



Essays on environments and child development : evidence from Vietnam

Thi Hoai An Nguyen

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Essays on environments and child
development: evidence from Vietnam
*Essais sur les environnements et le développement de
l'enfant : témoignages du Vietnam*

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sous la direction de **Stéphane GOUTTE**, Professeur des universités,
la co-direction de **Duc Khuong NGUYEN**, Maître de conférences

Thèse soutenue à Guyancourt, le 29 Mars 2023, par

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Titre: Essais sur les environnements et le développement de l'enfant : témoignages du Vietnam

Mots clés: Développement de l'enfant, Inégalité, Environnements

Résumé: Cette thèse explore différents aspects de l'environnement et du développement des enfants vietnamiens. Le chapitre 1 est un travail conjoint avec Stéphane Goutte, qui examine l'effet de l'éducation préscolaire précoce sur les compétences, le niveau d'instruction et la santé des enfants pauvres. Nous avons constaté que commencer l'école maternelle plus jeune augmente considérablement la note la plus élevée obtenue et crée une réponse comportementale d'augmentation de l'investissement parental ultérieur dans l'éducation. Nous trouvons des effets positifs à court et moyen terme du fait de commencer l'école maternelle plus jeune sur les compétences cognitives de l'enfant, mais peu de preuves sur les compétences non cognitives de l'enfant. Nous découvrons également l'impact négatif à court terme de commencer l'école maternelle plus jeune avec des mesures de la santé de l'enfant. Ce chapitre fournit donc l'implication que l'élargissement de l'accès à l'éducation préscolaire doit améliorer la qualité de l'éducation préscolaire pour atteindre le développement global de l'enfant. Le chapitre 2 étudie l'impact de la sécheresse sur l'éducation, le travail et l'utilisation des soins de santé des enfants vietnamiens. Comprendre l'impact hétérogène de la sécheresse sur les enfants et les caractéristiques des ménages associées à la résilience à la sécheresse peut fournir des informations précieuses pour les politiques visant à renforcer la résilience et à réduire l'impact négatif sur la pauvreté et les inégalités à long terme. En exploitant l'écart exogène des précipitations par rapport à la moyenne à long terme dans les zones locales, je constate que la gravité de la sécheresse est significativement associée au fait d'être plus susceptible de travailler pour des activités économiques et d'utiliser moins de services ambulatoires. Les résultats montrent des effets plus puissants pour la cohorte plus jeune, ce qui suggère

que les familles sont plus susceptibles d'utiliser le travail des jeunes enfants pour faire face à la perte de revenus due aux graves sécheresses. Les garçons et les enfants issus de milieux défavorisés sont particulièrement vulnérables à la sécheresse sévère. Ils sont plus susceptibles d'abandonner leurs études et de travailler pour des activités économiques lorsqu'ils connaissent une grave sécheresse. Les preuves empiriques soutiennent fortement l'effet de revenu en tant que canal par lequel la sécheresse affecte les résultats des enfants. Les résultats confirment l'importance de l'éducation et des allocations sociales, qui peuvent amortir les effets néfastes de la sécheresse et renforcer la résilience des enfants à la sécheresse. Le chapitre 3 vise à déterminer l'impact de la transformation de la couverture terrestre sur les résultats scolaires et professionnels des enfants des ménages agricoles et ruraux. En exploitant la variation de la couverture des terres cultivées et des terres urbaines au sein des communes locales, j'ai constaté que la couverture des terres urbaines et des terres cultivées affecte le travail des enfants dans la même direction. Alors que l'expansion de la couverture terrestre urbaine est significativement associée à une diminution de la main-d'œuvre agricole dans les activités agricoles des ménages, une diminution des terres cultivées dans le quartier entraîne une participation plus élevée des enfants à ces activités. Je montre également que le changement de la couverture terrestre du rural vers l'urbain peut avoir des impacts disproportionnés sur les enfants ruraux en fonction de leur situation économique. Les enfants issus de ménages agricoles sont plus susceptibles de travailler pour un salaire en dehors du ménage. Ainsi, ils peuvent être plus vulnérables en raison du processus d'urbanisation dans les zones rurales par rapport à ceux des ménages d'affaires. Ces différents effets peuvent aggraver les inégalités entre les enfants ruraux.

Title: Essays on Environments and Child Development: Evidence from Vietnam

Keywords: Child Development, Inequality, Environments

Abstract: This Ph.D. dissertation explores different aspects of the environment and development of Vietnamese children. Chapter 1 is joint work with Stéphane Goutte, looking at the effect of early preschool education on the skills, educational attainment, and health of poor children. It is acknowledged that better quality early childhood environment benefits child development. In this respect, early preschool attendance could be an essential policy to boost human capital accumulation. In this chapter, we estimate the impact of preschool starting age on the skills, educational attainment, and health of poor children in Vietnam. Exploiting the longitudinal Young Lives survey and applying the double machine learning estimator to produce the estimates of average treatment effects, we found that starting preschool younger significantly increases the highest grade achieved and creates a behavioral response of increasing subsequent parental investment in education. We find short and medium-term positive effects of starting preschool younger on child cognitive skills but little evidence on child non-cognitive skills. We also uncover the short-term negative impact of starting preschool younger with measures of child health. This chapter thus provides the implication that expanding access to preschool needs to improve the quality of preschool education to achieve comprehensive child development. Chapter 2 studies the impact of drought on the education, labor, and healthcare utilization of Vietnamese children. Understanding the heterogeneous impact of drought on children and the household characteristics associated with resilience to drought can provide valuable inputs for policies to strengthen the resilience and reduce the negative impact on poverty and inequality in the long run. Exploiting the exogenous rainfall deviation from the long-run average within local areas, I find that drought severity is significantly associated with being more likely to work for

economic activities and using fewer outpatient services. The results show more potent effects for the younger cohort, suggesting that families are more likely to use young child labor to cope with income loss due to severe droughts. The heterogeneity analysis shows that boys and children from disadvantaged backgrounds are particularly vulnerable to severe drought. They are more likely to drop out and work for economic activities when experiencing severe drought. The empirical evidence strongly supports the income effect as the channel through which drought affects child outcomes. The findings support the importance of education and social allowance, which can buffer the detrimental impacts of drought and strengthen the resilience of children to drought. In Vietnam, land has conversed massively from rural to urban purposes. Rural-to-urban land conversion changes the livelihood of rural and agricultural households and leads to a rapid transformation of land cover. Chapter 3 aims to determine the impact of this transformation on the education and labor outcomes of children from agricultural and rural households. Exploiting the variation in the cropland and urban land cover within local communes, I found that urban land and cropland cover affect child labor in the same direction. While expansion in urban land cover is significantly associated with a decrease in agricultural labor in household agricultural activities, a fall in cropland in the neighborhood leads to higher participation of children in these activities. I also show that land cover change from rural to urban can have disproportionate impacts on rural children depending on their economic background. Children from agricultural households are more likely to work for wages outside the household. Thus, they can be more vulnerable due to the urbanization process in rural areas compared to those from business households. These different effects can worsen inequality among rural children.

*Dành tặng bố mẹ thân yêu
Tặng ba Minh và em Voi
To Linh*

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Summary

This Ph.D. dissertation explores different aspects of the environment and development of Vietnamese children.

Chapter 1 is joint work with Stéphane Goutte. We look at the effect of early preschool education on the skills, educational attainment, and health of poor children. It is acknowledged that better quality early childhood environment benefits child development. Early preschool attendance could be an essential policy to boost human capital accumulation. In this chapter, we estimate the impact of preschool starting age on the skills, educational attainment, and health of poor children in Vietnam. We exploit the longitudinal Young Lives survey and apply the double machine learning estimator to produce the estimates of average treatment effects. The results show that starting preschool younger increases significantly the highest grade achieved and creates a behavioral response of increasing subsequent parental investment in education. We find short and medium-term positive effects of starting preschool younger on child cognitive skills but little evidence on child non-cognitive skills. In contrast, we uncover the short-term negative impact of starting preschool younger with measures of child health, namely weight-for-age, and BMI-for-age. Thus, this chapter implies that expanding access to preschool needs to improve the quality of preschool education to achieve comprehensive child development.

Chapter 2 studies the impact of drought on the education, labor, and healthcare utilization of Vietnamese children. Vietnam is among the five countries most affected by climate change, including drought risks, while younger generations are and will be more exposed and vulnerable to extreme weather events. Understanding the heterogeneous impact of drought on children and the household characteristics associated with resilience to drought can provide valuable inputs for policies to strengthen resilience and reduce the adverse effects on poverty and inequality in the long run. Exploiting the exogenous rainfall deviation from the long-run average within local areas, drought severity is significantly associated with being more likely to work for economic activities and using fewer outpatient services. The results show more potent effects for the younger cohort, suggesting that families are more likely to use young child labor to cope with income loss due to severe droughts. The heterogeneity analysis shows that boys and children from disadvantaged socio-economic backgrounds (uneducated, ethnic minority, rural, agriculturally dependent, and non-social allowance households) are particularly vulnerable to severe drought. They are more likely to drop out and work for economic activities when experiencing severe drought. The empirical evidence strongly supports

the income effect as the channel through which drought affects child outcomes. The findings support the importance of education and social allowance, which can buffer the detrimental impacts of drought and strengthen the resilience of children to drought.

In Vietnam, land has been massively converted from rural or agricultural to urban or non-agricultural purposes. Rural-to-urban land conversion changes the livelihood of rural and agricultural households and leads to a rapid transformation of land cover in the neighborhood. **Chapter 3** aims to determine this transformation's impact on the education and labor outcomes of children from agricultural and rural households. Exploiting the variation in the change of share of cropland and urban land cover within local communes, I found that urban land and cropland cover affect child labor in the same direction. While expansion in urban land cover is significantly associated with a decrease in child labor in household agricultural and domestic activities, a decrease in cropland in the neighborhood leads to higher agricultural and domestic work. I also show that land cover change from rural to urban can disproportionately impact rural children depending on their economic background. Compared to children from business households, those from agricultural families are more likely to work for wages outside the family and can be more vulnerable due to the urbanization process in rural areas. These different effects can worsen inequality among rural children.

Résumé

Le succès de la croissance économique et de la réduction de la pauvreté a amélioré la qualité de vie de nombreux enfants au Vietnam. Pourtant, près de 5,5 millions d'enfants au Viet Nam (un enfant sur cinq) grandissent encore dans des environnements défavorisés avec au moins deux privations en matière d'éducation, de santé, de nutrition, d'abri, d'eau, d'assainissement ou d'inclusion sociale. Les enfants au Vietnam sont très exposés et vulnérables aux risques climatiques, tandis que le processus d'urbanisation rapide a transformé les conditions de vie et les environnements dans lesquels grandissent de nombreux enfants vietnamiens. Alors que la littérature récente établit l'importance de l'environnement en dehors de la famille, à savoir la garde d'enfants, l'école et le quartier, sur le développement de l'enfant, la qualité de l'environnement de l'enfance des enfants défavorisés au Vietnam soulève de sérieuses inquiétudes quant à leurs perspectives de vie.

L'objectif de cette thèse est de contribuer à la littérature sur les rôles des environnements sur le développement des enfants et à l'étude du développement des enfants vietnamiens, en particulier des enfants défavorisés, en dénichant de nouvelles sources de données et en appliquant des méthodes quantitatives relativement nouvelles pour étudier l'inférence causale. Dans cette thèse, j'ai entrepris d'étudier l'impact de diverses conditions environnementales, allant de l'école aux environnements physiques, sur les résultats de l'enfant afin de fournir des implications politiques utiles. Parmi les différents segments de la population enfantine et adolescente du pays, cette thèse se concentrera sur les groupes défavorisés : enfants et adolescents issus de ménages pauvres, agricoles et ruraux.

Cette thèse est organisée autour de trois chapitres qui analysent ces trois thèmes d'environnements en utilisant une variété de sources de données et de méthodologies. L'objectif du chapitre 1 est de comprendre si l'éducation préscolaire précoce peut jouer un rôle dans la stimulation de la formation du capital humain des enfants pauvres. Avec Stéphane Goutte, nous examinons si l'âge préscolaire améliore les compétences cognitives, les compétences non cognitives et la santé des enfants jusqu'à l'âge de 15 ans. Dans le deuxième chapitre, j'examine dans quelle mesure l'exposition à la variabilité et aux chocs pluviométriques affecte le travail d'éducation des enfants, la santé et l'utilisation de la santé. Enfin, dans le dernier chapitre, je fournis des estimations sur les impacts du changement de la couverture terrestre sur l'éducation et le travail des enfants. Au total, cette thèse met en lumière trois défis majeurs du développement de l'enfant d'aujourd'hui : les environnements de la petite enfance, le changement climatique et l'urbanisation et ses implications pour la conception des politiques.

Afin d'aborder ces questions, cette thèse utilise une variété de sources de données. Dans le premier chapitre, pour étudier la question de recherche des impacts de l'éducation préscolaire précoce, nous utilisons des données longitudinales riches qui visent à documenter la pauvreté des enfants au Vietnam. Il s'agit d'un panel de données qui permet de suivre le développement de 2 000 enfants de 1 à 15 ans. Dans le deuxième chapitre, j'ai rassemblé une base de données sur le niveau de vie des ménages au niveau national et une base de données à haute résolution sur les précipitations, pour explorer la relation entre la variabilité des précipitations et les résultats des enfants. Enfin, dans le dernier chapitre, nous comblons les lacunes de la littérature existante en utilisant des données à haute résolution sur la couverture des terres pour caractériser les changements de couverture des terres urbaines et cultivées dans le processus d'urbanisation et examinons ses effets sur les enfants des ménages ruraux et agricoles. Chacune de ces sources de données fournit des ressources précieuses pour étudier différentes dimensions des environnements et leurs rôles dans le développement de l'enfant.

Les différents chapitres exploitent également différents outils d'analyse. Dans le premier chapitre, nous adoptons une approche de Double Machine Learning, exploitant des données de grande dimension et l'avancée de l'apprentissage automatique, pour comprendre les effets causals de l'âge préscolaire sur la formation de capital humain. Cette méthode permet d'utiliser de nombreuses variables de contrôle et leur forme fonctionnelle flexible de manière objective et basée sur les données pour rendre plausible l'hypothèse d'indépendance conditionnelle (CIA). Dans le deuxième chapitre, j'utilise des régressions communes à effets fixes et j'exploite les écarts exogènes des précipitations par rapport aux valeurs moyennes à long terme au sein de la commune. J'étudie également les effets de sous-groupe, qui donnent donc un aperçu des parties de la population les plus vulnérables à la variabilité des précipitations - ce qui sert à identifier ceux qui ont le plus besoin de protection par la politique économique et sociale. Le dernier chapitre exploite la variation des couvertures des terres urbaines et des terres cultivées à la fois au sein des ménages agricoles et ruraux en estimant le modèle à effets fixes des ménages. L'équation d'estimation comprend des mesures de la couverture terrestre, des déterminants sociodémographiques individuels, des ménages et des communes des résultats des enfants et, dans les analyses ultérieures, des interactions des deux. Chaque ensemble de données permet l'application de différents estimateurs pour comprendre les relations causales entre les caractéristiques environnementales du développement de l'enfant.

Milieu de la petite enfance : Education préscolaire

L'âge auquel les enfants défavorisés fréquentent l'école maternelle importe-t-il ? Bien qu'un corpus croissant de preuves montre les effets bénéfiques de l'éducation préscolaire sur les enfants défavorisés, aucune des études examinées ne semble

évaluer directement l'effet de l'âge préscolaire sur les résultats des enfants. La question est particulièrement pertinente pour un pays comme le Vietnam, qui a déjà une scolarisation préscolaire universelle pour les enfants un an avant l'école primaire. L'avantage avéré de l'inscription préscolaire précoce incitera des pays comme le Vietnam à promouvoir ou même à exiger que les enfants issus de ménages défavorisés, de zones pauvres locales et de minorités ethniques entrent tôt à l'école maternelle pour lutter contre la pauvreté et les inégalités à long terme.

Nous abordons cette question en analysant l'effet de l'âge préscolaire sur le développement des enfants pauvres au Vietnam. Nous utilisons le Young Lives Survey, qui vise à documenter la pauvreté des enfants au Vietnam. Il fournit une multitude de mesures des compétences des enfants et des informations sur les investissements du ménage, de la communauté et des parents dans les enfants. Les données hautement dimensionnelles rendent l'utilisation de l'hypothèse d'indépendance conditionnelle probablement plausible en fournissant un énorme ensemble de variables de contrôle. Nous appliquons le cadre de l'apprentissage automatique double qui permet l'utilisation de cet ensemble de variables de contrôle sous une forme fonctionnelle flexible de manière objective et axée sur les données pour permettre l'hypothèse d'indépendance conditionnelle (CIA). L'approche d'apprentissage automatique double estime le résultat et le traitement par des algorithmes d'apprentissage automatique et combine les estimations pour dériver l'estimateur de l'effet de traitement moyen. La méthode d'apprentissage automatique adaptative aux données fournit des estimations à petites erreurs des paramètres de nuisance pour débiaiser les estimations de l'effet moyen du traitement.

