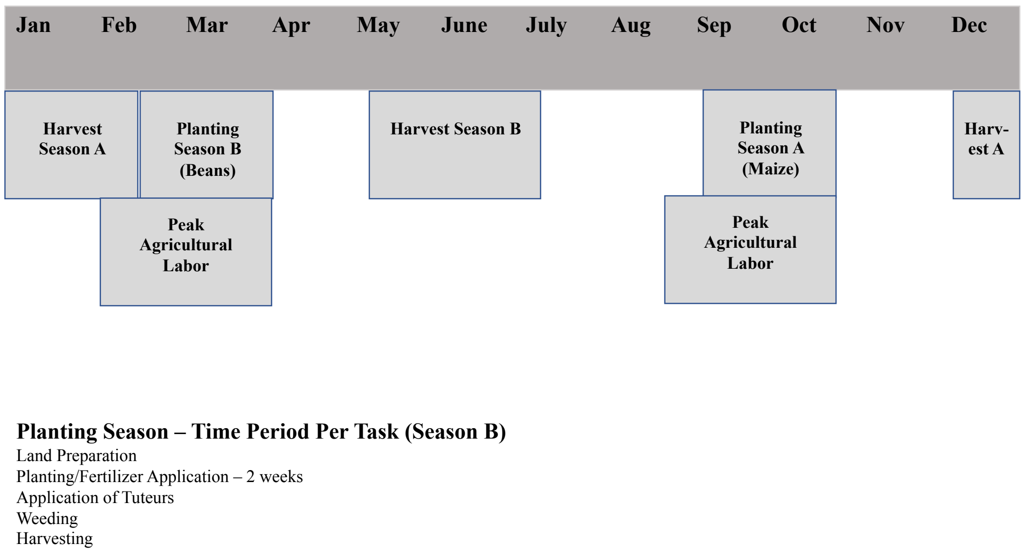
Notes: This figure shows the proportion of 1AF clients that planted randomly audited maize fields using properly spaced row planting each season. The green dots show the proportion of Rwandan 1AF clients that planted randomly audited maize fields using row planting. The blue dots show this information for Burundi. 1AF was not operating in Burundi in the period between the dashed lines. Data comes from 1AF Monitoring and Evaluation reports.

Figure A4.3: Map of Study Area



Notes: This figure shows a map of the areas (highlighted in blue) that the study was located in, in Burundi.

Figure A4.4: Burundian Agricultural Calendar

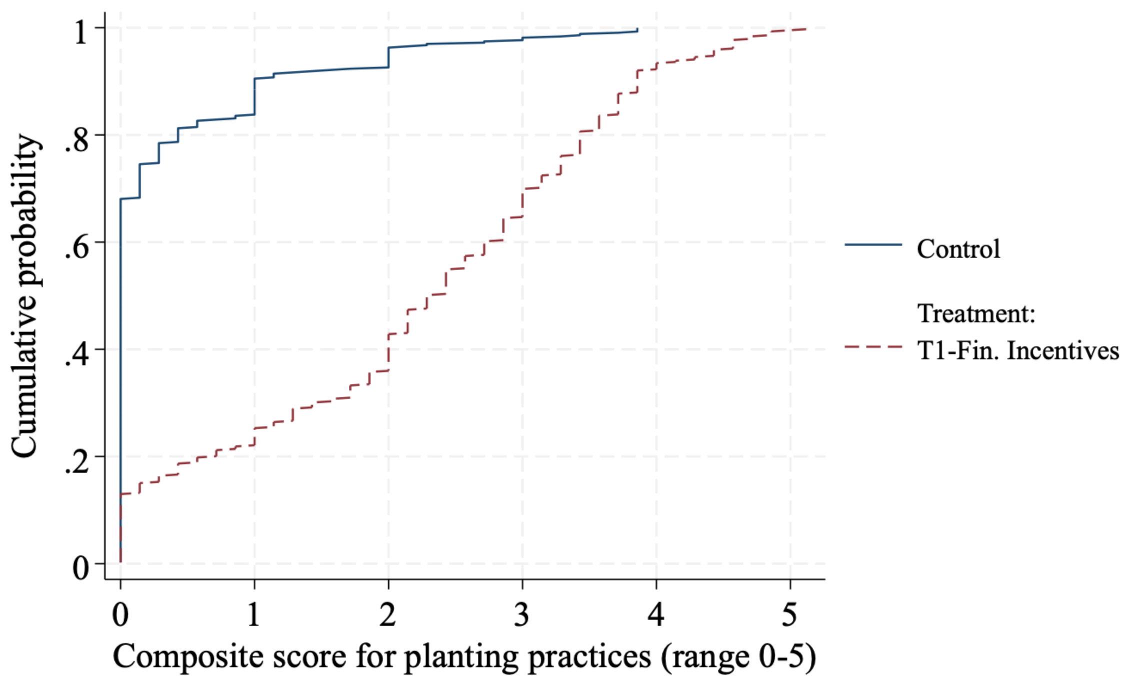


Notes: This figure shows details of the agricultural calendar and labor requirements in Burundi. The figure is based partially on a similar figure in Vinck (2008)

Figure A4.5: Pictures of Row-Planting and Traditional Seedings Practices

Notes: These images show farmers' fields planted using different seeding techniques. The top image shows a field planted using row planting, the technique encouraged as part of the training. The bottom image shows a field planted using broadcasting, the traditional method of planting.

Figure A4.6: Improvement of laborer's skills in incentivized task



Notes: This figure shows the cumulative distribution function of scores (from 0 to 5) obtained by laborers (trainee) in an incentivized planting practice activities after training happened. The blue solid line shows the CDF of scores in the control group, the red dashed line shows the score in the treatment group. Laborers were shown a small plot of land of equal size, and given 4 minutes to plant in "modern" way. At the end, the enumerator would measure the distance between pockets and rows, which we translated in a score ranging from 0 to 5. This task tested two crucial aspects for employability of laborers: (i) accuracy of spacing between pockets, (ii) speed. Laborers were told that, conditional on performing above a certain threshold in the task, they would be entered in a lottery to win a prize of the value of one day of unskilled labor.