En exploitant les données de grande dimension et les progrès de l'apprentissage automatique, nous arrivons aux conclusions suivantes. Premièrement, nous découvrons des effets favorables à court et moyen terme de l'inscription préscolaire précoce sur les compétences cognitives et le niveau d'instruction des enfants, mais peu de preuves de l'impact sur les compétences non cognitives. Plus précisément, à 15 ans, un âge préscolaire inférieur d'un an augmente les compétences linguistiques de l'enfant de 0,091 écart-type et augmente la note la plus élevée atteinte de 0,047 an. Nous constatons que les impacts favorables pourraient s'expliquer par le comportement d'investissement des parents (représenté par le nombre d'heures de cours supplémentaires suivis par les enfants) car la scolarisation précoce en préscolaire est associée à une augmentation du nombre d'heures de cours supplémentaires à tous les âges observés dans l'enquête. . Deuxièmement, nous analysons l'impact sur la santé des enfants à l'aide de scores anthropométriques. Nous découvrons l'effet défavorable à court terme de l'inscription préscolaire précoce sur le poids pour l'âge et le score z de l'IMC pour l'âge. Une inscription préscolaire un an plus tôt diminue le score z du poids pour l'âge et le score z de l'IMC pour l'âge de 0,056 et 0,092 écart type à 8 ans, respectivement. Cette découverte était inattendue et suggère que la quantité de valeur nutritive de l'alimentation préscolaire pourrait

être inférieure à celle de l'alimentation à domicile. Fait intéressant, il existe une association négative entre l'âge préscolaire et la probabilité d'être mince à 15 ans, ce qui suggère un lien entre les résultats en matière de santé et le niveau de scolarité.

Au total, ce chapitre jette un doute sur la qualité de l'alimentation scolaire des enfants pauvres au Vietnam. Alors que le préscolaire au Vietnam pourrait enrichir l'apprentissage cognitif des enfants pauvres par rapport aux alternatives de garde d'enfants ou aux environnements familiaux, nous soutenons que l'amélioration de la qualité des repas scolaires et la stimulation des compétences non cognitives sont essentielles pour parvenir au développement global de l'enfant.

Changement climatique : Sécheresse

Le Vietnam fait partie des cinq pays les plus touchés par le changement climatique, y compris les risques de sécheresse. En 2015-2016, le Vietnam a souffert de la pire sécheresse en 100 ans. L'UNISDR (2020) estime qu'il a affecté les moyens de subsistance de deux millions de personnes dans 18 provinces. Parmi les personnes touchées, 1,5 million vivaient dans le delta du Mékong et 500 000 vivaient dans la région des hauts plateaux du centre touchée par la sécheresse, la région la plus pauvre du pays. Parmi les personnes touchées par la sécheresse, les enfants issus de milieux défavorisés et de zones pauvres sont particulièrement vulnérables à la sécheresse, ce qui suscite des inquiétudes quant aux perspectives de pauvreté et d'inégalité à long terme. Comprendre l'impact hétérogène de la sécheresse sur les enfants et les caractéristiques des ménages associées à la résilience à la sécheresse peut fournir des informations précieuses pour les politiques visant à renforcer la résilience à la sécheresse et à réduire l'impact négatif sur la pauvreté et les inégalités à long terme.

J'exploite l'écart exogène des précipitations par rapport à la moyenne à long terme dans les zones locales pour explorer la relation entre la gravité de la sécheresse et les résultats des enfants. Les résultats montrent que l'exposition à une sécheresse sévère a des impacts significatifs à court terme sur les résultats des enfants et que les effets sont plus puissants pour la cohorte plus jeune. Nous constatons que la sévérité de la sécheresse est significativement associée au fait d'être plus susceptible de travailler pour des activités économiques et d'utiliser moins de services ambulatoires. Lorsque nous examinons différentes cohortes, les impacts sont plus robustes et significatifs pour les résultats du travail dans la cohorte plus jeune et deviennent plus faibles ou non significatifs pour la cohorte la plus âgée. Les résultats suggèrent que les familles sont plus susceptibles d'avoir recours au travail des jeunes enfants pour faire face à la perte de revenus due aux graves sécheresses. En particulier, les effets nocifs sur l'utilisation des services de santé restent statistiquement significatifs pour toutes les tranches d'âge, l'ampleur la plus importante pour la cohorte la plus jeune. Comme la sécheresse augmente le risque de maladie,

la réduction de l'utilisation des soins de santé et des soins de santé potentiellement préventifs en raison des chocs de sécheresse soulève de sérieuses inquiétudes quant aux résultats à long terme pour la santé des enfants au Vietnam.

L'analyse de l'hétérogénéité montre que les garçons et les enfants issus de milieux socio-économiques défavorisés (ceux issus de ménages sans instruction, issus de minorités ethniques, ruraux, dépendants de l'agriculture et ne bénéficiant pas d'allocations sociales) sont particulièrement vulnérables à une grave sécheresse. Ils sont plus susceptibles d'abandonner leurs études et de travailler pour des activités économiques lorsqu'ils connaissent une grave sécheresse. Cette constatation est conforme à nos attentes puisqu'il a été prouvé que la sécheresse réduit la production agricole et la production qui est la principale source de revenus des ménages agricoles et ruraux. Nos preuves empiriques appuient fortement l'effet de revenu en tant que canal par lequel la sécheresse affecte les résultats des enfants. Les résultats suggèrent également que l'éducation et les allocations sociales peuvent amortir les effets néfastes de la sécheresse et renforcer la résilience des ménages à la sécheresse.

Étant donné que les enfants issus de ménages défavorisés commencent derrière et sont plus vulnérables à l'impact néfaste que ceux élevés dans des environnements favorisés, nos résultats mettent en évidence la menace d'augmentation des inégalités économiques existantes et de réduction de la mobilité sociale à long terme en raison du changement climatique. L'étude souligne l'importance de l'intervention publique pour minimiser l'impact de la sécheresse sur les enfants. Les programmes d'assistance ciblant directement les ménages pour les aider à faire face aux chocs de revenus peuvent protéger les enfants défavorisés des effets néfastes des catastrophes.

Environnement physique : Couverture du sol et urbanisation

Au Vietnam, la conversion des terres rurales en terres urbaines a été observée à grande échelle ; l'expansion urbaine et l'industrialisation rurale supplantent les espaces naturels et les terres agricoles. Cependant, des politiques d'utilisation des sols et des stratégies d'urbanisme inefficaces conduisent à un modèle de développement spatial non réglementé et non coordonné au Vietnam. Ce schéma modifie les moyens de subsistance des ménages ruraux et agricoles et conduit à une transformation rapide de l'occupation du sol. En exploitant la variation de la couverture des terres cultivées et urbaines au sein des communes locales, ce chapitre analyse les effets de la couverture des terres au sein des communes locales sur les enfants d'âge scolaire dans les zones rurales du Vietnam. Il vise à contribuer à la fois à la littérature sur l'impact de l'urbanisation et à la branche des études axées sur l'impact des environnements physiques sur les résultats des enfants.

En appliquant le modèle à effets fixes des ménages, j'ai constaté que les parts des terres urbaines et des terres cultivées affectent le travail des enfants dans la même direction. Alors que l'expansion de la couverture terrestre urbaine est significativement associée à une diminution du travail des enfants dans les activités agricoles des ménages, une diminution des terres cultivées dans le quartier entraîne une plus grande participation des enfants à ces activités. L'ampleur est plus importante pour la couverture terrestre urbaine, ce qui suggère l'effet négatif global du changement de couverture terrestre résultant de la conversion des terres rurales en terres urbaines.

Je montre que si la couverture des terres cultivées a des effets stimulants sur l'éducation et les résultats professionnels des enfants des ménages agricoles, les enfants des ménages d'entreprises sont plus sensibles au changement de la couverture des terres urbaines. Les impacts de la couverture des terres cultivées deviennent nettement plus faibles pour les ménages ruraux dont les revenus dépendent fortement de l'agriculture ou des activités agricoles. En revanche, les enfants issus de ménages d'entreprises sont plus susceptibles de réduire la probabilité de travailler lorsque la part du foncier urbain dans la commune augmente. Les impacts disproportionnés de la couverture terrestre sur les enfants ruraux nécessitent des recherches supplémentaires pour clarifier la voie par laquelle le changement de couverture terrestre affecte les résultats des enfants. Une politique efficace d'utilisation des terres a fortement besoin de ces preuves pour éviter l'aggravation des inégalités parmi les enfants ruraux.

1 - General Introduction

Success in economic growth and poverty reduction has improved the life quality of many children in Vietnam. Nevertheless, nearly 5.5 million children in Vietnam (one in five) still grow up in disadvantaged environments with at least two deprivations in education, health, nutrition, shelter, water, sanitation, or social inclusion ([UNICEF, 2022](#)). Children in Vietnam are highly exposed and vulnerable to climate risks, while rapid urbanization has transformed the living conditions and environments in which many Vietnamese children grow up. As recent literature establishes the importance of environment outside the family, namely childcare, school, and neighborhood, on a child's development, the quality of childhood environment of disadvantaged children in Vietnam raises serious concerns about their life prospects.

This dissertation aims to contribute to the literature on the roles of environments on children's development and the study of the development of Vietnamese children, especially disadvantaged children, by unearthing new data sources and applying a relatively new quantitative method to study causal inference. In this thesis, I set out to investigate the impact of various environmental conditions, ranging from school to physical environments, on child's outcomes to provide useful policy implications. Among the different segments of the country's child and adolescent population, this thesis will focus on the disadvantaged groups: children and adolescents from poor, agricultural, and rural households.

I start the dissertation with this general introduction chapter, which begins with an introduction to the context and motivation to study the roles of environments in Vietnamese child development. Section highlights the structure and critical contributions of the dissertation. The last three sections provide the chapter-specific main findings, their contributions in the areas, and policy relevance.

1.1 . Context and Motivation

Vietnam has had significant success in economic development and poverty reduction in the past two decades, in which the annual GDP growth rate of Vietnam from 1999 to 2019 is 6.5 percent, and poverty has declined remarkably to below 10% in 2020 (Figure 1.1). Rapid economic growth allows Vietnam to improve its children's well-being quickly. This success has been reflected in several indicators, including education and health. The net enrollment rate has increased rapidly over the period. Primary school attendance has been almost universal, from 85 percent in 1992-1993 to almost 99 percent in 2014 (Figure 1.2). Vietnam has also made tremendous progress for lower and upper secondary net enrolment rates according

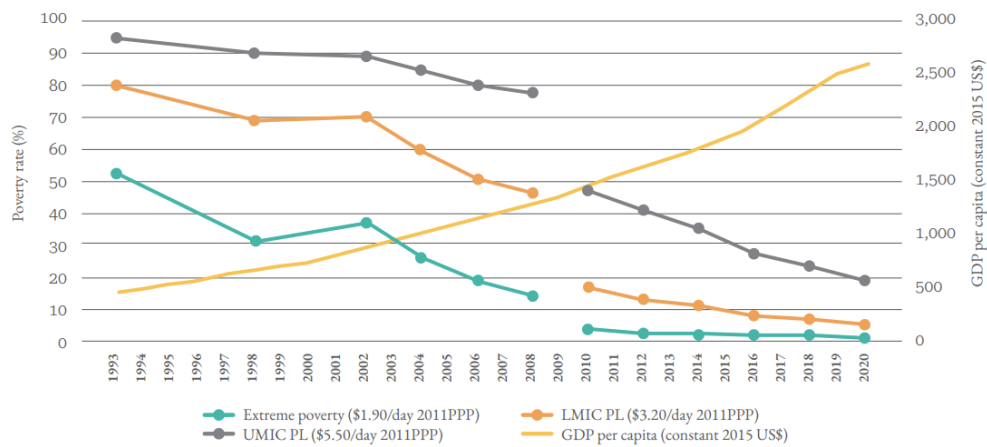


Figure 1.1: Annual GDP Growth Rate of Vietnam (World Bank, 2022)

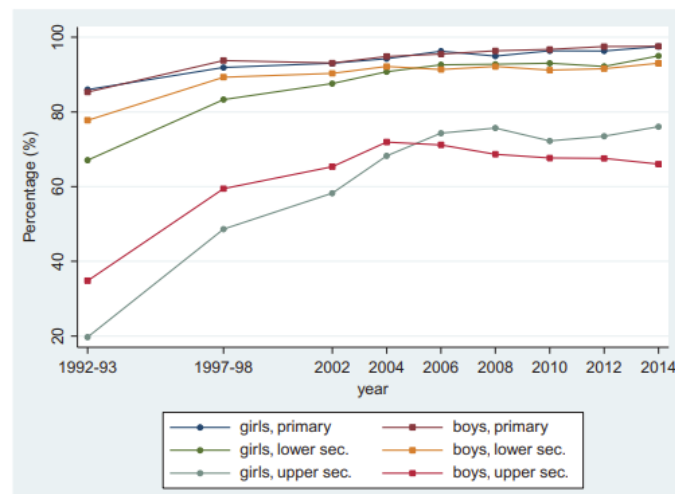


Figure 1.2: Net enrolment rate by school level and gender, Vietnam 1992-2014 (percentage). (Dang and Glewwe, 2018)

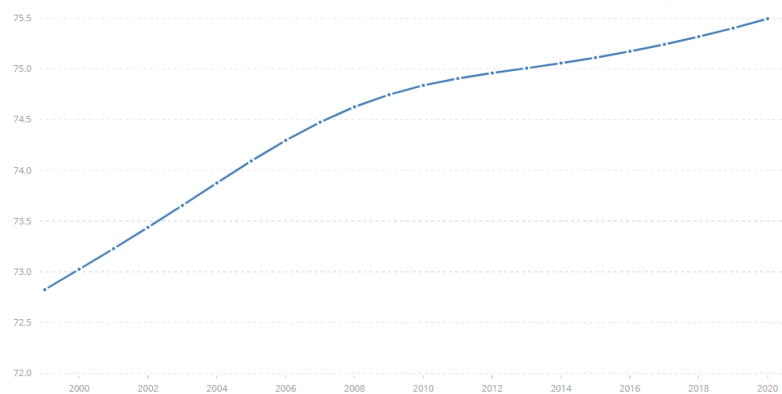


Figure 1.3: Life expectancy at birth, total years (World Bank, 2022)

to Figure 1.2. The net lower secondary enrolment rate has climbed from 65 to 90 percent, while the upper secondary rate has rocketed from 30 to 70 percent between 1992 and 2014. Regarding health outcomes, Figure 1.3 shows that younger generations expect to live longer than the older generation, with life expectancy being more than 75 years old for the youngest generation.

Despite its success, children from disadvantaged households are heavily affected by poverty. Children from poor households are less likely to enroll in school than their peers from affluent households when growing up. Figure 1.4 shows that the enrollment gap between children from poor households and children from wealthy households appears from lower secondary school and widens to reach more than 60% in higher education. Figure 1.5 also shows that children from households in the bottom quintile live in lower-quality conditions regarding drinking water sources and sanitation facilities. The differences in opportunity for children remain large among different population groups, especially for ethnic minority children. Ethnic minority children are more likely to drop out when they get to a higher grade and have less access to safely managed water and sanitation (Figure 1.6, Figure 1.7). Children in the Northern Midland and Mountain and the Central Highlands, where there are a large proportion of ethnic minorities, have a higher level of deprivation in nutrition, healthcare access, education, access to information, and living condition than those in other regions. (UNICEF, 2021).

Vietnam currently faces many challenges in improving children's well-being. Vietnam is among the five countries most affected by climate change, including drought risks (WB and ADB, 2021). As climate change leads to a dramatic escalation in magnitude and the likelihood of extreme weather and climate events, younger generations will be more exposed and vulnerable to extreme weather events Thiery et al. (2021). Of people affected by weather extremes, children from disadvantaged backgrounds are particularly vulnerable to drought as they have fewer coping strategies and safety nets, leading to concern about long-term poverty and inequality prospects.

Economic development in Vietnam has fostered urbanization and spatial transformation in which the growth of urban land cover has accelerated dramatically for the last ten years (Figure 1.8, Figure 1.9). Both theoretical and empirical evidence suggests a significant influence of neighborhood environments on child development. In rural areas, the conversion of rural to urban purposes has dramatically transformed the physical neighborhood environment where rural children grow up. Consequently, rural-to-urban land conversion can significantly impact child development, leading to important policy implications for urban planning in Vietnam.