Spillover Experiment: profit distribution

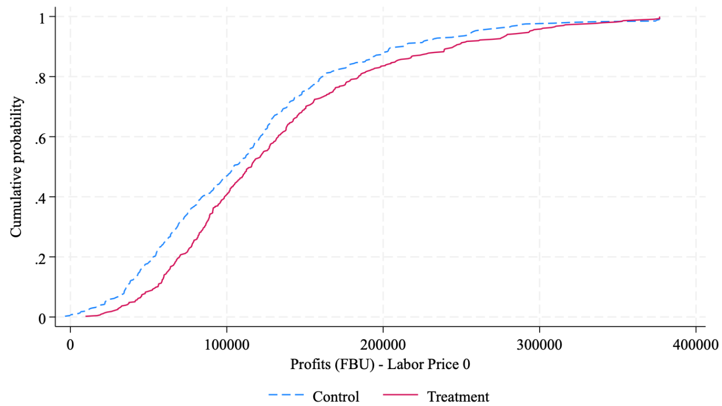


Figure A4.7: Trainees

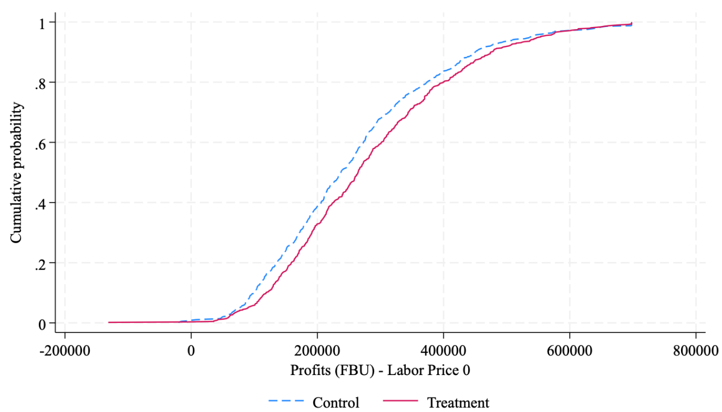


Figure A4.8: Trainer-employers

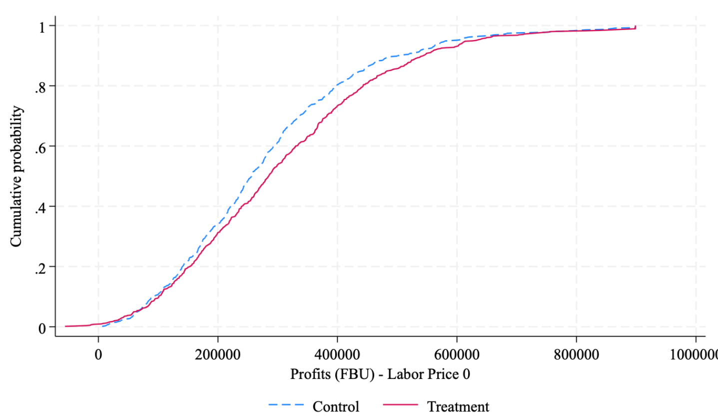
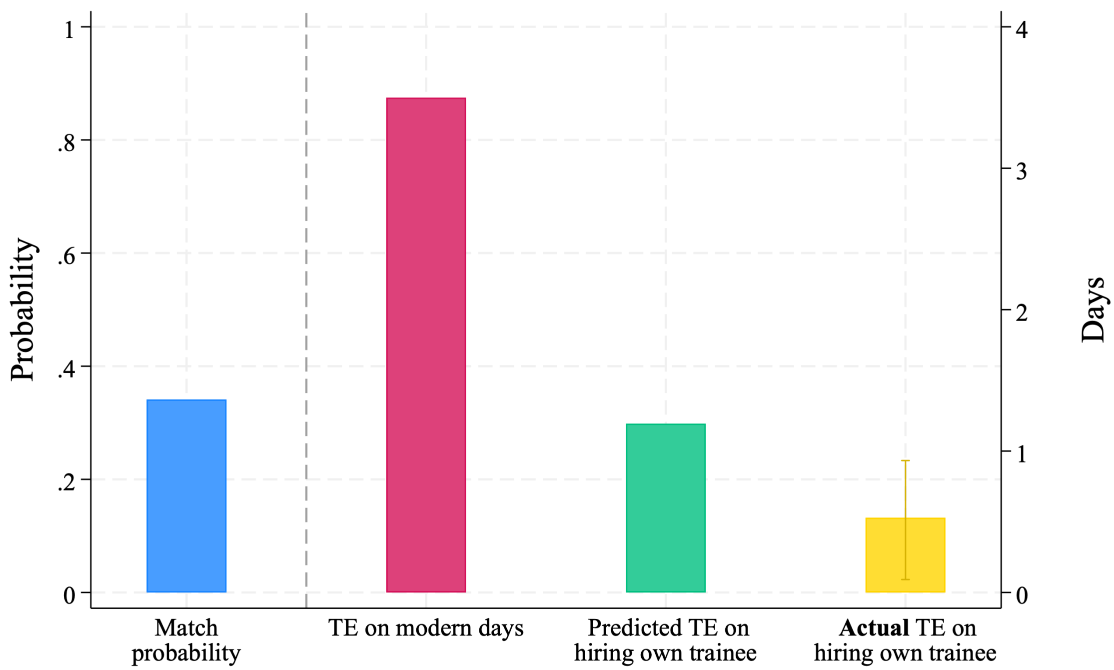


Figure A4.9: Spillover-employers

Notes: This figure shows the CDF of Farm profits for trainees (Panel A4.7) trainer-employers (Panel A4.8) and spillover employers (Panel A4.9) in the Spillover Experiment, in both T1-Financial Incentives to Train and Control Villages. Profits are winsored at the 99th percentile. The price of family labor in these figures is assumed to be 0.

Figure A4.10: Predicted and measured training Spillovers



Notes: This figure shows the spillovers predicted by the training intervention and those measured. The blue bar is the days weighted churn rate as measured for control group trainees - the interpretation of this number (0.3) is that if a trainee worked for an employer in the prior year, then they spend 30% of their working days in the current year working for them. This is measured for the trainees in the second season of the experiment. The red bar is the number of additional days that trainees in the treatment group work in the labor market using the techniques that they were trained to do. The green bar is the number of days of modern practices that one would therefore predict using the control group churn rate that employers who train would be able to hire their own train to do these techniques: it is the number in the blue bar multiplied by the number in the red bar. The yellow bar is the number of days that trainer-employers actually hired their trainee to use these techniques.

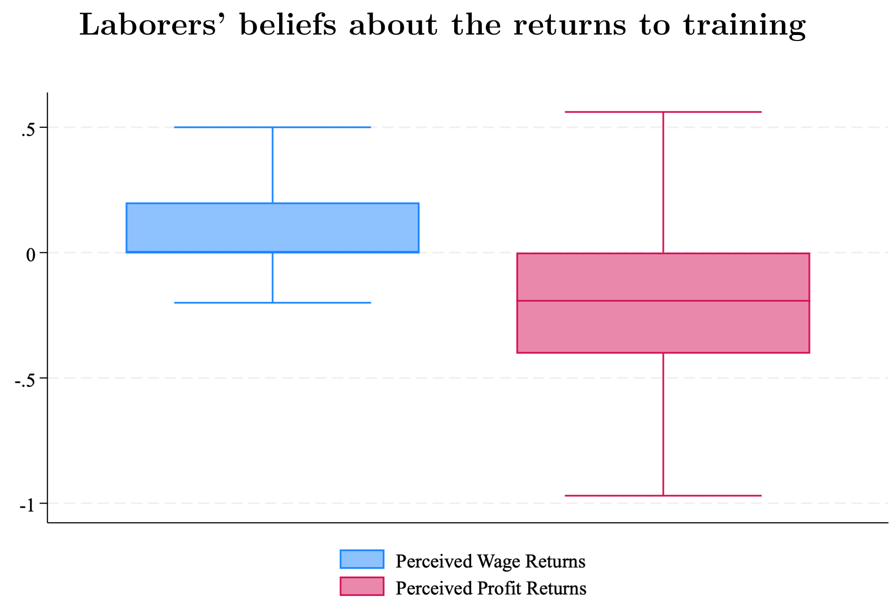


Figure A4.11: Perceived wage and profit returns

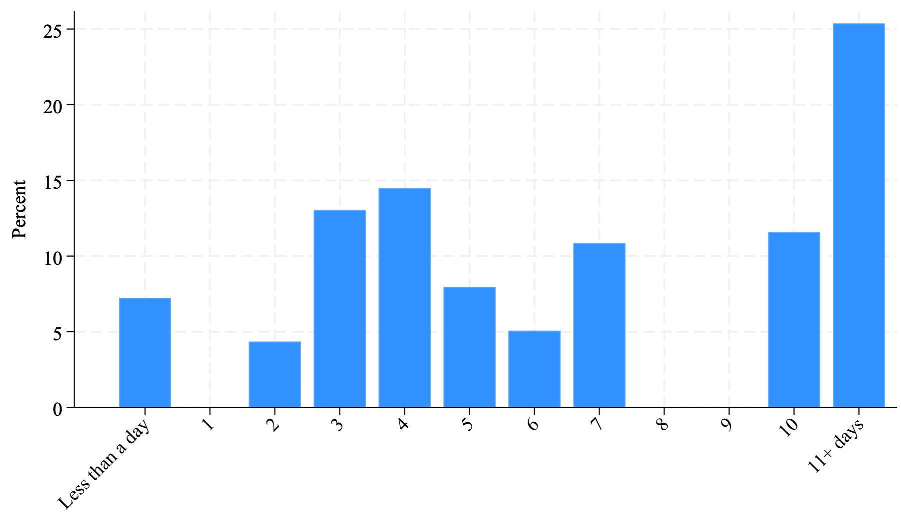


Figure A4.12: Perceived time need to learn techniques

Notes: Descriptive Statistics related to beliefs about returns to training for a holdout sample of local laborers. The top figure shows the perceived wage and farm profit returns, as a proportional increase over current earnings. The bottom figure shows the number of days trainees believe they would need to receive training in order to have skills such that they could sell them in the labor market.

13.2 Appendix Tables

Table A4.1: Balance table - Contract Experiment

Variable	Trainees Control Mean (1)	Trainees Treatment Mean (2)	Trainees P-value Δ (3)	Trainer-Employers Control Mean (4)	Trainer-Employers Treatment Mean (5)	Trainer-Employers P-value Δ (6)
Demographics						
Age	34.2	34.8	0.71	45.1	46.7	0.40
	(12.6)	(11.0)		(11.7)	(14.2)	
Sub-Primary Education	0.7	0.7	0.77	0.8	0.9	0.26
		(0.4)	(0.4)	(0.4)	(0.3)	
Household Size	4.9	5.1	0.43	6.0	5.3	0.02
	(2.2)	(2.0)		(2.1)	(2.0)	
Unmarried	0.2	0.2	0.43	0.0	0.0	0.43
	(0.4)	(0.4)		(0.2)	(0.1)	
Male	0.2	0.3	0.09	0.5	0.3	0.04
	(0.4)	(0.5)		(0.5)	(0.5)	
Savings (FBU)	7.9	8.5	0.31	10.8	10.9	0.72
	(4.2)	(3.9)		(2.1)	(1.9)	
Baseline farm and knowledge						
Land (plots)	4.7	5.2	0.16	9.0	8.1	0.13
	(2.2)	(3.0)		(4.7)	(4.5)	
Land (ares)	14.9	17.9	0.08	39.8	41.8	0.59
	(12.6)	(12.1)		(22.2)	(30.4)	
Beans value (Past B)	101935.3	130094.4	0.04	322141.2	294563.6	0.22
	(77877.7)	(114055.5)		(173752.9)	(141726.2)	
Fields (Past B)	4.7	5.1	0.16	7.5	7.3	0.55
	(1.9)	(2.8)		(3.2)	(2.9)	
Planted in lines (Past season)	0.1	0.1	(0.94)	1.0	1.0	
	(0.3)	(0.3)		(0.0)	(0.0)	
Row planted all fields (number of times past 5 years)				1.1	1.2	0.83
				(1.8)	(1.9)	
Labor Market						
Past supply	1.0	1.0		0.1	0.1	0.96
	(0.0)	(0.0)		(0.2)	(0.2)	
Mandays supplied	14.0	12.7	0.24	0.3	0.3	0.99
	(7.7)	(7.3)		(1.1)	(1.1)	
Past demand	0.1	0.2	0.12	1.0	1.0	
	(0.4)	(0.4)		(0.0)	(0.0)	
Mandays demand				23.5	19.7	0.24
				(21.8)	(23.5)	
Observations	102	99		102	99	

Notes: This table shows the balance between trainer-employers and trainees in the Contract experiment. Variables were collected at baseline and corresponds to the entire sample. In columns (1) and (4), we show the mean and standard deviation for the variable of interest among the Control group. In columns (2) and (5), we show the same fro the Treatment group. Finally, in columns (3) and (6) we show the p-value for a T-test of equality of means. The p-values of the difference in means test come from SEs clustered at the village level.