This dissertation aims to contribute to understanding the roles of different contexts of environments arising from these challenges on children's development in Viet-

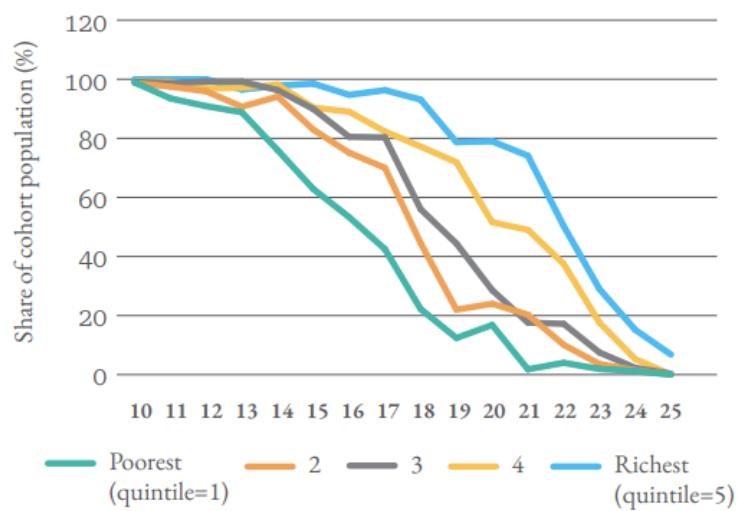


Figure 1.4: Enrolment rates by household wealth quintile and age, 2020 (Bank, 2022)

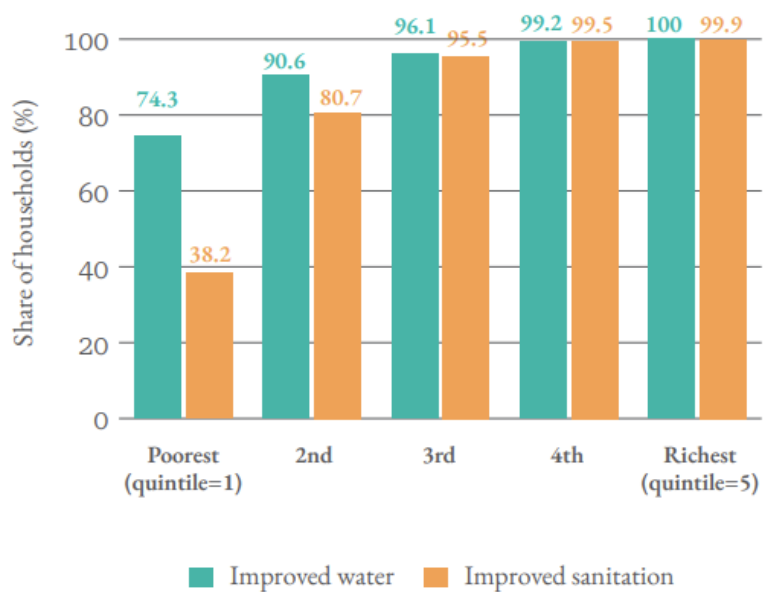


Figure 1.5: Access to improved drinking-water sources and sanitation facilities, by income quintiles, 2014 (Bank, 2022)



Figure 1.6: Enrolment rates by ethnicity and age, 2020 (Bank, 2022)

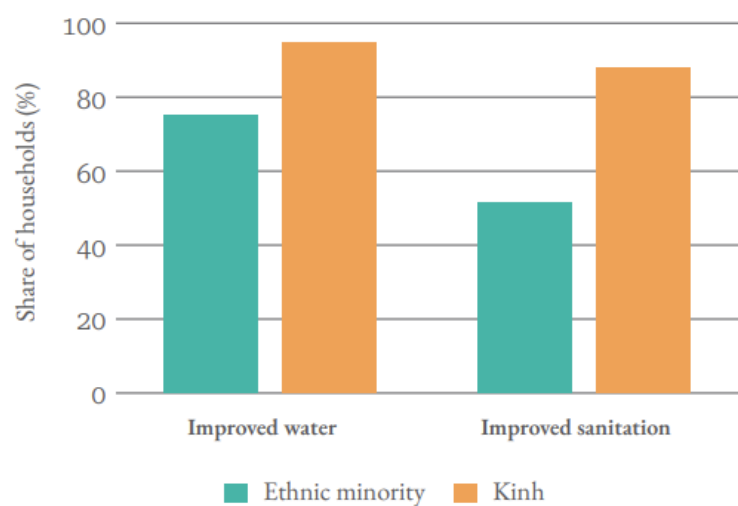


Figure 1.7: Access to improved drinking-water sources and sanitation facilities, by ethnicity, 2014 (Bank, 2022)

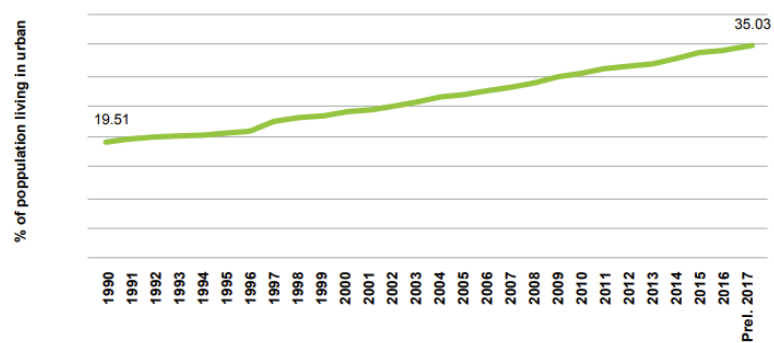


Figure 1.8: Urbanization rate: Vietnam, 1990-2017 (Bank, 2020)

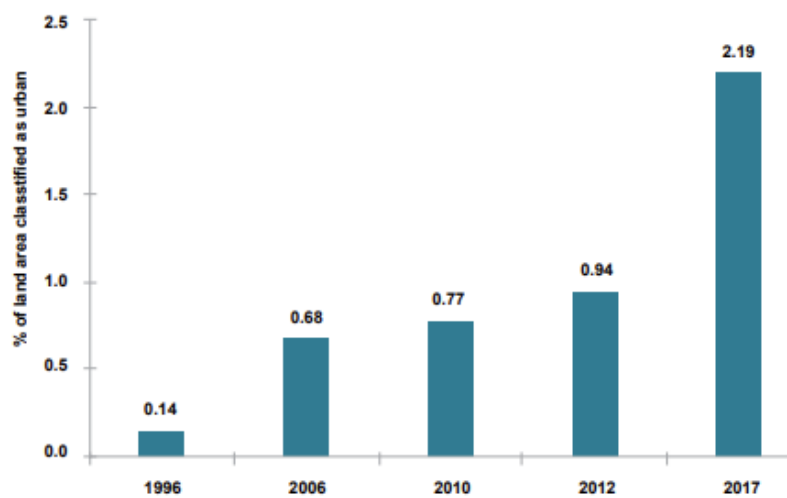


Figure 1.9: Aggregate land area covered by urban areas: Vietnam, 1996-2017 (Bank, 2020)

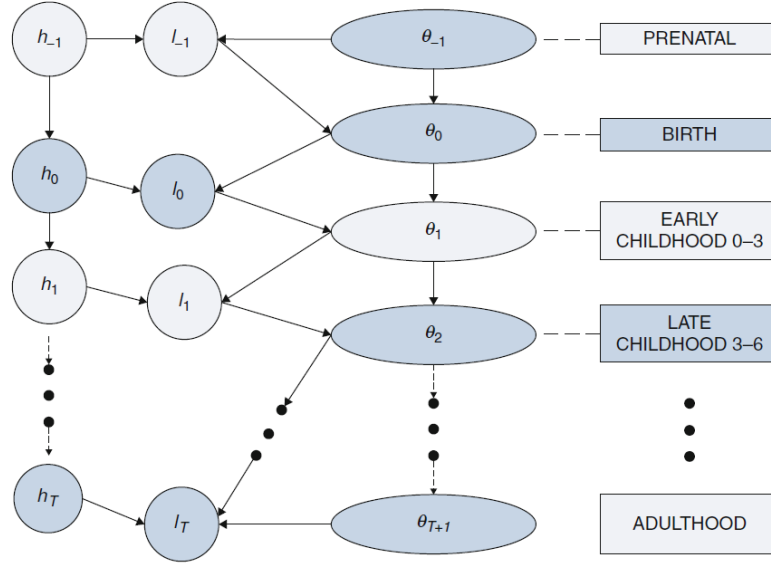


Figure 1.10: A life-cycle framework for conceptualizing child well-being (Conti and Heckman, 2012)

nam. Findings from the thesis may provide helpful information for policymakers to design and implement policies for the development of Vietnamese children.

1.2 . Theoretical Perspective

In formulating a theoretical perspective for studying the role of environments in children's development, a model of human development built by Cunha et al. (2010) is a valuable prototype. This model provides a dynamic framework ("the technology of skill formation") characterizing how environments and investments joined with stocks of skill affect the evolution of skill and relating how skills causally affect various child and adult outcomes. In the center of this model, environments directly impact skill formation, which forms the child's outcomes.

$$\theta_{t+1} = f_t(\theta_t, I_t, h_t, \theta^P) \quad (1.1)$$

The stock of period $t + 1$ skills (θ_{t+1}) is function of the stock of period t skills (θ_t), investments I_t , environments h_t , and parental traits θ^P .

$$Y_t^k = g^k(\theta_t, e_t^k) \quad (1.2)$$

The outcome k at age t (Y_t^k) is function of the stock of period t skills (θ_t) and effort e_t^k devoted to activity k at time t .

The individual possesses a vector of skills at each age. These skills are multidimensional and range from cognitive skills to non-cognitive skills. Outcomes such as test scores are affected by both cognitive skills and non-cognitive skills. Investment can be family and school inputs if children are of school age. The technology of skill formation is a multistage process. The first important feature of this technology is *self-productivity*, which means the skills at one stage determine the skills at the next stage. The second key feature is *dynamic complementary* which means that the skills at one stage increase the productivity of investment at the subsequent stage. These two features create a mechanism that explains investment and the environment's effect on human development.

The principles of the model of human development have been applied to many studies of child development, such as the long-term effect of child capabilities and the production of capabilities (Conti et al., 2010, 2011; Goodman et al., 2011; Cunha and Heckman, 2008, 2009; Cunha et al., 2010), and impact evaluation on policies to promote child development (Attanasio et al., 2020). This empirical evidence has provided strong support for the persistent impacts of the quality of childhood environments over a lifetime.

1.3 . Structure and Contributions

This thesis sheds light on three significant challenges in today's child development: early childhood environments, climate change, and urbanization and its implications for policy design. This thesis is organized around three chapters that analyze these three themes of environments using various data sources and methodologies. The focus of chapter 1 is to understand whether early preschool education can play a role in boosting the human capital formation of poor children. Together with Stephane Goutte, we look at whether preschool starting age improves children's cognitive skills, non-cognitive skills, and health until age 15. In the second chapter, I examine how exposure to rainfall variability and shocks affects child education labor, health, and health utilization. Finally, in the last chapter, I estimate the impacts of land cover change on child education and labor.

In order to tackle these questions, this thesis uses a variety of data sources. In the first chapter, to study the research question of the impacts of early preschool education, we use rich longitudinal data to document child poverty in Vietnam. It is a panel dataset that tracks the development of 2,000 children from 1 to 15 years old. In the second chapter, I put together a household living standard database at the national level and a high-resolution precipitation database to explore the relationship between rainfall variability and child outcomes. Finally, in the last chapter, we fill the gaps in the existing literature by using high-resolution land cover data to characterize urban and cropland cover changes in urbanization and examine its effects on children from rural and agricultural households. These data

sources provide valuable resources to study different dimensions of environments and their roles in child development.

The different chapters also exploit different analytical tools. In the first chapter, we adopt a Double Machine Learning approach and exploit high-dimensional data and the advance of machine learning to understand the causal effects of preschool starting age on human capital formation. This method allows using many control variables and their flexible, functional form in an objective and data-driven way to make the conditional independence assumption (CIA) plausible. In the second chapter, I use commune fixed-effects regressions and exploit exogenous deviations in rainfall from long-run mean values within the commune. I also investigate subgroup effects that therefore bear insight into which parts of the population are most vulnerable to rainfall variability — which serves to identify those most in need of protection by economic and social policy. The final chapter exploits variation in covers of urban and cropland within agricultural and rural households by estimating the household fixed-effects model. The estimation equation includes measures of land cover, individual, household, and commune socio-demographic determinants of child outcomes, and—in subsequent analyses — the interactions of both. Each dataset allows the application of different estimators to understand the causal relationships between environmental characteristics on child development.

1.4 . Early Childhood Environment: Preschool Education

Does it matter at what age disadvantaged children attend preschool? Although an accumulating body of evidence shows the beneficial effects of preschool education on disadvantaged children ([Berlinski et al., 2008](#); [Figlio and Roth, 2009](#); [Fredriksson et al., 2010](#); [Felfe and Huber, 2016](#)), none of the studies reviewed appears to assess the effect of preschool directly starting age on child outcomes. The question is specifically relevant to a country such as Vietnam, which already has universal preschool take-up for children one year before primary school. The proven benefit of early preschool enrollment will motivate countries like Vietnam to promote or even to require children from disadvantaged households, local poor areas, and ethnic minorities to enter preschool early to tackle poverty and inequality in the long run.

We address this question by analyzing the effect of preschool starting age on the development of poor children in Vietnam. We use the Young Lives Survey to document child poverty in Vietnam. It yields a wealth of measurement of child skills and information on the household, community, and parental investments in children. The highly dimensional data makes use of the conditional independence assumption likely plausible by providing an enormous set of control variables. We apply the framework of double machine learning ([Chernozhukov et al., 2018](#)), which allows using this set of control variables in a flexible, functional form in an objective

and data-driven way to permits the conditional independence assumption (CIA). The double machine learning approach ([Chernozhukov et al., 2018](#)) estimates outcome and treatment by machine learning algorithms and combines the estimates to derive the average treatment effect estimator. The data-adaptive machine learning method provides small-mistake estimates of nuisance parameters to de-bias estimates of the average treatment effect.

Exploiting high-dimensional data and the advance of machine learning, we reach the following findings. First, we uncover short- and medium-term favorable effects of early preschool enrollment on child cognitive skills and educational attainment but little evidence of the impact on non-cognitive skills. Specifically, at 15, a one-year younger preschool starting age raises child language skills by 0.091 standard deviations and increases the highest grade achieved by 0.047 per year. We find that the favorable impacts could be, at least in part, explained by parental investment behavior (proxied by the number of hours of extra classes children attended), as early preschool enrollment is associated with an increase in the number of hours of extra classes in all ages observed in the survey. Second, we analyze the impact on child health using anthropometric scores. We uncover the unfavorable short-term effect of early preschool enrollment on weight-for-age and BMI-for-age z-score. A one-year earlier preschool enrollment decreases weight-for-age z-score and BMI-for-age z-score by 0.056 and 0.092 standard deviation at age 8, respectively. This finding was unexpected and suggests that the quantity of nutritious value of preschool feeding might be less than home feeding. Interestingly, there is a negative association between preschool starting age and the probability of being thin at age 15, suggesting a link between health outcomes and educational attainment.

This chapter casts doubt on the quality of school feeding for poor children in Vietnam. While preschool in Vietnam might enrich the cognitive learning of poor children compared to childcare alternatives or home environments, improving the quality of school meals and non-cognitive skill stimulation is essential to achieve comprehensive child development.

1.5 . Climate change: Drought

Vietnam is among the five countries most affected by climate change, including drought risks ([WB and ADB, 2021](#)). In 2015-2016, Vietnam suffered from the worst drought in 100 years. [UNISDR \(2020\)](#) estimates that it has affected the livelihood of two million people in 18 provinces. Among those affected, 1.5 million lived in the Mekong Delta, and 500,000 lived in the drought-affected Central Highlands Region, the poorest region in the country. Of people affected by drought, children from disadvantaged backgrounds and poor areas are particularly vulnerable to drought, leading to the concern about prospects of long-term poverty and inequality. Understanding the heterogeneous impact of drought on children and the

household characteristics associated with resilience to drought may provide valuable inputs for policies to strengthen resilience to drought and reduce the negative impact on poverty and inequality in the long run.

To explore the relationship between drought severity and child outcomes, I exploit the exogenous rainfall deviation from the long-run average within local areas. The results show that severe drought exposure has significant short-term impacts on child outcomes and that the effects are more potent for the younger cohort. Drought severity is significantly associated with being more likely to work for economic activities and using fewer outpatient services. When we look at different cohorts, the impacts are more robust and significant for labor outcomes in the younger cohort and become weaker or insignificant for the oldest cohort. The results suggest that families are more likely to use young child labor to cope with income loss due to severe droughts. In particular, the harmful effects on health utilization remain statistically significant for all age ranges, with the most substantial magnitude for the youngest cohort. As drought increases the risk of illness ([Lohmann and Lechtenfeld, 2015](#)), reducing health care utilization and potentially preventative health care due to drought shocks raises serious concern about the long-term health outcomes of children in Vietnam.

The heterogeneity analysis shows that boys and children from disadvantaged socioeconomic backgrounds (uneducated, ethnic minority, rural, agriculturally dependent, and non-social allowance households) are particularly vulnerable to severe drought. They are more likely to drop out and work for economic activities when experiencing severe drought. This finding is consistent with our expectation since the drought has been proven to reduce agricultural output and production ([Lohmann and Lechtenfeld, 2015](#); [Kuwayama et al., 2019](#); [Wheaton et al., 2008](#)), which is the primary income source of agricultural and rural households. Our empirical evidence strongly supports the income effect as the channel through which drought affects child outcomes. The results also suggest that education and social allowance can buffer the detrimental impacts of drought and strengthen the resilience of households to drought.

Since children from disadvantaged households start behind and are more vulnerable to the detrimental impact than those raised in advantaged environments, our findings highlight the threat of increasing existing economic inequalities and reducing social mobility in the long run because of climate change. The study emphasizes the importance of public intervention to minimize the impact of drought on children. Assistance programs targeted directly to households to help them cope with income shocks can protect disadvantaged children from the detrimental impacts of disasters.

1.6 . Physical Environment: Land Cover and Urbanization

In Vietnam, rural-to-urban land conversion has been observed on a massive scale; urban expansion and rural industrialization are supplanting natural areas and farmlands. However, ineffective land-use policies and urban planning strategies lead to an unregulated and uncoordinated spatial development pattern in Vietnam. This pattern changes the livelihood of rural and agricultural households and leads to a rapid transformation of land cover. Exploiting the variation in the cropland and urban land cover within local communes, this chapter analyzes the effects of land cover in local communes on school-aged children in rural Vietnam. It aims to contribute to both the literature about the impact of urbanization and the branch of studies focusing on the impact of physical environments on child outcomes.

Applying the household fixed-effect model, I found that both shares of urban land and cropland affect child labor in the same direction. While expansion in urban land cover is significantly associated with a decrease in child labor in household agricultural activities, a fall in cropland in the neighborhood leads to higher participation of children in these activities. The magnitude is more substantial for urban land cover, suggesting the overall negative effect of the land cover change resulting from rural to urban land conversion.