Table A4.2: Contract Experiment: Summary Statistics - Social Capital

Variable	Proportion of Employers
Previous hire	0.6
Ask Advice	0.0
Discuss Agriculture	0.0
Poorer	0.5
Socialize Regularly	0.1
Receive Money	0.0
Lent Money	0.2
Provide Assistance	0.2
Related	0.1
Observations	201

Notes: This table shows summary statistics related to the social capital shared between trainer-employers and trainees in the Contract Experiment. The first column describes a relationship or activity that an employer might have with their trainee. The second column reports the proportion of employers stating they have interacted in that way with their employee. All variables are binary.

Table A4.3: Hired and Family Labor

Panel A: Trainer-Employers	Days Family Skilled Labor (1)	Days Family and Hired Skilled Labor (2)
T1 -Financial Incentives	0.73	1.57
Train	(0.82)	(0.91)
	[0.37]	[0.09]
Obs.	1205	1205
Control mean	13.17	15.08
Panel B: Spillover-Employers		
T1 -Financial Incentives	0.29	1.45
Train	(0.75)	(0.83)
	[0.70]	[0.09]
Obs.	1453	1453
Control mean	10.42	12.71

Notes: This table shows the effect of the Financial Incentive to Train treatment on total household labor applied to the trained techniques, as well as the sum of household and hired labor for the training techniques. Panel A shows regression results for the sample of Trainer-employers. Panel B shows regression results for the sample of spillover-employers. The dependent variable in column 1 is total days of family labor used to do the trained techniques (row planting and fertilizer microdosage). The dependent variable in column 2 is total days of hired and family labor to do the trained techniques. Standard errors are clustered at the village level.

Table A4.4: Social Learning

Panel A: Spillover Employers	Knowledge Score (1)	P(Adoption and Hired) (2)	P(Adoption and Not Hired) (3)	P(Adoption and Hired) (4)	P(Adoption and Not Hired) (5)	P(Adoption and Hired) (6)	P(Adoption and Not Hired) (7)
T1-Financial Incentives	0.43	0.19	-0.10	0.13	0.05	0.05	0.00
Train	(0.12)	(0.03)	(0.03)	(0.05)	(0.04)	(0.06)	(0.05)
	[0.00]	[0.00]	[0.00]	[0.02]	[0.28]	[0.01]	[1.00]
T1 X [Heterogeneity]				0.08	-0.18	0.04	-0.12
	()	()	()	(0.06)	(0.05)	(0.06)	(0.06)
	[]	[]	[]	[0.18]	[0.00]	[0.56]	[0.04]
Obs.	1466	1466	1466	1466	1466	1466	1466
Control mean	0.52	0.36	0.40	0.36	0.40	0.36	0.40
Heterogeneity Var				Previously Used	Previously Used	Used last season	Used last season
Panel B: Spillover Non-Employer	Any Plots Modern (1)	Plots Modern (2)	Hired Modern (3)				
T1-Financial Incentives	0.04	0.10	0.10				
Train	(0.05)	(0.08)	(0.08)				
	[0.45]	[0.20]	[0.20]				
Obs.	584	584	584				
Control mean	0.42	0.50	0.11				

Notes: This table shows the effect of the Financial incentive treatment on various measures of hiring, adoption and knowledge for spillover farmers. Panel A is restricted to farmers who are spillover employers. Panel B is restricted to farmers who are in the spillover sample but were identified as non-employers at baseline. The outcome in panel a, column 1 is a composite spacing knowledge score. The outcome in panel a, column 2, 4 and 6 is the probability that a farmer adopted and hired labor for the skilled task. The outcome in Panel a, column 3, 5 and 7 is the probability that a farmer adopted and without hiring any labor for the skilled task. Regressions in Panel A are run either directly on the treatment, or as an interaction with a measure of heterogeneity: whether the farmer previously used the modern seeding practices, and whether the farmer planted in lines the prior season. The outcome in Panel B, column 1 is whether the farmer planted any fields with the modern seeding techniques. The outcome in Panel B, column 2 is whether the number of fields planted with the modern seeding techniques. The outcome in Panel B, column 3 is the number of days of labor hired to do the skilled task. Robust standard errors are clustered at the village level.

Table A4.5: Employer Heterogeneity in Treatment Effects

Employers (All)	Days Hired Skilled Task (1)	Fields Row Planting (2)	Days Hired Skilled Task (3)	Fields Row Planting (4)
T1 - Financial Incentives	0.10	0.13	0.59	0.37
Train	(0.52)	(0.21)	(0.32)	(0.13)
	[0.85]	[0.53]	[0.07]	[0.01]
T1 - Financial Incentives	0.16	0.04		
Train x Fields	(0.08)	(0.03)		
	[0.06]	[0.10]		
T1 - Financial Incentives			0.04	0.00
Train x Days Hired			(0.02)	(0.00)
			[0.04]	[0.37]
Obs.	2682	2682	2682	2682
Control mean	2.0	1.9	2.0	1.9

Notes: The table shows treatment effect heterogeneity for the sample of employers. The outcome variables in columns 1 and 3 are the number of days the individual hired a worker to do tasks involving the trained techniques. Outcome variables in columns 2 and 4 are the number of fields planted using the trained techniques. The heterogeneity measure in columns 1 and 2 are the number of fields the farmer planted the prior agricultural season. The heterogeneity measure in columns 3 and 4 are the number of days the employer hired the prior agricultural season. Regressions are weighted using inverse probability weights to make the results representative of employers at the village level. Robust standard errors are clustered at the village level.

Table A4.6: Adoption by Spillover Employers - Heterogeneity by knowledge/past usage

	Fields Row Planting (1)	Fields Row Planting (2)
T1 - Financial Incentives Train	0.45	0.40
	(0.14)	(0.17)
	[0.00]	[0.02]
T1 X [Heterogeneity]	0.05	0.10
	(0.17)	(0.20)
	[0.77]	[0.63]
Obs.	1466	1466
Control mean	1.64	1.64
test Treat+TreatxHet=0	0.00	0.00
Heterogeneity Var	Previously Used	Used last season

Notes: This table shows intensive margin treatment effects on the number of fields planted using the improved agricultural technology for the sample of spillover employers. Regressions show heterogeneous effects by the variable mentioned at the bottom of the table. The heterogeneity variable in column 1 is whether the employer previously had used the improved planting technique. The heterogeneity variable in column 2 is whether the employer previously had used the improved planting technique the prior season. Robust standard errors are clustered at the village level.

Table A4.7: Treatment Effect Heterogeneity by whether hired previously - Trainees

Trainees	Days Modern (1)	Wage (2)	Employers (3)
T1 - Financial Incentives	3.31	111.25	0.17
Train	(0.50)	(102.76)	(0.13)
	[0.00]	[0.28]	[0.189]
T1 X Hired Previously	0.15	125.97	0.05
	(0.68)	(106.86)	(0.18)
	[0.83]	[0.24]	[0.795]
Obs.	730	614	730
Control mean	0.46	2,304	1.9
p-val T+TxHired=0	0.00	0.02	0.10

Notes: This table shows the effect of the Financial Incentive to Train treatment on the labor market outcomes of trainees allowing for heterogeneous effects for whether the trainee previously worked for the trainer. The outcome variable in column 1 is the number of days that the trainee worked doing the skilled labor task. The outcome in column 2 is the wage. The outcome in column 3 is the number of employers that the trainee worked for. Regressions are run on an indicator variable for treatment status, an indicator variable for having hired the trainee previously, and the interaction term of the two, as well as controls. Robust standard errors are clustered at the village level.

Table A4.8: Treatment effect heterogeneity by previous hiring – Trainer-employers

Trainees	Hired Own Trainee (1)	Hired Trained Technique (2)	Unable to hire trainee (3)
T1 - Financial Incentives	0.55	0.16	0.16
Train	(0.15)	(0.05)	(0.06)
	[0.00]	[0.00]	[0.01]
T1 X Hired Previously	-0.05	0.03	-0.03
	(0.23)	(0.06)	(0.08)
	[0.83]	[0.58]	[0.74]
Obs.	1216	1216	484
p-val T+TxHired=0	0.02	0.00	0.01
Control mean	0.43	0.39	0.24

Notes: This table shows the effect of the Financial Incentive to Train treatment on the hiring practices of farmer-trainers conditional on whether they had previously hired the trainee they identified. The outcome variable in column 1 is an indicator variable equal to 1 if the individual reported hiring the trainee they identified to bring to the training event. The outcome variable in column 2 is an indicator variable equal to 1 if the individual reported hiring any individual to perform the skilled labor task. The outcome variable in column 3 is an indicator variable equal to 1 if the individual reported being unable to hire their trainee after attempting to hire them. Regressions are run on an indicator variable for treatment status, an indicator variable for having hired the trainee previously, and the interaction term of the two, as well as controls. Robust standard errors are clustered at the village level.

Table A4.9: Village level output prices

	Output Prices						
	Bush Bean	Climbing Bean	Sweet Potato	Wheat	Potato	Maize	Cassava
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T1 - Financial Incentives	19.65	29.57	-3.01	18.59	-8.90	-151.50	20.62
Train	(22.59)	(18.99)	(3.39)	(47.68)	(16.63)	(89.77)	(20.75)
	[0.39]	[0.12]	[0.38]	[0.70]	[0.59]	[0.10]	[0.32]
Obs.	80	80	80	36	80	38	80
Control mean	1,241	1,330	224	1,440	708	1,260	1,213

Notes: This table shows treatment effects for the average reported sales price of crops in villages, by the price of the crop at the nearest market. Crops with fewer observations mean that some crops were not sold in particular villages. Robust standard errors in parentheses.

Table A4.10: Changes to Farm Labor in Response to Treatment

	Farm Labor	
	Total Household Labor	Respondent Farm Labor
Panel A: Trainees	(1)	(2)
T1 - Financial Incentives	1.19	-0.03
Train	(1.62)	(0.77)
	[0.47]	[0.97]
Control mean	33	20
Obs.	842	842
Panel B: Trainer (Employers)		
T1 - Financial Incentives	1.47	-0.42
Train	(2.05)	(0.69)
	[0.48]	[0.54]
Control mean	52	26
Obs.	1205	1205
Panel C: Spillover (Employers)		
T1 - Financial Incentives	-0.91	-1.06
Train	(1.62)	(0.87)
	[0.65]	[0.23]
Obs.	1453	1453
Control mean	47	25

Notes: This table shows treatment effects on family farm labor provided during the planting period. The outcome in column 1 is total household supply of labor. The outcome in column 2 is the respondent's own supply of farm labor. Panel A corresponds to the sample of trainees. Panel B corresponds to the samples of trainer-employers. Panel C corresponds to the sample of spillover-employers. Standard Errors are clustered at the village level.

Table A4.11: Robustness of results: trainer-employers

	Trainees Skilled Task Days	Hired Skilled Task Days	Adoption Total Fields
Trainer (Employers) - Benchmark	(1)	(2)	(3)
T1 - Financial Incentives	0.84	0.70	0.46
Train	(0.20)	(0.32)	(0.13)
	[0.00]	[0.03]	[0.00]
	[0.000]	[0.022]	[0.001]
Trainer (Employers) - 99% Winsor			
T1 - Financial Incentives	0.80	0.81	0.36
Train	(0.19)	(0.26)	(0.15)
	[0.00]	[0.00]	[0.02]
Trainer (Employers) - Lasso Selected Controls			
T1 - Financial Incentives	0.87	0.73	0.43
Train	(0.20)	(0.34)	(0.13)
	[0.00]	[0.03]	[0.00]
Control mean	0.67	1.96	2.47
Obs.	1216	1216	1216

Notes: This table shows robustness of the primary results to different specifications. The sample is limited to spillover-employers. The dependent variable in column 1 is the number of days an employer hired someone who was invited to the training events to do skilled tasks (row planting and fertilizer microdosage). The dependent variable in column 2 is the number of days hired for skilled tasks on farm, of all laborers. The dependent variable in column 3 is the number of fields in the farmer's household that the improved planting practices were used. Panel A uses unadjusted outcome variables, and includes randomization inference p-values in the second set of brackets. Panel B winsorizes the outcome variable at the 99% level. Panel C controls for variables selected following the post-double-selection LASSO procedure from Belloni et al. (2014). Robust standard errors are clustered at the village level.