I show that while cropland cover has stimulating effects on the education and labor outcomes of children from agricultural households, children from business households are more responsive to the change in urban land cover. The impacts of cropland cover on rural households whose income is heavily dependent on agriculture or who have agricultural activities are significantly weaker for domestic labor but more vital for wage labor outside the household. In contrast, children from business households are more likely to reduce the probability of working when the share of urban land in the commune increases. The disproportionate impacts of land cover on rural children require further research to clarify the pathway through which land cover change affects child outcomes. Effective land-use policy strongly needs this evidence to avoid inequality aggravation among rural children.

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2 - School Environment: Pre-school Education

Abstract: Using a longitudinal Young Lives survey in Vietnam, this paper analyzes the effect of preschool starting age on poor children's skills, educational attainment, and health. Implementing the double machine learning estimator, we find short and medium-term positive effects of starting preschool younger on child cognitive skills but little evidence on child non-cognitive skills. Starting preschool younger increases significantly the highest grade achieved and creates a behavioral response of increasing subsequent parental investment in education. In contrast, we uncover the short-term negative impact of starting preschool younger with measures of child health, namely weight-for-age, and BMI-for-age. The findings imply that expanding access to preschool and improving the quality of preschool education are essential to achieve comprehensive child development.

2.1 . Introduction

Does it matter at what age disadvantaged children attend preschool? Numerous scholars have correctly observed that parents tend to delay their children's entry into kindergarten in developed countries. This tendency is referred to as "red-shirting", which is particularly common among boys and those from socioeconomically advantaged households. The benefits of starting later can be categorized into two mechanisms: relative maturity and absolute maturity ([Dee and Sievertsen, 2018](#)). First, relative maturity deals with the benefits of higher developmental stages leading to better performance relative to the peers in the short and long-term ([Frey, 2005](#)). Second, absolute maturity focuses on the argument that formal education can bring more benefits to older children than younger ones ([Greenburg and Winsler, 2020](#)). There needs to be more research investigating the phenomenon among children from socioeconomically disadvantaged backgrounds and in the context of developing countries. As early childhood education can be an important policy tool to tackle long-run poverty and inequality, understanding the impact of school starting age on disadvantaged children in developing countries provides essential evidence for policy implication.

Early childhood experiences have persisted and profound impact on brain development—affecting the accumulation of life-relevant skills and, ultimately, well-being ([Sapolsky, 2004](#); [Knudsen et al., 2006](#)). Adverse early childhood environments raise serious concerns about accumulating these skills and, eventually, the life prospects of disadvantaged children. Recent studies prove the beneficial effect of high-quality

early childhood education programs on the development of disadvantaged children by enriching their learning and nurturing environments ([Attanasio et al., 2020](#)). Other accumulating body of evidence focusing on preschool education shows their beneficial effects on disadvantaged children in the context of developed countries ([Berlinski et al., 2008](#); [Figlio and Roth, 2009](#); [Fredriksson et al., 2010](#); [Felfe and Huber, 2016](#)). Theoretical evidence proposed by [Cunha et al. \(2010\)](#) also suggests that early childhood education can have a long-term impact on skills by directly improving current skills, which will beget later skills (i.e., self-productive) and increasing the productivity of later investment (i.e., dynamic complementary). Based on this evidence, we might expect that early preschool enrollment would benefit disadvantaged children in developing countries by preventing the negative effect of early life conditions and shaping the skills that promote their later life outcomes.

The question is specifically relevant to a country such as Vietnam, which already has universal preschool take-up for children one year before primary school. The proven benefit of early preschool enrollment will motivate countries like Vietnam to promote or even to require children from disadvantaged households, local poor areas, and ethnic minorities to enter preschool early to tackle poverty and inequality in the long run.

We address this question by analyzing the effect of preschool starting age on the development of poor children in Vietnam. In exploring this relationship, the contribution of our study is three folds. First, instead of focusing on pure preschool enrollment as most studies do, we directly tackle the effect of preschool starting age on a wide range of outcomes, including cognitive skills, non-cognitive skills, health, and educational attainment over a 10-year development period of children. This broad coverage of outcomes over a long period makes it possible to have a complete picture of the impact until adolescence. Second, we also contribute to the literature by assessing the potential pathway through which early preschool enrollment improves child outcomes suggested by theory. Understanding the underlying mechanisms can help design and improve the early childhood education policy for disadvantaged children to benefit these children and the entire society. Finally, the paper contributes to the causal machine learning literature by applying the double machine learning estimator ([Chernozhukov et al., 2018](#)) empirically for average treatment effects. Depending on conditional independence assumptions such as propensity score matching requires identifying a set of control covariates entering the analysis and the functional form. Many times the functional form needs to be clarified, and many control variables are needed. The recently introduced framework of double machine learning ([Chernozhukov et al., 2018](#)) allows using many control variables and their flexible, functional form in an objective and data-driven way to make the conditional independence assumption (CIA) plausible.

We use the Young Lives Survey, which aims to document child poverty in Vietnam.

It yields a wealth of measurement of child skills and information on the household, community, and parental investments in children. The highly dimensional data makes use of the conditional independence assumption likely plausible by providing an enormous set of control variables. The treatment variable is the preschool starting age of children. Outcomes include cognitive skills measured by mathematics and language; non-cognitive skills captured by self-efficacy, self-esteem, parent-child relations, and peer relations; and health captured by height-for-age, weight-for-age, and BMI-for-age z-scores. We also look at other outcomes comprising education attainment and nutritional status. These measures cover a wide range of aspects of child development that can be positively affected by early preschool enrollment. Finally, to analyze a potential channel through which early preschool enrollment affects child development, we assess the impact on parental investment in education proxied by the number of hours of extra classes.

Exploiting high-dimensional data and the advance of machine learning, we reach the following findings. First, we uncover short- and medium-term favorable effects of early preschool enrollment on child cognitive skills and educational attainment but little evidence of the impact on non-cognitive skills. Specifically, at 15, a one-year younger preschool starting age raises child language skills by 0.091 standard deviations and increases the highest grade achieved by 0.047 per year. We find that the favorable impacts could be, at least in part, explained by parental investment behavior (proxied by the number of hours of extra classes children attended), as early preschool enrollment is associated with an increase in the number of hours of extra classes in all ages observed in the survey. Second, we analyze the impact on child health using anthropometric scores. We uncover the unfavorable short-term effect of early preschool enrollment on weight-for-age and BMI-for-age z-score. A one-year earlier preschool enrollment decreases weight-for-age z-score and BMI-for-age z-score by 0.056 and 0.092 standard deviation at age 8, respectively. This finding was unexpected and suggests that the quantity of nutritious value of preschool feeding might be less than home feeding. Interestingly, there is a negative association between preschool starting age and the probability of being thin at age 15, suggesting a link between health outcomes and educational attainment.

Although previous literature proves that the positive effect of preschool enrollment is higher for disadvantaged children, our study casts doubt on the quality of school feeding for poor children in Vietnam. While preschool in Vietnam might enrich the cognitive learnings of poor children compared to childcare alternatives or home environments, we argue that improving the quality of school meals and non-cognitive skill stimulation is essential to achieve comprehensive child development.

The paper unfolds as follows. Section 2 presents the relevant literature. Section 3 describes the data. Section 4 outlines the methodology. Section 5 presents our empirical results, and section 6 concludes.

2.2 . Literature Review

Whereas the literature has provided evidence on the effectiveness of universal preschool education on outcomes of disadvantaged children, they only look at the effect of pure preschool attendance without considering variation in the age when children enter preschool. A dearth of non-cognitive skills, long-term outcomes, and developing contexts also limits this current evidence stock. There is little understanding of the medium- or long-run effects of preschool attendance on health, non-cognitive skills, and parental investment. Even though research has remained mainly confined to developed countries, the mechanisms by which it has generated the impacts have yet to be fully discovered. Analyses of preschool education in developing country contexts still need to be improved and conclusive. Assessing the role of preschool education on disadvantaged child development is especially important in these contexts, where expanding access to preschool provision has been one of the main education policies for addressing inequality, breaking the cycle of poverty, and improving outcomes later in life.

Within developing countries, the recent study of [Shafiq et al. \(2018\)](#) attempts to assess the relationship between participation in early childhood education (ECE) and various long-term outcomes in 12 low- and middle-income countries. They find positive and statistically significant associations between ECE participation and post-ECE educational attainment but fewer cases of positive associations between ECE and long-term socio-emotional outcomes. They also find mixed evidence of ECE and labor market outcomes, with positive associations for skill use but weak associations with earnings. Other studies of the impact of preschool education on long-term outcomes have mainly been confined to developed countries and on outputs such as school enrollment or test scores. [Fredriksson et al. \(2010\)](#) analyze the effects of preschool attendance on test scores at age 13 for four cohorts of children born in Sweden. Controlling for general cohort-specific trends, they find that preschool attendance significantly reduces the language score disparity between children of immigrants and those of native-born parents but does not affect the gap in scores on another test or academic secondary school degree completion. [Berlinski et al. \(2008\)](#) using data on children aged 7-15 in Uruguay and controlling for family fixed effects, find that preschool attendance is positively associated with school attendance and level of education with substantial effect for children with low-educated parents or living outside the capital city. Exploiting variation in childcare prices as an instrument for preschool participation, [Black et al. \(2014\)](#) uncover a positive effect of government-subsidized preschool on children's future national exam grades at age 16 in Norway, with the most significant impacts for children from low-income families. [Hazarika and Viren \(2013\)](#) study effects on adolescents in India using a presence in the village of a center or a school offering preschool classes as an instrumental variable. They find that preschool participation increases school enrollment and also speeds grade progression conditional on

enrollment. [Drange et al. \(2016\)](#) using a difference-in-difference approach to study the long-run effect on schooling of mandating kindergarten at age 5–6 in Norway, find no effect both overall, across sub-samples and over the grading distribution. [Dhuey \(2011\)](#), using a similar strategy, detects the negative effect of kindergarten expansions on grade retention among Hispanic children, non-English speakers, children of immigrants, and children from low socioeconomic status households in the US.

The impact of universal preschool education on measurements of child skills (e.g., cognitive or non-cognitive capabilities) has only been assessed in short-term outcomes in developed countries, especially in the US. Using the birthday cut-off for enrollment to construct RDD, ([Gormley Jr et al., 2005](#); [Gormley et al., 2008](#)) find positive effects of Oklahoma’s universal pre-kindergarten program on children’s literacy and math, as well as socio-emotional development, with the most prominent benefits for disadvantaged children. [Fitzpatrick \(2008\)](#) uses a difference-in-difference method to show that Georgia’s universal pre-kindergarten program increased the reading and math scores of disadvantaged children and those in small towns or rural areas while reducing the probability of grade retention. Employing the presence or absence of a public pre-kindergarten program in the student’s local zoned elementary school as an instrument, [Figlio and Roth \(2009\)](#) document that attending public pre-kindergarten school in Florida reduces behavior problems and suspension or grade retention rates in short-term with the most significant benefits from children from families with low levels of education or disadvantaged neighborhoods. Applying the same approach with individual distance to the nearest preschool facility as an instrumental variable, [Felfe and Huber \(2016\)](#) found significant short-term gains in children’s literacy. Preschool attendance also increases the prevalence of vaccinations but does not affect other observed health outcomes for Roma children in Europe.

When assessing the impact of preschool education, the fundamental identification problem is that preschool attendance is likely endogenous. The current literature uses different approaches to tackle this problem. The rigorous research used the quasi-experimental method and their methodological strategies, yet they have some crucial drawbacks. For example, several research exploiting regional and time variations by using the difference-in-difference framework ([Fitzpatrick, 2008](#); [Drange et al., 2016](#)) is inherent to a crucial drawback that if there are any differences in trends of unobserved characteristics between treatment and control group, the difference-in-difference estimates capture the differences in trend rather than the effect of the programs. Other literature ([Gormley Jr et al., 2005](#)) exploited the nature of the data in the US to shape the regression discontinuity design on age eligibility. This strategy faces the problem of insufficient children to identify the impact in the cut-off’s vicinity and selective attrition from the sample ([Elango et al., 2016](#)).

Our paper aims to address these concerns and contribute to the literature in three aspects. First, instead of focusing on pure preschool enrollment, we focus on the impact of preschool starting age on a broad set of outcomes representing the development of poor children over ten years. This applies to a country like Vietnam, which already has universal preschool enrollment among five-year-old children. Second, we assess the relationship between preschool starting age and child development using a new empirical approach compared to previous studies. In particular, we exploit the double machine learning approach dealing with a high-dimensional set of control variables while prior studies adopt the quasi-experiment method as the identification strategy. The richness of our longitudinal data allows us to construct numerous potential control variables. These variables controlled in flexible, functional forms make the conditional independent assumption workable. Finally, we contribute to the literature by testing a potential channel through which preschool starting age improves child outcomes.

2.3 . Data sets

The data used here are the Young Lives Survey of Younger Cohort, which aims to document child poverty. The Young Lives survey uses quantitative and qualitative data collection methods, tracking 2,000 children in five rounds in 2002, 2006, 2009, 2013, and 2016, corresponding to the ages of 1, 5, 8, 12, and 15 of the Younger Cohort. The Young Lives data is intended to gather information on diversified life aspects of children, their caregivers, and their families. The survey has collected comprehensive information on child characteristics, families, caregiver/parent characteristics and resources, their preferences and feelings, and school and community factors. Moreover, the survey provides specific information for measuring children's cognitive and non-cognitive skills, allowing us to study children's development.

Although the Young Lives household survey sampling is not designed to represent the Vietnamese population, it considers the diversity of children in the country regarding various attributes and experiences. These surveys use a sentinel-site sampling design, including a complex consultative process with a pro-poor selection rule based on each commune's poverty ranking. The data consists of 20 purposely selected sites representing diversity and pro-poor bias in five provinces: Lao Cai, Hung Yen, Da Nang, Phu Yen, and Ben Tre. Each province contains four sites, and each comprises one or two communes, with 36 communes. At the site level, children were selected randomly in 2001, such that the data represents the birth cohort at each site.

2.4 . Preschool systems and descriptive analysis

2.4.1 . Preschool education in Vietnam

Depending on the child's age, there are three types of institutions for early childhood education in Vietnam. Children can attend nurseries/creches from three months to three years old. They go to kindergartens from three to six years old. Preschools in Vietnam incorporate the functions of these two schools and welcome infants from the age of 3 months up to the age of 6 years (Vu, 2021). From age 3, preschool is an educational facility that promotes developmental learning and growth and prepares children for primary education. As a result, this study only considers preschool starting from three years old. This exclusion also makes preschool in Vietnam similar to that of other countries.

In Vietnam, most children from ages three to five attend public kindergartens. Education Law 2005 emphasized the importance of early childhood education in Vietnam and targeted to universalized pre-primary education. The policy promoted the construction of public preschools, especially in communes with harsh socioeconomic conditions, such as mountainous and border areas. According to the Minister of Education and Training (MOET), in 2015, the enrollment rates of 5-year-old children in kindergarten increased remarkably from 72 to 98 percent. Indeed, Figure 2.1 from the World Development Indicators show that the gross enrollment rate for pre-primary education reached 100% in 2018 with very little difference between girls and boys.

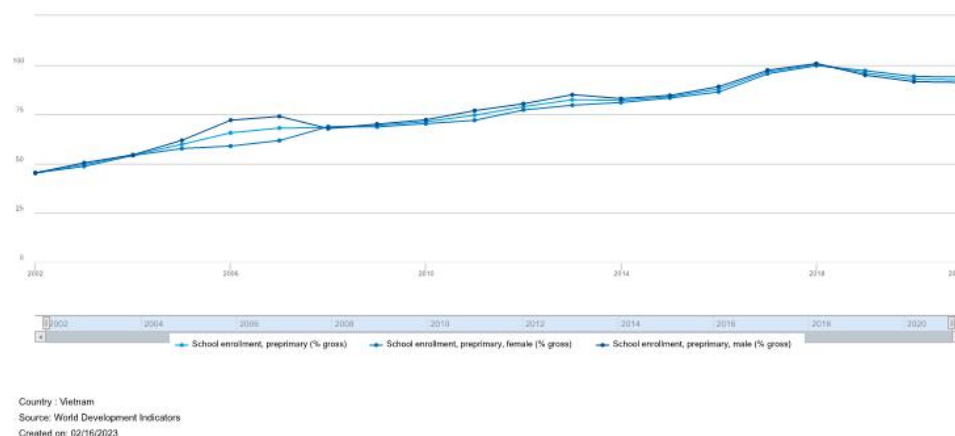


Figure 2.1: School Enrollment, Pre-primary (% gross)

2.4.2 . Preschool starting age

The Young Lives Survey provides us with a wide variety of child characteristics. The primary explanatory variable is the child's preschool starting age, collected in the second round when the child is five years old. We exclude children who did not attend preschool or started preschool before three years, accounting for 11% and 0.7% of the total number of young cohort children in the survey, respectively. Table 2.1 reports the preschool starting age summary statistics. The average years

of preschool starting age are approximately 3.72 years old. Children start preschool latest at 5.75 years old.

Table 2.1: Summary statistics of preschool starting age variable

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|------------------------|-------|-------|----------|-------|----------|----------|-------|
| Preschool starting age | 1,763 | 3.723 | 0.757 | 3.000 | 3.000 | 4.167 | 5.750 |

2.4.3 . Child skills and education

We cover two dimensions of a child's cognitive skills: math and language. They are measured by mathematic tests (rounds 3, 4, and 5), Peabody Picture Vocabulary test (rounds 3,4, and 5), Early Grade Reading Assessment (rounds 3), and Reading Comprehension test (rounds 4 and 5). We construct measures of mathematics and language skills using the Rasch model based on the mathematics test and the combination of vocabulary and reading tests. The Rash model is a one-parameter of the Item Response Theory model using logistic regression analyses where item responses are predicted by the difference between the item difficulty and the child's ability. The equation for the Rasch model is:

$$P(\theta_j, b_i) = \frac{e^{(\theta_j - b_i)}}{1 + e^{(\theta_j - b_i)}}, i = 1, 2, 3, \dots, n$$

P is the probability that a child j with ability θ_j get the right item i . b_i is the item difficulty. n is the number of items in the test. θ_j is the child's ability parameter.

We apply marginal maximum likelihood estimation to estimate item and person parameters (Rasch score) and then construct θ score for each child.

The non-cognitive skills are measured by self-efficacy, self-esteem, parent-child relations, and peer relations in rounds 4 and 5 ([Tran, 2017](#)). We use factor analysis ([Yong et al., 2013](#)) to compute the non-cognitive skills based on the respondent's degree of agreement or disagreement with some statements. Agreement ranges from "strong agreement" to "strong agreement" with a 4-point scale; all the items are recorded to reflect positive statements. The number of items in the questionnaire related to self-efficacy, self-esteem, parent-child relations, and peer relations is ten, eight, nine, and eight, respectively. The simple mathematical model for factor analysis is:

$$X_j = a_{j1}F + e_j, j = 1, 2, \dots, p$$

p denotes the number of items in the group $(X_1, X_2 \dots, X_p)$. The factor loading a_{j1} is the factor loading of j^{th} variable on the factor F , and e_j is a residual variate. We assume that a group of items only represents one underlying non-cognitive skill dimension called a factor. Since the data can violate the assumption of multivariate normality, we use the Principal Axis Factor for factor extraction and oblique rotation for the rotation method, as suggested by Yong, & Pearce, 2013. We run four factor analysis for four measures of non-cognitive skills. Depending on the result, we only choose significant items with a factor loading value greater than 0.4. We end up with nine, six, eight, and eight items in round 3 and six, six, eight, and seven items in round 4 to construct final measures of self-efficacy, self-esteem, parent-child relations, and peer relations, respectively. We also assess the impact on educational attainment using the highest grade achieved.

We explore one potential mechanism through which preschool starting age can affect child development by assessing its impact on parental investment in education proxied by the number of hours of extra classes. As theoretical evidence suggests, early investment can promote subsequent investment and increase its return.

2.4.4 . Child health

We measure child health with the child's anthropometry, including height-for-age, weight-for-age, and BMI-for-age z-score. The Young Lives data estimated z-scores using World Health Organization (WHO) reference tables and software. All anthropometric scores are adjusted by the child's age and sex. Since the WHO reference tables apply only to children of certain ages, the weight-for-age z score is computed for the Younger Cohort only up in Round 3. We also consider the nutritional statuses built on the child's anthropometry. The survey used the WHO table (2007) to construct Stunting, Underweight, and Thinness based on height-for-age, weight-for-age, and BMI-for-age z-scores, respectively. We observe three dummy variables taking the value of one of the corresponding z-score below the tables' cut-off of -2 and zero otherwise. The summary statistics of all outcomes variables are shown in Appendix A

2.5 . Empirical Framework

2.5.1 . Identification

We estimate the effect of preschool starting age on child skills, long-term health, and educational attainment. Our empirical strategy is motivated by a new double machine learning estimator for average treatment effects and the availability of longitudinal rich data of poor children in Vietnam. The double machine learning method and the advance of machine learning in solving prediction problems provide a promising way to draw causal inferences from observational data. The fundamental problem of confounding is that preschool attendance is likely endogenous since the preschool investment decision of parents reflects several factors, such as

their taste, resources, and information about the current evolution of their child's skills that may be correlated with child skills, education, and health.

To eliminate confounding, we rely on the existence of a vector of covariates X_i such that the following two assumptions are fulfilled:

1. Conditional independence: The treatment status D_i is as good as randomly assigned and not correlated with potential outcome Y_i^t conditional on covariates X_i

$$Y_i^t \perp\!\!\!\perp D_i | X_i$$

2. Common support: Any unit needs to have a non-zero probability of receiving each of the treatments:

$$P[D_i = t | X_i = x] > 0$$

In this case, the CIA requires observing all variables that influence the parent's decision to send children to preschool and the outcomes of interest simultaneously.

Following [Cunha et al. \(2010\)](#), inherited traits and prenatal investments affect skills at birth, which correlate with investments in early childhood and child outcomes. We control this concern by considering the child's characteristics, including age, sex, ethnic minority, number of brothers and sisters in the household, and child health using the child's anthropometry at age 1, parental background, and parental education. Moreover, household and community environments impact both child investment and child development. We consider the household environment by controlling for household socioeconomic characteristics and the sentinel site environment by controlling for sentinel site id.

Parent assesses the cost of preschool depending on parental labor supply and other childcare options. A working caregiver is more likely to search for other support. We control the caregiver's working activity, and the support caregiver can receive inside and outside of the household. The support can be childcare directly, mainly from household members, not household members or creche. She can also receive general support from groups for which she is a member or any other sources for which she can look. All these supports represent social capital that can impact the relative cost of preschool education.

Preschool investment decisions of parents also reflect parental taste, parental altruism toward the child, and parental expectation. We include the caregiver's attitude and perception and child care history to control for these factors.

We extract 50 potential control variables from the Young Lives survey. All the control variables are measured in the first round except for the caregiver's attitude

and perception. We assume the caregiver's attitude and perception are updated once the child attends primary school.

2.5.2 . Estimation

The double machine learning approach ([Chernozhukov et al., 2018](#)) estimates outcome and treatment by machine learning algorithms and combines the estimates to derive the average treatment effect estimator. The data-adaptive machine learning method provides small-mistake estimates of nuisance parameters to de-bias estimates of the average treatment effect.

The equations models outcome and treatment as follows:

$$Y_i = \theta_0 D_i + g_0(X_i) + e_i, \quad E[e_i | D_i, X_i] = 0 \quad (2.1)$$

$$D_i = m_0(X_i) + u_i, \quad E[u_i | X_i] = 0 \quad (2.2)$$

The confounding factors X_i affect the treatment variable D_i via the propensity score, $m_0(X_i) := E[D_i | X_i]$, and the outcome variable via the function $g_0(X_i)$. e_i and u_i are stochastic errors. Given the conditional independence assumption, θ_0 is interpreted as a structural or causal parameter that can be inferred from equation (2.1). The double/debiased ML estimator $\hat{\theta}_0$ solves the following condition:

$$E[\psi(W, \theta_0; \eta_0)] = 0 \quad (2.3)$$

Where $\psi(W; \theta, \eta) = (Y - D\theta - g(x)(D - m(x)))$ is score function, $W = (Y, D, X)$, θ_0 is the parameter of interest, and $\eta = (g, m)$ denotes nuisance functions with population value $\eta_0 = (g_0, m_0)$. The score ψ satisfies the *Neyman orthogonality condition* $\partial_\eta E\psi(W; \theta_0, \eta)|_{\eta=\eta_0} = 0$ which ensures that the condition (2.3) used to identify and estimate θ_0 is insensitive to small perturbations of the nuisance function η around η_0 and to the replacement of η_0 with $\hat{\eta}_0$ for high-quality inference. Therefore, the estimation $\hat{\theta}_0$ of θ_0 is constructed based on the score ψ , which replaces the nuisance functions η_0 with $\hat{\eta}_0$ produced by data-adaptive machine learning method and on the moment conditions (2.3).

This estimator is semi-parametric efficient under weak conditions due to an extra step of sample splitting. Since using one sample to fit the nuisance parameter, obtain prediction and construct the estimate of θ_0 causes overfitting and thus bias, sample splitting would help to avoid overfitting and thus reduce bias. [Chernozhukov et al. \(2018\)](#) propose randomly split the sample to k -folds equal partitions $(1, 2, \dots, N)$. For each set I_k , let I_k^c denote all observation indices, not in I_k . The nuisance parameters are estimated in the auxiliary sample I_k^c : $\hat{\eta}_{0,k} = \hat{\eta}_{0,k}((W_i)_{i \in I_k^c})$. Then we use this estimation to construct the estimation $\hat{\theta}_0$ as the solution to the equation:

$$\frac{1}{N} \sum_{k=1}^K \sum_{i \in I_k} \psi(W_i; \hat{\theta}_0, \hat{\eta}_{0,k}) = 0 \quad (2.4)$$

The asymptotic variance of $\hat{\theta}_0$ is estimated by:

$$\hat{\sigma}^2 = \hat{J}_0^{-2} \frac{1}{N} \sum_{k=1}^K \sum_{i \in I_k} [\psi(W_i; \hat{\theta}_0, \hat{\eta}_{0,k})]^2$$

$$\hat{J}_0 = \frac{1}{N} \sum_{k=1}^K \sum_{i \in I_k} \psi_a(W_i; \hat{\eta}_{0,k})$$

where $\psi_a(W; \eta) = -(D - m(X))(D - m(X))$

The specific sample splitting creates an additional source of variation, impacting estimation results asymptotically in finite samples (Chernozhukov et al., 2018). They suggest further adaptation by re-partitioning the data multiple times and then aggregating it by the median of the resulting estimates as the final average treatment effect. The estimated standard errors are also corrected to capture the spread of the estimates.

We implement the double machine learning approach of Chernozhukov et al. (2018) applying the DoubleML package (Bach et al., 2021) in R. We use eXtreme Gradient Boosting - XGBoost by Chen and Guestrin (2016) to fit the nuisance parameters. XGBoost is a gradient-boosted decision-tree-based ensemble Machine Learning algorithm that focuses on computational speed and model performance¹. This model does not require the form of nuisance parameters to be specified and automatically handles missing data, implicitly conducting feature selection and characteristics. XGBoost is fast and dominates structured or tabular datasets on classification and regression predictive modeling problems². We fit XGBoost to estimate each nuisance function with parameters chosen by internal tuning using five-fold cross-validation.

2.6 . Results

We report estimates obtained using five-fold cross-fitting. All results are based on taking 100 different sample splits. The results are summarized across the sample splits using the median method.

2.6.1 . Impact on skills, educational attainment and parental investment

Panel A and B of Table 2.3 show the effects of preschool starting age on a child's cognitive skills. All skill variables are standardized to have zero mean and variance

¹Gradient boosting is an approach where new models are created that predict the residuals or errors of prior models and then added together to make the final prediction. It is called gradient boosting because it uses a gradient descent algorithm to minimize the loss when adding new models.

²Since its introduction, this algorithm has been credited with winning numerous Kaggle competitions

one. The double machine learning estimates show a negative effect of preschool starting age on mathematics and language skills at 8. The estimates imply that starting preschool one year younger increases the mathematics score by about 0.09 standard deviations and language score by about 0.06 standard deviations. At ages 12 and 15, attending preschool one year earlier is only significantly associated with an increase in a child's language skills, in which the estimates are almost 0.07 and 0.09 standard deviations, respectively. In particular, the magnitude of these estimates tends to increase over time. Under the light of the technology of skill formation proposed by [Cunha et al. \(2010\)](#), these findings support the idea of *self-productivity* for language skills in which "skills beget skills." However, we do not find enough evidence of *self-productivity* for mathematics skills. Our findings are consistent with a study from [Drange and Havnes \(2019\)](#), which proved that children enrolling in childcare at age 1-2 tend to have higher development in language and mathematics at age 6-7 even though this study did not directly look at the preschool level.

We find little evidence of the effect on non-cognitive skills. As shown in panel B of Table 2.3, early preschool enrollment is only significantly associated with self-esteem at age 12, but the effect disappears when children reach age 15. The estimates of other dimensions of non-cognitive skills turn out not statistically significant. Overall, panel C reports the impact on educational attainment. Our estimates suggest that starting preschool one year younger raises the highest grade achieved by 0.034 year at age eight and 0.47 year at age 15.

Our estimated impacts of starting preschool younger converge on the prior research about the impact of preschool participation reviewed earlier. In particular, [Shafiq et al. \(2018\)](#) show positive statistically significant and positive associations between early childhood education participation and long-term cognitive skills and educational attainment in Vietnam. However, using different measurements of non-cognitive skills, they find mixed evidence on socio-emotional skills with both negative and positive impacts. Their data consist of urban adults from 20 to 64 years old in 2014, so this would have been a different preschool program and underlying population with our study. However, an implication of the findings is the possibility that preschool education in Vietnam might focus on cognitive stimulation rather than enriching the learning of non-cognitive skills.

We explore an important channel through which preschool starting age affects child skills and education. According to [Cunha et al. \(2010\)](#), early investment increases the stock of future skills that promote the productivity of future investment. We test the hypothesis that early preschool enrollment boosts the future parental investment in education, explaining the effect of preschool starting age on a child's outcome. Several research studies have shown parental investment's reinforcement effects on the human capital formation process ([Giannola, 2022](#); [Berry et al., 2020](#);

Table 2.3: Estimated effect of preschool starting age on child skills, education attainment and parental investment.

| | Age 8 | Age 12 | Age 15 |
|--|----------------------|----------------------|---------------------|
| | (1) | (2) | (3) |
| Panel A: Cognitive Skills | | | |
| Mathematics | −0.089*** (0.034) | −0.034 (0.037) | −0.051 (0.038) |
| Language | −0.061* (0.033) | −0.077** (0.036) | −0.091** (0.037) |
| Panel B: Non-cognitive Skills | | | |
| Self-esteems | | −0.090** (0.042) | −0.007 (0.043) |
| Self-efficacy | | −0.050 (0.043) | −0.049 (0.043) |
| Parent-child Relation | | −0.022 (0.044) | 0.007 (0.042) |
| Peer Relation | | −0.069 (0.044) | −0.03 (0.045) |
| Panel C: Educational Attainment | | | |
| Highest grade achieved | −0.034** (0.017) | −0.032 (0.025) | −0.047* (0.025) |
| Panel C: Parental Investment | | | |
| Number of hours of extra-classes | −0.576*** (0.192) | −0.582*** (0.176) | −0.673** (0.251) |

Note: *Note:* * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Outcome variables of Panel A and B are scaled to have mean 0 and variance 1. Estimated effects and standard errors from partially linear regression effect model based on orthogonal estimating equations. Results are based on 100 sample splits and the standard errors adjusted for variation across splits are provided in parentheses.

[Almås et al., 2023](#)). Estimates of preschool starting age on parental investment in education are reported in panel C of Table 2.3. We use the hours of extra classes as a proxy for parental investment in education. Attending preschool earlier is accompanied by short- and medium-term increases in the hours children attend extra classes during an average week. Indeed, the magnitude of the effect increases over time. Starting preschool one year younger increases the number of extra-class hours an average week by 0.576, 0.582, and 0.673 at ages 8, 12, and 15 years, respectively. The significant short and medium-term effects on parental investment in education can partly explain the positive effect of early preschool enrollment on educational attainment.

2.6.2 . Impact on Health

We present the estimates of the effects of preschool starting age on child health in Table 2.4. Panel A presents results on height-for-age, weight-for-age, and BMI-for-age scores. Panel B shows the impacts on nutritional status. We find a short-term negative effect of starting preschool younger on weight-for-age and BMI-for-age z-score. Starting one year younger is associated with a decrease in weight-for-age and BMI-for-age z-score by 0.073 and 0.089 standard deviations. Given gender, BMI-for-age and weight-for-age reflect current and long-term health status, respectively ([Le and Nguyen, 2020](#)). It is suggestive that preschool starting age can harm the current health of young children. These findings are less surprising if we consider the study of ([Baker et al., 2008](#)), who found adverse effects of publicly-financed universal childcare on child health status and illness. In the long run, we do not find enough evidence for the long-term impact of preschool starting age on health. We also find no evidence of nutritional status except for being thin at age 15. Incorporated with the short-term effect on cognitive skills, a possible reason for this discrepancy might be that most time in preschool in Vietnam's poor area is spent on cognitive stimulation. At the same time, the quality of nutrition is inferior to that of the meal at home. However, the long-term effects on education and health outcomes support the implication from the theoretical model that educational attainment can enforce health outcomes.

Table 2.4: Estimated effect of preschool starting age on child health.

| | Age 8 | Age 12 | Age 15 |
|---------------------------------------|--------------------|-------------------|---------------------|
| | (1) | (2) | (3) |
| Panel A: Child's anthropometry | | | |
| Height-for-age z-score | 0.005 (0.033) | −0.011 (0.033) | −0.011 (0.034) |
| Weight-for-age z-score | 0.073** (0.033) | | |
| BMI-for-age z-score | 0.089** (0.038) | 0.045 (0.039) | 0.044 (0.040) |
| Panel B: Nutritional statuses | | | |
| Stunting | 0.000 (0.014) | −0.009 (0.014) | −0.010 (0.012) |
| Underweight | −0.008 (0.015) | | |
| Thinness | −0.015 (0.012) | −0.005 (0.013) | −0.026** (0.013) |

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Outcome variables of Panel A are scaled to have mean 0 and variance 1. Estimated effects and standard errors from partially linear regression effect model based on orthogonal estimating equations. Results are based on 100 sample splits and the standard errors adjusted for variation across splits are provided in parentheses.