Table A4.12: Robustness of Results - Spillover Employers

	Trainees Skilled Task Days	Hired Skilled Task Days	Adoption Total Fields
Spillover (Employers) - Benchmark	(1)	(2)	(3)
T1 - Financial Incentives	1.25	1.67	0.45
Train	(0.19)	(0.50)	(0.13)
	[0.00]	[0.00]	[0.00]
	[0.000]	[0.000]	[0.001]
Spillover (Employers) - 99% Winsor			
T1 - Financial Incentives	1.13	1.29	0.47
Train	(0.16)	(0.32)	(0.12)
	[0.00]	[0.00]	[0.00]
Spillover (Employers) - Lasso Selected Controls			
T1 - Financial Incentives	1.27	1.75	0.44
Train	(0.20)	(0.61)	(0.13)
	[0.00]	[0.01]	[0.00]
Control mean	0.23	2.29	1.90
Obs.	1466	1466	1466

Notes: This table shows robustness of the primary results to different specifications. The sample is limited to spillover-employers. The dependent variable in column 1 is the number of days an employer hired someone who was invited to the training events to do skilled tasks (row planting and fertilizer microdosage). The dependent variable in column 2 is the number of days hired for skilled tasks on farm, of all laborers. The dependent variable in column 3 is the number of fields in the farmer's household that the improved planting practices were used. Panel A uses unadjusted outcome variables, and includes randomization inference p-values in the second set of brackets. Panel B winsorizes the outcome variable at the 99% level. Panel C controls for variables selected following the post-double-selection LASSO procedure from Belloni et al. (2014). Robust standard errors are clustered at the village level. Robust standard errors are clustered at the village level.

Table A4.13: Robustness of Results - Laborer

	Modern Practices		Agricultural Work						Own Fields
	Total Days	Total Earnings	Total Days	Total Earnings	Worked	Any non-modern	Total Employers	Wage	Modern Fields
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Trainees - Benchmark									
Treatment	3.435	8432.530	0.839	3370.691	0.005	-0.226	0.159	184.167	1.145
	(0.384)	(961.754)	(0.547)	(1449.421)	(0.026)	(0.037)	(0.092)	(77.631)	(0.074)
	[0.000]	[0.000]	[0.129]	[0.023]	[0.834]	[0.000]	[0.086]	[0.020]	[0.000]
	[0.000]	[0.000]	[0.138]	[0.027]	[0.816]	[0.000]	[0.083]	[0.012]	[0.000]
Winsor 99%									
Treatment	3.298	8208.683	0.770	2761.989	0.005	-0.226	0.130	161.412	1.130
	(0.362)	(921.473)	(0.536)	(1243.763)	(0.026)	(0.037)	(0.080)	(68.822)	(0.073)
	[0.000]	[0.000]	[0.155]	[0.029]	[0.834]	[0.000]	[0.107]	[0.022]	[0.000]
Lasso Selected Controls									
Treatment	3.404	8412.677	0.806	3312.366	-0.004	-0.238	0.138	201.362	1.161
	(0.371)	(934.414)	(0.546)	(1426.812)	(0.026)	(0.038)	(0.090)	(79.344)	(0.076)
	[0.000]	[0.000]	[0.144]	[0.023]	[0.888]	[0.000]	[0.131]	[0.013]	[0.000]
Control mean	0.459	983.614	7.327	1.7e+04	0.843	0.814	1.901	2303.988	0.152
Obs.	848	848	848	832	848	832	848	710	848

Notes: This table shows robustness of the primary results to different specifications. The sample is limited to trainees. The dependent variable in column 1 is the total number of days the laborer worked during season B doing work that involved the techniques taught during the training. The dependent in column 2 are the earnings from this work. Columns 3 and 4 are days worked and earnings from any kind of agricultural work during season B. Column 5 is an indicator variable for whether the laborer did any agricultural work during agricultural season B. Column 6 is an indicator variable for whether the trainee did any labor that did not involve the techniques taught during the training. Column 7 is the number of employers that the trainees worked for. Column 8 is the weighted average wage earned. Panel B winsorizes the outcome variable at the 99% level. Panel C controls for variables selected following the post-double-selection LASSO procedure from Belloni et al. (2014). Robust standard errors are clustered at the village level.

14 Derivations

14.1 Model Section 1

Since wages are determined by nash bargaining the training firm's problem is:

$$\max_{\tau}\ (1-q)(1-\beta)\left(f(\tau)-(p_w\beta f(\tau))\right)-c(\tau)$$

This implies the level of training chosen by the firm satisfies:

$$(1-q)(1-\beta)\left(f'(\tau^*)-\left(p_w\beta f'(\tau^*)\right)\right)=c'(\tau^*)$$

The level of training is positive as long as $p_w < 1$ or $\beta < 1$.

But the social surplus from training is:

$$\begin{aligned}
&= \underbrace{(1-q)(1-\beta)\Big(f(\tau)-((1-p_w\beta)\,f(\tau))\Big)-c(\tau)}_{\text{Expected profits of training firm}} + \underbrace{qp_w(1-\beta)f(\tau)}_{\text{Expected profits of non-training firm}}\\
&+ \underbrace{(1-q)\beta\Big(f(\tau)-p_w\beta f(\tau)\Big)+qp_w\beta f(\tau)}_{\text{Expected Earnings of Trained Workers}}\\
&= (1-q)f(\tau)+qf(\tau)-c(\tau)
\end{aligned}$$

Implying the FOC:

$$f'(\tau)=c'(\tau)$$

Comparing to the social optimum FOC, firms invest less in training than the social optimum if:

$$(1-q)(1-\beta)\left(f'(\tau)(1-p_w\beta)\right)<f'(\tau)$$

15 Additional Context

This section provides some additional details not provided in the main context section of the paper.