2.7 . Conclusion

While most studies have shown the favorable effect of preschool enrollment on child outcomes, no study, to the best of our knowledge, investigates the impact of preschool starting age. Given the conditional independence assumption, we apply the double machine learning approach to investigate the effect of preschool starting age on the development of poor children in Vietnam. Our results suggest that early preschool enrollment has significantly positive short- and medium-term effects on child cognitive skills and educational attainment. However, we find little evidence of the effect on non-cognitive skills. An increase in parental investment in education can partly explain the favorable effect of early preschool enrollment. Specifically, earlier preschool enrollment promotes the number of hours of extra classes in all survey rounds.

We uncover the unfavorable short-term effect of early preschool starting age on two measures of child health: BMI-for-age and weight-for-age, while we find no ef-

fect on height-for-age, the probability of the child being stunted, and underweight. Although starting preschool younger does appear to benefit child skills and education, the downsides for child health imply that the quantity and quality of school feeding still need to be higher for poor children. Nonetheless, we find a positive effect on the probability of the child being thin when children reach the age of 15 years. Incorporating the prior results, this might be suggestive of a link between health and education attainment.

The positive effect of younger preschool starting age signals that “earlier is better” for the development of poor children. However, preschool education in Vietnam might only enrich cognitive learning without nurturing environments for non-cognitive skills and health. Our findings suggest that improving the quality of preschool education is as important as, if not more than, expanding access to preschool to achieve sustainable development goals.

This study confines to poor children in Vietnam. Therefore its results cannot be generalized for the whole society. Further research needs to be done to assess the impact across different groups of children, cohorts, and countries.

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3 - Climate Change: Drought

Abstract: The chapter uses commune fixed-effects regressions to estimate the effect of drought on education, labor, and healthcare utilization of children in Vietnam and subsequently examines heterogeneous effects by gender, age, and different socio-economic background. I find that severe drought exposure has significant negative short-term impacts on child outcomes and that the effects are more potent for the younger cohort. The heterogeneity analyses further show that boys and children from disadvantaged socio-economic backgrounds and households without social protection are particularly vulnerable to severe drought.

3.1 . Introduction

Human-induced climate change leads to a dramatic escalation in magnitude and the likelihood of extreme weather and climate events such as droughts, floods, heat-waves, and tropical cyclones ([Stott, 2016](#)). Of all the natural disasters, drought-associated events affect most people globally, involving an estimated 2.8 billion people from 1900 to 2022 and causing about 11.7 million deaths ([CRED, 2022](#)). There is a consensus that drought exposure during childhood can have long-lasting adverse effects on later-life outcomes. [Shah and Steinberg \(2017\)](#) estimate the impact of rainfall shocks on children's human capital in rural India and finds that drought exposure in utero to age four is associated with lower test scores, school enrollment, and human capital attainment of young adults. [Maccini and Yang \(2009\)](#) show a significant negative impact of early life rainfall on Indonesian women's adult health, education, and socio-economic outcomes. Focusing only on women from 19 countries in sub-Saharan Africa, [Hyland and Russ \(2019\)](#) find a significant relationship between drought experience in infancy and wealth, education, height, and empowerment in adulthood. Specifically, they are the first to show that exposure increases the probability of having a child with low birth weight, providing evidence for the intergenerational transmission of drought.

Vietnam is among the five countries most affected by climate change, including drought risks ([WB and ADB, 2021](#)). In 2015-2016, Vietnam suffered from the worst drought in 100 years. [UNISDR \(2020\)](#) estimates that it has affected the livelihood of two million people in 18 provinces. Among those affected, 1.5 million lived in the Mekong Delta, and 500,000 lived in the drought-affected Central Highlands Region, the poorest region in the country. Of people affected by drought, children from disadvantaged backgrounds and poor areas are particularly vulnerable to drought, leading to the concern about prospects of long-term poverty and inequality. Understanding the heterogeneous impact of drought on children and the

household characteristics associated with resilience to drought may provide valuable inputs for policies to strengthen resilience to drought and reduce the negative impact on poverty and inequality in the long run.

This study aims to estimate the contemporaneous effects of drought severity on education, labor, and health care utilization of children in Vietnam and subsequently study heterogeneous effects by gender, age, and different socio-economic backgrounds. This paper makes several distinct contributions to the literature on the impacts of climate shocks on child development. First, while previous literature on the Vietnamese context focuses on children from rural areas ([Trinh et al., 2020](#); [Pham, 2022](#)), I provide the evidence at the national level using Vietnam-representative household survey data. Understanding the impact on a national level can provide practical implications for drought response and preparedness strategies. Second, the study estimates the heterogeneous short-term effects of drought on child outcomes by age range and socio-economic background. Finally, this study underscores the disproportionately detrimental effects of climate change on children from rural and agricultural households.

In order to explore the relationship between drought severity and child outcomes, I exploit the exogenous rainfall deviation from the long-run average within local areas. I use the Multi-Source Weighted-Ensemble Precipitation (MSWEP) dataset to calculate the Standardized Precipitation Index (SPI) over three months for each commune in Vietnam. Drought month is defined when the 3-month SPI value of a commune is below -1 ([Svoboda et al., 2012](#)). Our primary explanatory variable is drought severity, measured by taking the sum of the absolute value of SPI for all drought months in the last twelve months before the survey. I then combined the commune-level measure of drought severity with Vietnam Household Living Standard Surveys in 2010, 2012, 2014, 2016, and 2018 by utilizing the geographic location of the household's residential commune. Using a rich set of fixed effects and control variables, I apply commune fixed-effects regression and exploit variation between children from households who experienced severe drought and those from households living in the same commune during times of normal rainfall.

The results show that severe drought exposure has significant negative short-term impacts on child outcomes and that the effects are more potent for the younger cohort. Drought severity is significantly associated with being more likely to work for economic activities and using fewer outpatient services. When I look at different cohorts, the impacts are more robust and significant for labor outcomes in the younger cohort and become weaker or insignificant for the oldest cohort. The results suggest that families are more likely to use young child labor to cope with income loss due to severe droughts. In particular, the harmful effects on health utilization remain statistically significant for all age ranges, with the most substantial magnitude for the youngest cohort. As drought increases the risk of illness

([Lohmann and Lechtenfeld, 2015](#)), reducing health care utilization and potentially preventative health care due to drought shocks raises serious concern about the long-term health outcomes of children in Vietnam.

The heterogeneity analysis shows that boys and children from disadvantaged socio-economic backgrounds (uneducated, ethnic minority, rural, agriculturally dependent, and non-social allowance households) are particularly vulnerable to severe drought. They are more likely to drop out and work for economic activities when experiencing severe drought. This finding is consistent with our expectation since the drought has been proven to reduce agricultural output and production ([Lohmann and Lechtenfeld, 2015](#); [Kuwayama et al., 2019](#); [Wheaton et al., 2008](#)), which is the primary income source of agricultural and rural households. Our empirical evidence strongly supports the income effect as the channel through which drought affects child outcomes. The results also suggest that education and social allowance can buffer the detrimental impacts of drought and strengthen the resilience of households to drought.

Since children from disadvantaged households start behind and are more vulnerable to the detrimental impact than those raised in advantaged environments, our findings highlight the threat of increasing existing economic inequalities and reducing social mobility in the long run because of climate change. The study emphasizes the importance of public intervention to minimize the impact of drought on children. Assistance programs targeted directly to households to help them cope with income shocks can protect disadvantaged children from the detrimental impacts of disasters.

The chapter unfolds as follows. Section 2 presents the relevant literature. Section 3 describes the data. Section 4 outlines the methodology. Section 5 presents our empirical results, and section 6 concludes.

3.2 . Literature Review

Our empirical model to estimate the effects of drought on child education and labor is guided by the theoretical framework proposed by [Shah and Steinberg \(2017\)](#). The effect of drought on education and labor depends on the underlying channel, which can be categorized into income and substitution effects. Human capital investment model ([Shah and Steinberg, 2017](#)) points out that drought can decrease schooling by reducing agricultural productivity and income, especially for agricultural and credit-constrained households. Income loss reduces consumption, lowering the return on schooling relative to consumption, leading to a cutback in school attendance and education investment (income effect). However, a drought simultaneously reduces the opportunity cost of education, encouraging schooling and improving human capital (substitution effect). The net impact, therefore, can

be ambiguous, depending on the magnitudes of these effects.

The literature from developing countries provides evidence supporting both income effect ([Jensen, 2000](#); [Björkman-Nyqvist, 2013](#); [Joshi, 2019](#)), and substitution effect ([Shah and Steinberg, 2017](#)) in the short run. [Jensen \(2000\)](#) estimates the impact of adverse rainfall shock on education investment and malnutrition of children in Côte d'Ivoire and finds that adverse rainfall shock decreases the school enrollment rates by between one-third and one-half and doubles malnutrition. [Björkman-Nyqvist \(2013\)](#) finds that shortage of rainfall compared to the long-term mean harms enrollment in primary schools and on girls' test scores, but not boys in Uganda. Looking at children's educational outcomes in rural Maharashtra, a state in central India, [Joshi \(2019\)](#) reports that the test scores declined after a severe drought shock in 2012, significantly more in girls and children from lower socio-economic strata. In contrast, [Shah and Steinberg \(2017\)](#) find that a negative rainfall shock between 2005 and 2009 lowers contemporaneous schooling and test scores of children from 5 to 16 years old in rural India. While [Shah and Steinberg \(2017\)](#) studies the impact of rainfall variation by years on children from all rural districts in India, [Joshi \(2019\)](#) focuses on a severe drought in the most drought-prone state in India. These studies have focused mainly on education outcomes, while limited research investigates the relationship between drought and child labor.

Prior studies in the Vietnamese context suggest that drought adversely affects agricultural output and revenues from crop sale ([Lohmann and Lechtenfeld, 2015](#)), income and expenditure ([Aroui et al., 2015](#)) of rural and agricultural households. Households in drought-prone areas tend to have limited access to formal credit and insurance sources, hence being unable to smooth their consumption. As the consumption of rural and agricultural households is more vulnerable to droughts, the education and labor outcomes of children from those households are expected to be more responsive to drought shocks. Income effects are expected to be more critical for these children. Our analysis provides an in-depth investigation of the heterogeneous impact of drought at national levels, providing evidence of climate change inequality in Vietnam.

There are several pathways in which drought might affect healthcare utilization. First, well-established literature shows the detrimental impact of drought across a wide range of child health outcomes, including mental health ([Dean and Stain, 2010](#)), infectious diseases ([Bandyopadhyay et al., 2012](#)), and child mortality rates ([Henry and Dos Santos, 2013](#)). Drought tends to reduce the quantity, quality, and stability of agricultural output, raising food prices, lowering the nutritional quality of food, and increasing the probability of under-nutrition ([Phalkey et al., 2015](#); [Lloyd et al., 2011](#); [Davenport et al., 2017](#)). Indeed, [Hyland and Russ \(2019\)](#) show for the first time that the effect can span generation by proving the association between maternal exposure to drought and under-nutrition in the newborn. More-

over, drought is mainly associated with events, such as wildfires or deterioration of drinking water quality, that increase the risk of diseases due to toxicant exposure. In Vietnam, [Lohmann and Lechtenfeld \(2015\)](#) confirm this channel by proving the negative short-term impacts of drought on health by increasing the likelihood of diseases. Drought-related health shocks hence can increase healthcare utilization. However, higher food prices might reduce the scope for preventative healthcare. The effect is robust for agricultural, poor, or credit-constraint households. Income shocks and limited coverage of the national health insurance scheme might further dissuade healthcare utilization after each drought episode in Vietnam, causing serious concerns about the long-term health of affected children. Given the importance of income effects, this chapter makes empirical contributions to the literature on how extreme weather due to climate change and income shocks affects children's outcomes.

3.3 . Data and Descriptive Analysis

3.3.1 . Survey data

The first geo-referenced data source used in this analysis is the Vietnam Household Living Standard Surveys (VHLSS) in 2010, 2012, 2014, 2016, and 2018. These national representative surveys intend to collect rich information to monitor the living standards of different population groups in Vietnam, including basic demography, education, health, income, employment, expenditure, accommodation, fixed assets, durable appliances, and participation in poverty alleviation and hunger eradication programs. The nationwide data sets represent national, regional, urban, rural, and provincial levels.

The analysis focuses predominantly on school-aged children from 6 to 18 years old. Table 3.1 presents descriptive statistics of these children. The number of school-aged children declined from 2010 to 2018, reflecting the change in population structure and the lowering fertility rate in Vietnam. The share of males was slightly higher than that of females and remained stable at around 51% during five waves. The average age of children was about 12 years old and slightly decreased over time. Table 3.1 shows an increase in enrollment rate along with a decrease in working rate even though there was no clear trend in educational achievement.

Table 3.1: Summary statistics of children variables

| | 2010 | 2012 | 2014 | 2016 | 2018 |
|-------------------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
| | Mean (St. Dev.) | | | | |
| Age | 12.313 (3.802) | 12.165 (3.798) | 11.928 (3.766) | 11.846 (3.670) | 11.803 (3.706) |
| Gender (male = 1, female = 0) | 0.515 (0.500) | 0.514 (0.500) | 0.514 (0.500) | 0.513 (0.500) | 0.517 (0.500) |
| Enrollment | 0.586 (0.493) | 0.660 (0.474) | 0.679 (0.467) | 0.689 (0.463) | 0.703 (0.457) |
| Working | 0.210 (0.407) | 0.184 (0.387) | 0.146 (0.353) | 0.117 (0.322) | 0.103 (0.304) |
| Highest grade achieved | 5.784 (3.579) | 5.626 (3.591) | 5.491 (3.546) | 5.548 (3.471) | 5.577 (3.563) |
| Number of observations | 9,011 | 8,420 | 7,817 | 7,690 | 7,554 |

3.3.2 . Data on drought

Precipitation data is from the Multi-Source Weighted-Ensemble Precipitation (MSWEP) dataset ([Beck et al., 2019](#)). MSWEP provides 3-hourly data on precipitation at the 0.1-degree grid cell level (approximately 11×11 km at the equator) from 1979 to approximately 3 hours from real-time. This dataset combines gauge, satellite, and reanalysis data to obtain the highest-quality precipitation estimates at every location.

Since the residential communes of households are known in the VHLSS survey. I can compute the indicator of drought for each commune using the MSWEP dataset. Drought is a period of adequate rainfall deficiency leading to a water shortage. The climatology experts recommend the Standardized Precipitation Index (SPI) as an appropriate, powerful, and flexible index to characterize meteorological droughts ([Svoboda et al., 2012](#)). The SPI also allows comparison across regions with different climate characteristics. I compute drought severity indicators in this study based on the three-month SPI. Three-month SPI computes the deviation of precipitation over a specific 3-month period from the mean of the same 3-month period for all the years included in the historical record. A three-month SPI adequately indicates short- and medium-term moisture conditions, which are especially important for agricultural activities ([Svoboda et al., 2012](#)). The three-month SPI for each month is calculated for each grid and then aggregated to obtain the SPI value for each commune. I consider a month dry if SPI is less than -1, which means a one-standard deviation shortage of rainfall from the historical mean. I construct the drought severity indicator by taking the sum of the absolute SPI of the commune's overall dry months of the last 12 months before the interview. This commune-specific drought severity measurement allows the indicator to be

matched to geo-referenced household surveys with the same reference period.

Similar to [Lohmann and Lechtenfeld \(2015\)](#), I construct a continuous rather than a binary measure of drought since it provides more variation and avoids the problem of choosing the drought definition with the highest explanatory power. I use SPI rather than the shortage in precipitation (in millimeters) since precipitation cannot be compared between different communes with different geographic and meteorological characteristics.

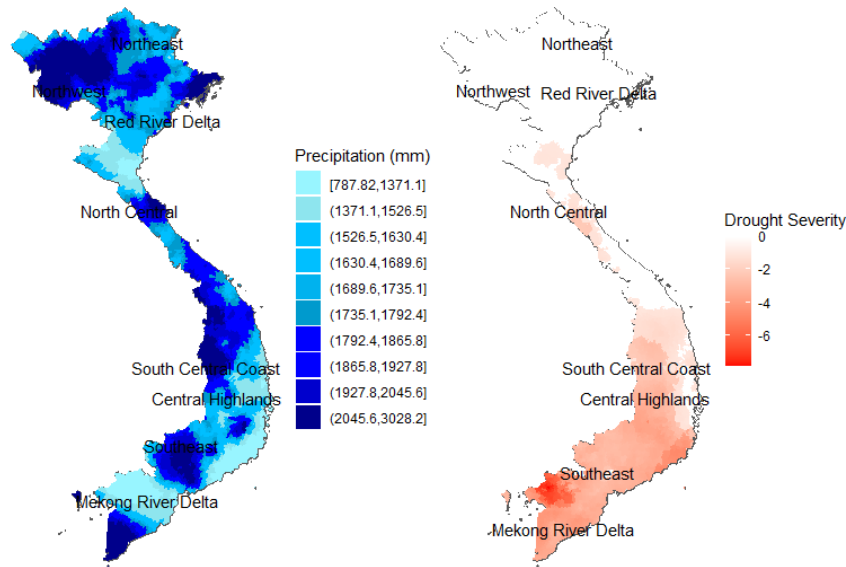


Figure 3.1: Rainfall and drought in Vietnam in the year before the fifth survey wave (2016)

Figure 3.1 shows the map of total rainfall and drought severity in the last twelve months before the fourth wave for all communes in Vietnam. It can be seen in the first panel that most of the southern regions and North Central had low total rainfall, which was even below 1000 mm in several communes. However, this map does not correctly reflect the distribution of drought severity since it does not consider the departure of precipitation from long-term trends and specific geographic and meteorological characteristics of each commune. The drought severity indicator is mapped for each commune in the second panel of Figure 3.1. Drought concentrated in the South of Vietnam, and the Southeast and Mekong River Delta suffered the harshest drought. Even though the first panel shows the high rainfall in the Southeast and South of the Mekong Delta River, these regions suffered from severe drought with a substantial lack of rainfall compared to the long-run average. Indeed, in this period, Vietnam experienced the worst drought in nearly 100 years, with 52 out of the 63 provinces, mainly in the South, affected.

Eighteen provinces had to declare a state of emergency and provide humanitarian aid to about 500,000 people who lived in the drought-affected Central Highlands Region, and 1.5 million lived in the Mekong Delta (UNICEF, 2016). Appendix B provides the distribution of the drought indicator of five survey waves in Vietnam.

3.4 . Methodology

To examine the impacts of exposure to drought on child education and labor outcomes, I exploit the commune fixed-effect regression model,

$$Y_{ijt} = \beta_0 + \beta_1 \text{Drought}_{jt} + X_{it}\beta_2 + d_j + d_t + \epsilon_{ijt} \quad (3.1)$$

Y_{ijt} denotes the various short-term outcomes of the child i in commune j and surveyed in year t . As for education outcomes, I use enrollment and the highest grade the child has achieved. Labor outcomes are measured by a binary variable taking the value of one if a child takes waged/salaried employment, is involved in production or services regarding production, husbandry, forestry, and aquaculture for the household, or is engaged in production, business, or services of the household. I also consider the healthcare utilization of children measured by the number of inpatient and outpatient visits. The term Drought_{jt} measures drought severity during twelve months before the survey year t in commune j . The term β_1 is the impact of drought on the various education and labor outcomes. X_{jt} is the vector of socio-demographic and economic characteristics at the household and child level. I also denote by d_j , d_t commune, and year-fixed effects of accounting for time-invariant commune-specific factors and time trend, respectively. Finally, ϵ_{ijt} stands for the error term, and standard errors throughout the paper are clustered at the commune level. This specification assumes that even though the long-run precipitation pattern may be endogenous to child outcomes, rainfall deficiency from long-run means is expected to be more exogenous, especially after eliminating time-invariant commune-specific factors, time trends, and the control of observed variables.

The second outcome of interest is the heterogeneous impacts of drought on children. It allows the effect of drought to varying across gender, different cohorts, geographic regions, and different socio-economic backgrounds providing evidence for the effect on inequality among gender, age, and geographic location. The heterogeneous effect also reflects the characteristics that can make the households more resilient so that their children are less likely to be affected by drought.

3.5 . Results

3.5.1 . Main results

Table 3.2 show results from estimating Equation 4.1 for the impacts of drought severity on child outcomes. Each column presents the coefficients of a separate regression. The column headings show dependent variables, including school attendance, highest grade achieved, working for economic activities, number of times using outpatient services, and number of times using inpatient services, respectively. All specifications include demographic and socio-economic control variables at the child and household level, commune, and survey wave fixed effects. Standard errors are clustered at the commune level. I found the negative short-term effects of drought severity on child labor and healthcare utilization.

Specifically, children who live in the most drought-affected commune are 0.03 more likely to report having worked for economic activities in the following year than children who live in the least drought-affected commune. In addition, children who experience the most intense drought are less likely to visit outpatient services by 0.4 times compared to those who experience the least intense drought. The results have not shown any visible and statistically significant effects of drought on school enrollment, educational attainment measured by the highest grade achieved, and inpatient services utilization.

Table 3.2: Estimated effect of drought severity on child outcomes

| | Attending school | Highest grade achieved | Working for economic activities | Number of times using out- patient services | Number of times using inpatient services |
|-----------------------|---------------------|------------------------------|--|---|--|
| | (1) | (2) | (3) | (4) | (5) |
| Drought Severity | -0.0431 (0.0298) | 0.0282 (0.0566) | 0.0277** (0.0129) | - 0.3922*** (0.1078) | 0.0011 (0.0207) |
| <i>Fixed-effects</i> | | | | | |
| Commune | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes |
| <i>Fit statistics</i> | | | | | |
| Observations | 39,284 | 39,284 | 39,284 | 39,284 | 39,284 |
| R ² | 0.24663 | 0.88852 | 0.41662 | 0.26274 | 0.21700 |
| Within R ² | 0.05129 | 0.86668 | 0.23866 | 0.01910 | 0.00255 |

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.* Each column represents the coefficients in a separate regression. The column headings indicate dependent variables. All controls include household head's age, household's head highest diploma, household head gender, household size, proportion of female adults from 15 to 60 in households, proportion of female adults from 15 to 60 in households, ethnic minorities, proportion of members with upper-secondary degree, proportion of member with college/university, living area, whether the household resides in a rural area, whether the household is classified as poor, child's age, child's age squared, and male child indicator. Fixed Effects include year, and commune fixed effects. Robust standard errors are clustered at commune level.

3.5.2 . Cohort Analysis

In Table 3.3, I report these coefficients separately estimated for children aged 6-9, 10-14, and 15-18. The effect of drought on school attendance appears to be much larger and statistically significant for older children. Indeed, column 1 shows the coefficient of drought on the probability of attending school in the following year, estimated for each age group separately. It appears that experiencing the least intense drought from age 15 to 18 is associated with a decrease in the likelihood of dropping out. The estimates remain negative but are smaller and not statistically significant at the conventional levels for younger cohorts. As seen in column 3, drought in the previous year significantly affected labor outcomes for the group aged 6-9. In contrast, the effects on child labor are not visible beyond 9. Finally, I find that after a most intense drought, children in all age groups are significantly less likely to visit outpatient services than in the least intense drought, and the effect is more substantial for the younger cohort.

Table 3.3: Estimated effect of drought on school attendance, labor, and health care utilization by different age groups

| | Attending school (1) | Highest grade achieved (2) | Working for economic activities (3) | Number of times using out- patient services (4) | Number of times using inpatient services (5) |
|-----------------------------------|--------------------------------|---|---|--|---|
| Panel A: 6-9 years old | | | | | |
| Drought severity | -0.0405 (0.0471) | 0.0724 (0.0520) | 0.0245*** (0.0084) | -0.4768** (0.2281) | -0.0160 (0.0325) |
| Observations | 12,049 | 12,049 | 12,049 | 12,049 | 12,049 |

Panel B: 10-14 years old

| | | | | | |
|------------------|---------------------|--------------------|--------------------|-----------------------|---------------------|
| Drought severity | -0.0353 (0.0411) | 0.0139 (0.0759) | 0.0183 (0.0186) | -0.2964** (0.1406) | -0.0030 (0.0412) |
| Observations | 15,002 | 15,002 | 15,002 | 15,002 | 15,002 |

Panel C: 15-18 years old

| | | | | | |
|------------------|----------------------|--------------------|--------------------|-----------------------|--------------------|
| Drought severity | -0.0734* (0.0377) | 0.0630 (0.1341) | 0.0259 (0.0339) | -0.2964** (0.1406) | 0.0161 (0.0307) |
| Observations | 12,233 | 12,233 | 12,233 | 12,233 | 12,233 |

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.* In each panel, each column represents the coefficients in a separate regression. The panel names indicate the dimensions of heterogeneity. The column headings indicate dependent variables. Robust standard errors are clustered at commune level. See the note under ?? for more details.

3.5.3 . Heterogeneity Analyses

In this section, I explore the heterogeneous impacts of exposure to drought on child outcomes by ethnic minorities, household head level of education, household wealth position, household place of residence (i.e., rural or urban), and household agricultural activity. I estimate the Equation 4.1 for each sub-sample and present the estimated coefficient of drought in Table 3.4.

First, I investigate whether the effects of drought differ between boys and girls. As evident from Panels A and B of Table 3.4, drought exposure has more adverse health effects for boys than for girls. Boys are more likely to drop out, work for economic activities and reduce health care consumption. These findings suggest that households rely more on young male labor to cope with income shocks.

Secondly, I compare the effects of drought between children from households with uneducated household heads and those with educated household heads. Uneducated household heads are those who have not completed primary school. Educated household heads refer to at least primary school graduates. As evident from Panels C and D of Table 3.4, drought exposure has adverse effects on children regardless of the household head's level of education, but the impacts are minor in the educated group. Indeed, the effect on educational attainment in the educated group is opposite to that in the uneducated group. This result suggests that households with higher-educated heads might be less affected by income loss due to climate shocks.

Next, I examine whether poverty and ethnic minorities affect the impact of drought.

Ethnic minority children are more vulnerable to drought than Kinh regarding educational attainment. Possibly, ethnic minority children have to study in poor conditions, which cannot protect education performance from severe drought. The estimated heterogeneous effects of ethnic minorities are reported in Panels G and H of Table 3.4.

I also explore whether drought impacts differ by household's place of residence and household agricultural activity. Households with agricultural activity are those with income from crop production, husbandry, or agricultural services. Panel F and K of Table 3.4 suggest that children from rural areas and households with agricultural activity are more likely to work for economic activities in the following year when their household suffers from severe drought. Moreover, estimates provided in Panels E of Table 3.4 show that children from urban areas tend to complete higher grades after drought. Nevertheless, the impacts on school attendance and healthcare utilization do not differ significantly between these groups.

I finally investigate whether the social allowance can improve the resilience of children in drought. I found that children from households without social allowance are significantly more likely to suffer from severe drought. The estimates are not significant at a conventional level for a group of children from households with social allowance except for educational achievement. Indeed, children from households with social allowance tend to increase grades achieved after drought exposure.

Table 3.4: Interaction terms between drought variable and household variables in commune fixed-effects regressions

| | Attending school | Highest grade achieved | Working for economic activities | Number of times using out- patient services | Number of times using inpatient services |
|--|-----------------------|------------------------------|--|---|--|
| | (1) | (2) | (3) | (4) | (5) |
| Panel A: Boys | | | | | |
| Drought severity | -0.0722** (0.0357) | 0.0546 (0.0759) | 0.0350** (0.0171) | -0.3675** (0.1468) | 0.0054 (0.0271) |
| Panel B: Girls | | | | | |
| Drought severity | -0.0174 (0.0357) | -0.0503 (0.0775) | 0.0198 (0.0178) | - 0.3889*** (0.1361) | 0.0040 (0.0237) |
| Panel C: Relatively Low-Educated household head | | | | | |
| Drought severity | - 0.1388*** | 0.0013 | 0.0458** | - 0.4764*** | 0.0352 |

| | | | | | |
|--|-----------|-----------|----------|-----------|----------|
| | (0.0393) | (0.0814) | (0.0191) | (0.1718) | (0.0265) |
| Panel D: Relatively High-Educated household head | | | | | |
| Drought severity | 0.0968** | -0.0447 | 0.0071 | -0.3050** | -0.0518* |
| | (0.0437) | (0.0663) | (0.0174) | (0.1477) | (0.0310) |
| Panel E: Urban households | | | | | |
| Drought severity | -0.0174 | 0.2975*** | -0.0042 | -0.3729 | -0.0049 |
| | (0.0578) | (0.1053) | (0.0209) | (0.2281) | (0.0243) |
| Panel F: Rural households | | | | | |
| Drought severity | -0.0554 | -0.0638 | 0.0364** | - | 0.0028 |
| | (0.0349) | (0.0658) | (0.0156) | 0.3892*** | (0.0267) |
| Panel G: Ethnic Minority | | | | | |
| Drought severity | -0.1717** | -0.1671 | 0.0506 | -0.4400* | -0.0074 |
| | (0.0768) | (0.1886) | (0.0393) | (0.2392) | (0.0419) |
| Panel H: Non-Ethnic Minority | | | | | |
| Drought severity | -0.0038 | 0.1048* | 0.0193 | - | 0.0071 |
| | (0.0329) | (0.0549) | (0.0132) | 0.4162*** | (0.0219) |
| Panel K: Household with Agricultural Activity | | | | | |
| Drought severity | -0.0420 | -0.0819 | 0.0391** | - | 0.0152 |
| | (0.0359) | (0.0729) | (0.0172) | 0.3842*** | (0.0275) |
| Panel L: Household with Non-Agricultural Activity | | | | | |
| Drought severity | -0.0150 | 0.2650** | -0.0136 | -0.3445* | -0.0159 |
| | (0.0556) | (0.1033) | (0.0191) | (0.2038) | (0.0359) |
| Panel M: Household with Social Allowance | | | | | |
| Drought severity | -0.1328 | 0.3440* | 0.0319 | -0.4425 | -0.0035 |
| | (0.1048) | (0.2082) | (0.0504) | (0.4116) | (0.0873) |
| Panel N: Household with Non-Social Allowance | | | | | |
| Drought severity | -0.0302 | -0.0127 | 0.0327** | - | 0.0073 |
| | (0.0314) | (0.0593) | (0.0138) | 0.4218*** | (0.0200) |
| <i>All Controls</i> | Yes | Yes | Yes | Yes | |
| <i>Fixed-effects</i> | | | | | |
| <i>Commune</i> | Yes | Yes | Yes | Yes | Yes |

| Year | Yes | Yes | Yes | Yes | Yes |
|------|-----|-----|-----|-----|-----|
|------|-----|-----|-----|-----|-----|

Note: *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.* In each panel, each column represents the coefficients in a separate regression. The panel names indicate the dimensions of heterogeneity. The column headings indicate dependent variables. Robust standard errors are clustered at commune level. See the note under ?? for more details.

Our heterogeneity analyses show that boys, children from households with uneducated heads, poor households, rural areas, ethnic minorities, and households having agricultural activity are more vulnerable to drought. These findings suggest that children from rural, agricultural, and ethnic minority households must work in economic activities to mitigate income loss due to climate shocks. However, when it comes to school enrollment, there are no significant differences between rural and urban groups and between agricultural and non-agricultural groups. The household head's level of education and wealth can protect children from severe drought.

3.5.4 . Other Specifications and Measures

In this section, I employ different drought specifications to test our results' robustness. First, I measure drought severity as the number of drought months. This measure does not consider the intensity of drought but the time dimension of exposure to drought. The results in Table B.2 in Appendix B.2 show that impacts are significantly prevalent for labor and health care utilization. Second, I utilize logistic regressions for indicator outcomes (school enrollment and child labor) instead of linear probability regressions. The conclusions remain unchanged (Table B.3 in Appendix B.2).

3.5.5 . Discussions

This paper proves the short-term adverse effects of drought on child education, labor, and healthcare utilization. Overall, the results suggest that, on average, children living in a commune affected by more intense drought show a significantly higher likelihood of dropping out and working for economic activities. They also are more likely to reduce the number of health care utilization. When comparing children across the commune and all five survey years, exposure to the most intense drought is associated with an increase in the probability of dropping out and working for economic activities by about 6 and 3 percentage points, respectively. Children in commune with the most intense drought visited outpatient services .3 times less than those with less intense drought. These results are consistent with the expectation since households might be unable to smooth and reduce healthcare consumption in response to income shocks. Since households tend to increase labor supply to mitigate the loss of income and consumption (Kochar, 1999; Rose, 2001), increasing young labor supply can be an essential coping strategy for constrained households to climate shocks. The findings, along with the study of (Arouri et al.,

2015), which shows the harmful effects of disasters, including drought, on income and expenditure of rural households in Vietnam, support the dominance of income effects over substitution effects in the context of Vietnam.

The cohort analysis shows that the effects are apparent for younger children when drought has caused a detrimental effect on school attendance, labor, and health care utilization. The impact of drought on health care utilization remains latent for all age groups. In contrast, the effects of drought on attendance are not visible beyond the age of 9, and the effects on child labor are only statistically significant until 14. This finding suggests a disproportionate impact of drought on young children.

The heterogeneity analysis of the short-term impacts of drought on children implies the unequal distribution of effects with a more substantial burden on children from disadvantaged social-economic backgrounds. In particular, children from agricultural households, rural areas, ethnic minorities, and poor households tend to work more after a year of severe drought. This result can be explained by the fact that drought can immediately affect the income of disadvantaged households. Since they tend to have less financial and social capital and face more credit constraints, they look for primary resources, such as young labor, to respond to adverse shocks. The findings confirm existing evidence about the disproportionate detrimental effects of natural disasters on children (Joshi, 2019; Le and Nguyen, 2021).

3.6 . Conclusion

While previous analyses of the short-term impacts of droughts have tended to focus on schooling and human capital, I assess the impacts on education and labor outcomes, as well as health care utilization, and subsequently investigate the heterogeneous impacts by gender, age, and different socio-economic backgrounds. I find that severe droughts harm Vietnamese children's labor and healthcare utilization. Exposure to severe drought increases the probability of working for economic activities by 0.028 and decreases the number of times using outpatient services by 0.392.

The effect of drought tends to be stronger for boys and younger cohorts. This finding would suggest that the coping strategy of the household is likely to increase the labor of boys and young children. Ethnic minority children and those from households with high education heads have better educational outcomes than non-ethnic minorities and those with low education heads. Furthermore, the results undermine the importance of social allowances for helping households reduce the detrimental effects of drought on children. The findings also provide evidence that children from rural households with agricultural activity are more likely to work after an episode of severe drought. As in previous studies, these results confirm

that the channel through which severe drought affects child labor and healthcare utilization is likely partly due to its adverse impacts on agricultural output and income.

Our empirical findings underscore the need for policy interventions to mitigate the impacts of climate change and extreme weather events. Consistent with ([Hyland and Russ, 2019](#); [Aroui et al., 2015](#)), the results emphasize the importance of a safety net and assistance programs after disasters. As droughts have contemporaneous effects on children, failing to strengthen safety net programs and provide immediate assistance to vulnerable populations can translate to costly remediation of inequality in the long run.