15.1 Agriculture in Burundi

Burundi is among the poorest countries in the world and the third most densely populated country in Africa.[48]Due to small average farmable land and low agricultural productivity, the country faces a persistent risk of food insecurity (Verwimp and Muñoz-Mora, 2018). Burundi has three agricultural seasons per year. We conduct the experiment over the course of Season "B". This season generates most of the country's agricultural production, and lasts from February to July. The staple crop grown during this season is beans, which we use as the focus of the training intervention. As described in Section 15.2, farmers plant beans either according to traditional practices, or using improved agricultural techniques.

15.2 Row Planting and Fertilizer Microdosage - External Validity and Training Importance

While this project focuses on a failure to adopt modern planting techinques in Burundi, this fact is not limited to this context. Other studies have found that only ∼55% of teff farmers in Ethiopia and ∼10% of rice farmers in Ghana adopted (Fentie and Beyene, 2019; Donkor et al., 2016), despite several efforts to promote the technology. These studies have also confirmed the increased yields of row planting for these crops in agronomic trials and have cited the increased labor intensiveness of row planting as an impediment to adoption - in Ethiopia 100% of surveyed farmers who cited constraints to adoption mentioned labor intensity as a major impediment to the adoption of row planting (Fentie and Beyene, 2019). Research in other contexts also suggests that while the technique is seemingly simple, farmers have stated that viewing fields or having an oral description of the technique is not sufficient for them to adopt it - rather they require practical demonstrations and training in order to learn these techniques (Cafer and Rikoon, 2018), and has found relatively large impacts of training in the techniques, with almost no impact of extension without training (Zeweld et al., 2017). In a similar context, Deutschmann et al. (2022) provide evidence for the importance of training, finding evidence that part of the impact of the O1AF is relaxing informational constraints. Deutschmann et al. (2022) also find some evidence for potential knowledge depreciation of these techniques among Kenyan farmers, again pointing to the potential

[48] Agriculture is the dominant sector of the Burundian economy, representing approximately 50% of the GNP and 80% of its exports (Beekman and Bulte, 2012). According to the World Bank (2020), approximately 86% of the Burundian population is rural, composed mostly of subsistence farmers. The average Burundian household consumes around 72% of what it produces, and the rest is either marketed or exchanged through social networks Niragira et al. (2015).

importance of training for skill accumulation and retention.

15.3 Agricultural Labor Markets

Farm labor is supplied more by women than by men - with 90% of women involved in agricultural activities in rural households but only 65.5% of men (Vinck, 2008). Partially this is due to the fact that men migrate and provide seasonal labor (Vinck, 2008). This tendency of women to be involved in farm labor is particularly true for staple rather than cash crops. This tendency of both men and women to provide substantial amount of farm labor, both on and off own farm is consistent with other contexts (Fink et al., 2020; Guiteras and Jack, 2018; Palacios-Lopez et al., 2017). Finally, consistent with other contexts, laborers in such villages tend to be among the poorest in the village: another study found agricultural laborers to have access to limited land, and to be among the poorest in terms of assets in the village (Fink et al., 2020; Vinck, 2008).

The tasks of row planting and fertilizer microdosage are concentrated in a narrow window of around 2 weeks after the onset of the rains. Consistent with many farmers utilizing rainfed agriculture in Sub-Saharan Africa, Burundian farmers perceive higher returns to planting soon after the onset of rains, particularly for Season B given the already shorter growing season (Dodd and Jolliffe, 2001). Moreover, farmers are also encouraged to plant early by the government, which generally announces specific windows of time by which farmers must complete their planting. 1AF data documents a strong positive correlation between planting earlier and planting using row-spacing rather than broadcasting, consistent with the possibility that farmers change planting techniques as they run out of time.

There is one additional labor market that exists which is the market for exchange labor - however this constitutes a minor portion of overall labor input as employers in this setting obtain only 2-3 days of labor from this, so it constitutes a less important source of labor input overall.

15.4 Training Markets

What makes learning row planting a skill that requires training rather than information that can be described verbally, or learnt by observation from people's fields? Farmers describe three features that require training. First, they mention that row planting rather than broadcasting requires several pieces of equipment (sticks to measure distance, ropes to measure line to ensure planting is straight) and that understanding how to utilize this equipment is complicated from observation. Second, they note that while distances and techniques can be communicated verbally, often individuals find it hard to replicate without learning by doing. Finally, the repetition and practice of the technique is important to develop using the technique into a skill that can be sold in the labor market.

16 Additional Treatments

In the Spillover Experiment, 12 villages are also assigned to the following treatment:

T2 - Labor Insurance - In addition to what was provided in control in the Spillover Experiment, farmers in this condition were told that if they trained their laborer for two days for 180 minutes, we would ensure that this laborer, or another similarly skilled laborer, would return to work for them for 2 days at the prevailing unskilled wage in the village.

Implementation To implement this treatment without coercion we do the following. Before any treatment status of a village was revealed, we asked the 1AF Field Officer and local authorities to tell us: 1) what the approximate daily wage was of an individual who worked for another individual planting beans in the traditional way and 2) what the daily wage was of an individual who worked for another individual planting beans using the modern planting practices. On the day of the event, we explain to trainer-employers that if they train their trainee in the modern planting practices, our team would guarantee that, at planting time, a laborer skilled in these techniques would return to work for the farmer, and that the employer would be required to pay that laborer the wage that workers tend to work for when planting in the traditional manner.

To incentivize the worker to return after being trained by the trainer-employer, it was explained to workers that, if they returned to work for this employer during the planting season, then they would receive an additional top-up to their wage paid by the enumerator team. This in total ensured that the worked would receive a slightly higher wage than the skilled wage paid in the village conditional on returning to this employer.

We construct the design of this treatment in order to ensure that employers capture more of the returns of training conditional on training (by ensuring that the worker did not separate, and that the wage did not rise) while also not coercing the worker into working, by also offering them a wage that was higher than the wage paid for skilled labor in the village, and in cases where this was refused or the worker was not available for other reasons, providing another similarly skilled worker to the trainer-employer. To ensure that this offer did not lead to collusion/fake jobs, trainer-employers and trainees were told that all work would need to be scheduled in advance with the enumerator team, and payment to the worker at the end of the day occurred only if it was clear they had worked the entire day, and after the employer had paid their portion of the wage to the worker.

Results/Interpretation We interpret the results as suggesting that farmers become willing to train when they know that they will capture returns from training (because the wage does not rise and the laborer returns). However, there are several alternate interpretations of this treatment.

The first is that farmers are just willing to pay to forgo search costs in the planting season. In this interpretation, farmers do not care if the laborer they hire is skilled or unskilled, but are willing to pay a cost today (including a cost of effort involved in training) in order to overcome future search costs. This seems unlikely to explain the results since most employers hire the employee they train for the trained techniques. Moreover, the search costs associated with hiring an unskilled laborer are reported by trainer-employers in general as being relatively low. Therefore, it does not seem likely that this explanation explains the results.

The second possibility is that farmers respond to the training incentive purely because of the wage subsidy. This is unlikely to explain the results - the wage that the employer was calibrated to pay was designed to match the average unskilled wage in the village, and so there was not supposed to be any benefit of training if the employer did not perceive a positive return to training. Moreover, even if the employer did perceive that some subsidy to the worker might be passed through, this subsidy was not large, and is unlikely to explain the magnitude of the training response we observe.

The third possibility is that farmers perceive the returns to training as zero/negative, but value skilled labor, and believe that if they trained they could say that the worker did not worker show up and ask us to replace the worker with another skilled laborer. The fact that we see zero instances of this in practice suggests that this is not a primary motivation, but it is hard to rule out entirely. In order to rule out this possibility, the contract experiment did not include a replacement worker in the event the originally contracted worker did not show up.

17 Data Collection Details

Adoption During the planting survey, we ask all respondents to draw a map of all their fields, and then complete a plot roster. For each field we ask the crop (or crops) planted and whether that field was planted using row planting and fertilizer microdosage techniques. Conditional on planting in rows, farmers were also asked details about the distance between rows and pockets, and the consistency of this distancing across the plot (*i.e.* on what proportion of the field they used these techniques). These questions were incentivized by a portion of the respondents' survey compensation being offered conditional on the responses to these questions being found to be true during an audit of the farmers fields.

At least one field audit was conducted per respondent in which enumerators visited farmers' fields, and observed the planting method.

Hiring We measure hiring outcomes at the worker-task level. During the planting survey, we ask all employers to state the number of workers who were hired. For each worker we then ask the name. We match the name against the list of trainees to determine whether they were an individual invited to the training event, or not. We then ask for each laborer 1) the number of days worked, which tasks were done, the total amount paid, if the work involved the trained tasks, the number of days that were spent specifically on those tasks. In some surveys, we did not ask this last question - and therefore use an approximation based off of the task combination to estimate the number of days that were conducted on the trained task.[49]

Employment in Agricultural Labor Markets We measure agricultural employment outcomes at the worker-task level. During the planting survey, we ask all in the sample to state the number of employers who they worked for during the agricultural season. We then ask for each employer the number of days worked, which tasks were done, the total amount paid, if the work involved the trained tasks, the number of days that were spent specifically on those tasks.

Farm outcomes At harvest time, we ask farmers the quantities of all crops harvested. Prices at the nearest market are elicited and aggregated at the village level to create an average village level price. The amount spent on non-labor inputs is elicited for each input (e.g. fertilizer, pesticide, hired land). Due to thin land markets, we are unable to elicit an average rental price of land, and therefore in all profit calculations we do not subtract off the opportunity cost of own land utilized.

[49] Results are not changed if instead of measuring the number of days conducted on row planting and fertilizer microdosage, we instead use as an outcome measure the number of days on tasks that included row planting and fertilizer microdosage.

General conclusion

This doctoral thesis explored labor market and education issues, focusing on challenges related to underemployment and labor training. Using experimental and quasi-experimental methods, it sheds light on employers' perception of underemployment, the impact of underemployment on education as well as the interplay of training and technology adoption in agricultural settings.

Leveraging a recent and innovative experimental design that avoids deception inherent in audit studies, chapter one examines employer preferences regarding low-skill experiences of recent college graduates in economics and management in Burundi. The findings indicate that, low-skill experiences, often simply perceived as a way of generating income in the context of high unemployment, can become instrumental in the pursuit of high-skill jobs. The study suggests that this is not merely due to the tasks associated with these roles, but rather the character attributes they signify, such as grit, tenacity, and determination. Furthermore, in a context where enrollment in tertiary education is increasing rapidly, the risk of underemployment fueling Arab Spring types of crises should increase, hence it is important to highlight the benefits of low-skill experience.

Delving into chapter two, the focus shifts to Ethiopia for data availability reasons, and the narrative revolves around the consequences of underemployment on children's education. We hypothesize that underemployment doesn't merely impact the labor force, that its effects are felt in the educational endeavors of children still at school. We find that when adults transition from a situation where their educational attainment corresponds to their occupation to underemployment, children who live in their households find themselves engaged more in domestic responsibilities, potentially compromising their scholarly pursuits. The chapter's results advocate for more holistic interventions in developing countries that not only address direct educational concerns but also the labor market factors that may impact education.

In the third chapter, the focus is on labor training in general skills, elucidating the dynamics of the transfer of such skills. A compelling observation is made: training agricultural laborers in a novel technology leads to a broader adoption in the community, benefiting farmers who train, those who do not, as well as the trainees themselves. However, our research shows that employers might lack sufficient incentive to train in general skills, and that policies aimed at easing the spread of this information could yield significant multiplier effects. We show that a contract designed to increase the likelihood of a trained worker returning to their original employer significantly increases the likelihood of training.

In keeping with tradition, this thesis outlines the following main policy implications: advising recent college graduates to take on low-skill employment in the absence of high-skill jobs or internships, considering the effect of the labor market in the design of education interventions and increasing training in general skills by increasing the probability that a trained worker returns to work for the employer who trained them by offering a well calibrated financial incentive.

However, these policy suggestions may not be exhaustive. Predicting the precise utility of research beforehand is challenging, but the pursuit of truth must persist undeterred, as it may lead us into unexpected places.

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