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4 – Physical Environment: Land Cover

Abstract: In Vietnam, land has conversed massively from rural or agricultural to urban or non-agricultural purposes. Rural-to-urban land conversion changes the livelihood of rural and agricultural households and leads to a rapid transformation of land cover in the neighborhood. Exploiting the variation in the cropland and urban land cover within local communes, this chapter analyzes the effects of land cover within local communes on school-aged children in rural Vietnam. While expansion in urban land cover is significantly associated with a decrease in child labor in household agricultural activities, a fall in cropland in the neighborhood leads to higher participation of children in these activities. I also show that land cover change from rural to urban can disproportionately impact rural children depending on their economic background. Compared with children from business households, those from agricultural households are more likely to work and more vulnerable due to the urbanization process in rural areas.

4.1 . Introduction

A long literature has documented the significant effects of individual, family, school, and social neighborhood environments on child development. However, evidence of the physical neighborhood environment still needs to be discovered with the increasing policy interests due to rapid urbanization. This paper fills this gap by analyzing the effects of land cover within local communes on school-aged children in rural Vietnam. It can provide helpful information for policymakers to design effective land-use policies to promote child development in Vietnam.

There have, to date, been a few analyses on the role that physical features of neighborhood environments play in shaping child outcomes. Built physical environment features such as schools, roads, local services, or public transport can have a positive impact on children's physical activity, social interaction, network developments, exploration, and stimulation, hence influencing children's development (Davison and Lawson, 2006; Pont et al., 2009; Ferreira et al., 2007; on Environmental Health, 2009; Komro et al., 2011; Bejleri et al., 2009; Chomitz et al., 2011; Christian et al., 2015; Villanueva et al., 2016). In the process of urbanization, Kearns et al. (2012) found that children who lived in high-density neighborhoods in the UK were negatively impacted regarding behavioral problems, social withdrawal, and poor academic performance. High-density areas are more likely associated with crime, noise, and lower quality of schools than low-density suburban (McCulloch, 2012). However, as children living in low-density neighborhoods typically have limited access to essential local services such as schools, child care, and health ser-

vices, they have fewer opportunities to spend time outdoors interacting with other people and exploring environments (Trapp et al., 2012; Christian et al., 2013). This chapter contributes to the literature on the role of physical neighborhood environments by evaluating the impact of land cover change in the neighborhood on the education and labor outcomes of rural children in Vietnam.

Research in land cover still needs to pay attention to its relationship with child outcomes, even though a long and growing literature already links land cover in the neighborhood and human well-being in adulthood. Studies in this area have illustrated the relationship of land cover on indicators typically in adulthood such as subjective well-being (Li and Managi, 2021; Oswald and Wu, 2010), life satisfaction (Ambrey and Fleming, 2011; Brown et al., 2016; MacKerron and Mourato, 2009), happiness (MacKerron and Mourato, 2013; Ferrer-i Carbonell and Gowdy, 2007), health (Alcock et al., 2014, 2015; De Vries et al., 2003; Maas et al., 2009), and poverty (Adnan et al., 2020). This study aims to extend this investigation by examining the link between land cover and child outcomes.

The study focuses on the context of Vietnam for several reasons. Firstly, the urban population in Vietnam has proliferated since 1950, with an average increase rate of 3% from 2010 to 2020. In Vietnam, rural-to-urban land conversion has been observed on a massive scale; urban expansion and rural industrialization are supplanting natural areas and farmlands. However, ineffective land-use policies and urban planning strategies lead to an unregulated and uncoordinated spatial development pattern in Vietnam. This pattern changes the livelihood of rural and agricultural households and leads to a rapid transformation of land-use land cover. Secondly, the panel surveys on rural and agricultural households in Vietnam, combined with high-resolution land cover data, allow me to exploit the variation in land cover within a local commune.

In order to explore the relationship between land cover and child outcomes, I employ data from the Vietnam Household Living Standard Survey (VHLSS), including the geographic location of the child residential commune and the European Space Agency/Climate Change Initiative (ESA/CCI) Land Cover data. The VHLSS data provides rich information on households and household members, including basic demography, employment, labor force participation, education, health, income, expenditure, housing, fixed assets, and durable goods, and participation of households in poverty alleviation programs. They also provide geographic information about household living communes, combined with Global Administrative Areas (GADM) data to identify latitude and longitude coordinates. The European Space Agency/Climate Change Initiative (ESA/CCI) Land Cover data provides global annual and consistent Land Cover maps at 300m spatial resolution from 1992. I construct the share of urban and cropland in each commune from the ESA dataset as the main explanatory variables.

The primary model we estimate is household fixed-effect regression, which estimates the overall impact of land cover on child education and labor. To explore the heterogeneous impacts, which may shed light on some mechanisms, we also examine the impact of land cover by household economic activities.

The results show that urban and cropland cover in the neighborhood significantly negatively impacts the education and labor of children from rural and agricultural households. Share of urban and cropland in the local commune are significantly associated with being more likely to work in agricultural-related activities for households and to do housework. An increase in the share of urban and cropland in the local commune is associated with a decrease in the probability of working for agricultural activities, common property, and chores. The magnitude is more substantial for urban land cover, suggesting the potential adverse effect of changing the land cover from rural to urban.

The general picture emerging from the heterogeneous analysis is that land cover from rural to urban can disproportionately impact rural children depending on their economic background. The effects of land cover on children depend on the level of agricultural dependence and the economic activities of households. The impacts of cropland cover become significantly weaker for rural households whose income heavily depends on agriculture or agricultural activities. Children from agricultural households might be more likely to work and be more vulnerable because of the urbanization process in rural areas. Children from business households are more likely to reduce the probability of working when the share of urban land in the commune increases.

The chapter is divided into five sections. Section 2 describes the data. Section 3 is dedicated to the estimation method. Section 4 details the findings, and section 5 concludes.

4.2 . Data

4.2.1 . Survey data

The empirical analysis builds on the Viet Nam Access to Resources Household Survey (VARHS) covering 2008 to 2016. The VHRHS was conducted by the Central Institute for Economic Management (CIEM) of the Ministry of Planning and Investment of Vietnam (MPI) and the Institute of Labour Science and Social Affairs (ILSSA) of the Ministry of Labour, Invalids, and Social Affairs of Vietnam (MoLISA). The panel dataset covers more than 3,000 households in the rural areas of 12 North, South, and central Vietnam provinces. Figure 4.1 shows the location of twelve. The survey collects household and commune information on a broad range of topics. Household data include demography, rural employment, on-and off-farm income-generating activities, rural enterprises, property rights, savings,

investment, insurance, participation in formal and informal social networks, and migration. Commune database providing information on demographics, infrastructure, and local economic conditions. Information on school attendance and child

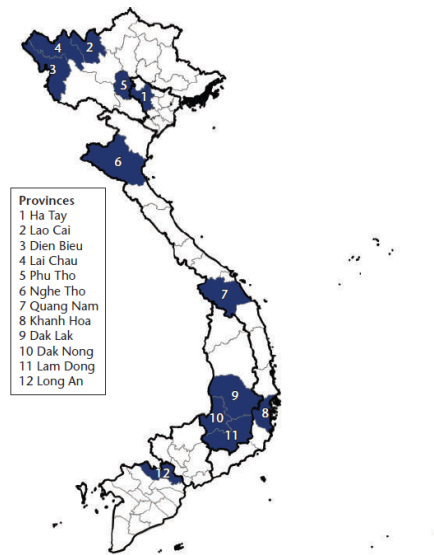


Figure 4.1: Location of the twelve VARHS provinces (Tarp, 2017)

labor for each household child are analyzed to study how land cover impacts child education and labor. Since the study focuses on school-aged children and the field-work consisted of interviews in June and July of the survey years, I only included children aged from 7 to 18 years old. A range of labor outcomes is considered, including working for a wage/salary outside the household, working in agriculture, participating in household production related to agriculture, forestry, and aquaculture, doing trading, services, transportation, or other business (self-employed) for the household, using common property resources to generate income for the household, and doing housework or chores. Table 4.1 provides the summary statistics of the child-level variables used in the empirical analysis for each wave in the dataset. The children in the dataset had an average age of about 13.4 in 2008 and tended to be younger over time. The dataset includes slightly more boys than girls, somehow reflecting the problem of gender imbalance in the population.

I use school attendance as the measurement of education. Table 4.1 shows that most children enroll in school, and the share has increased. For labor, I use the dummy variable indicating whether children and adolescents had to work for a wage, work in agriculture, be self-employed, work with common property, and do housework during the past 12 months. A minority of children work for a wage, are self-employed, or work with shared property, with less than 10%, 5%, and 2%, respectively. About 40% of children worked in agriculture in 2008, but the share dropped to about 20% in 2016. More than half of the children had to do housework

in 2008, and the share increased to more than 70% in 2016. While rural children tend to reduce working activities outside households, they seem to have to do more housework.

Table 4.1: Summary statistics of child-level variables

| | 2008 | 2010 | 2012 | 2014 | 2016 |
|-------------------------------------|------------------------------|------------------------------|------------------------------|------------------------------|------------------------------|
| | Mean (St. Dev.) [N] | | | | |
| Age | 13.373 (3.325) [2,509] | 13.364 (3.376) [2,177] | 12.917 (3.477) [2,315] | 12.752 (3.510) [2,161] | 12.654 (3.468) [2,017] |
| Gender (male = 1, female = 0) | 0.507 (0.500) [2,509] | 0.514 (0.500) [2,177] | 0.516 (0.500) [2,315] | 0.509 (0.500) [2,161] | 0.516 (0.500) [2,017] |
| School Attendance (Yes = 1, No = 0) | 0.800 (0.400) [2,505] | 0.807 (0.395) [2,176] | 0.876 (0.330) [2,315] | 0.890 (0.313) [2,160] | 0.888 (0.315) [2,017] |
| Working for a wage | 0.066 (0.248) [2,469] | 0.066 (0.249) [2,113] | 0.053 (0.224) [2,213] | 0.040 (0.196) [2,152] | 0.038 (0.192) [2,017] |
| Working in agriculture | 0.382 (0.486) [2,469] | 0.431 (0.495) [2,113] | 0.283 (0.451) [2,213] | 0.243 (0.429) [2,152] | 0.230 (0.421) [2,017] |
| Self-employed | 0.031 (0.173) [2,469] | 0.028 (0.166) [2,113] | 0.019 (0.138) [2,213] | 0.015 (0.123) [2,152] | 0.011 (0.106) [2,017] |
| Working with common property | 0.155 (0.362) [2,469] | 0.145 (0.352) [2,113] | 0.107 (0.309) [2,213] | 0.091 (0.287) [2,152] | 0.100 (0.300) [2,017] |
| Doing housework | 0.563 (0.496) [2,469] | 0.654 (0.476) [2,113] | 0.528 (0.499) [2,213] | 0.577 (0.494) [2,152] | 0.726 (0.446) [2,017] |

4.2.2 . Land Cover data

I employ the land cover dataset with 300m resolution from the European Space Agency/Climate Change Initiative (ESA/CCI), generated through Sentinel-2 and Sentinel-1 constellations, to study the impact of land cover change on child education and labor. I focus on two land cover categories: cropland (rainfed, irrigated, mosaic) and urban land. I calculate the shares of each type of land in each commune as the main variables of interest. Given that the panel land cover dataset is collected during survey periods, the land cover dataset hence can be merged with

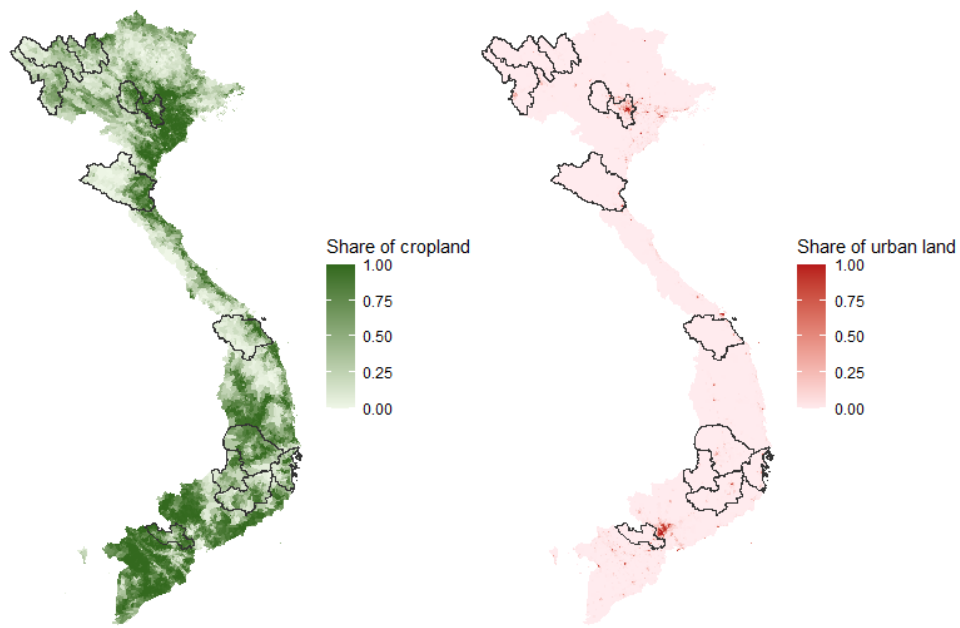


Figure 4.2: Share of each land in commune level in 2016

the panel household survey dataset.

Figure 4.2 presents the share of each type of land in the communes of Vietnam in 2016. The primary type of land in Vietnam is cropland, while most urban land is in the Red River and Mekong River Delta. Twelve provinces in the dataset are scarcely covered by urban land, but the share of urban land has increased rapidly over time. ?? shows the summary statistics of commune-level share of each type of land by region in the dataset. As expected, the Red River Delta and Mekong River Delta have the highest share of both urban land and cropland. The shares of urban land in all regions have increased over time; the growth rate is up to 300% in the Mekong River Delta. The opposite trends have been observed for cropland, with the decay rate up to 7% in the Red River Delta.

Table 4.2: The share of land type in commune by regions

| | Share of urban lands | | | | |
|-----------------|----------------------|----------------|----------------|----------------|----------------|
| | 2008 | 2010 | 2012 | 2014 | 2016 |
| Red River Delta | 0.05 (0.08) | 0.06 (0.08) | 0.07 (0.09) | 0.1 (0.11) | 0.1 (0.11) |
| North | 0.01 (0.05) | 0.01 (0.06) | 0.01 (0.06) | 0.02 (0.06) | 0.02 (0.06) |

Table 4.2: The share of land type in commune by regions

| | Share of urban lands | | | | |
|--------------------|----------------------|----------------|----------------|----------------|----------------|
| | 2008 | 2010 | 2012 | 2014 | 2016 |
| Central Coast | 0 (0.03) | 0.01 (0.03) | 0.02 (0.03) | 0.02 (0.05) | 0.02 (0.05) |
| Central Highlands | 0 (0.01) | 0 (0.01) | 0 (0.01) | 0.01 (0.02) | 0.01 (0.03) |
| Mekong River Delta | 0.01 (0.02) | 0.02 (0.03) | 0.02 (0.04) | 0.03 (0.05) | 0.03 (0.06) |

Table 4.3: The share of cropland in commune by regions

| | Share of cropland | | | | |
|--------------------|-------------------|----------------|----------------|----------------|----------------|
| | 2008 | 2010 | 2012 | 2014 | 2016 |
| Red River Delta | 0.86 (0.15) | 0.85 (0.15) | 0.84 (0.15) | 0.81 (0.15) | 0.8 (0.15) |
| North | 0.49 (0.21) | 0.49 (0.21) | 0.49 (0.21) | 0.49 (0.21) | 0.48 (0.21) |
| Central Coast | 0.69 (0.26) | 0.69 (0.26) | 0.69 (0.26) | 0.68 (0.26) | 0.68 (0.26) |
| Central Highlands | 0.48 (0.26) | 0.48 (0.26) | 0.48 (0.26) | 0.47 (0.26) | 0.47 (0.25) |
| Mekong River Delta | 0.85 (0.17) | 0.84 (0.17) | 0.84 (0.17) | 0.83 (0.17) | 0.83 (0.17) |

4.3 . Estimation Method

I estimate the effects of land cover on child education and labor with a household fixed-effect model given by:

$$Y_{ijct} = \beta_0 + L_{ct}\beta_1 + X_{jct} + C_{ct} + d_j + d_t + \epsilon_{ijct} \quad (4.1)$$

where the subscript i ; j ; c , and t refer to the child, household, commune, and survey year, respectively. The dependent variable Y_{ijct} represents child education and labor outcomes. The main variables of interest are shares of different types of land, represented by vector L_{ct} . X_{jct} is a vector of control variables at the household level, such as demographic and socio-economic variables; C_{ct} is a vector of control variables at the commune level, such as infrastructure; d_j is household fixed-effect; d_t is the dummy variable of survey year; ϵ_{ijct} is an error term.

Estimating the impacts of land cover is endogeneity when households choose to live in a particular commune because of reasons correlated with child outcomes.

The identifying assumption is that the land cover changes within communes are as good as random after controlling for time-invariant and observed time-variant household and commune-level confounders. Including household fixed effects eliminates confounding unobserved factors that are time-invariant within households. In other words, the within-household comparison alleviates the contamination due to household-level time-invariant factors correlating with land cover and child outcomes. The inclusion of household fixed effects absorbs the commune fixed effects as well. I control for time-variant demographic and socio-economic characteristics of households and time-variant characteristics of the commune; the table in the appendices provides summary statistics of all control variables. Summary statistics of explanatory variables are presented in Appendix C. Our coefficient of interest corresponds to the average change of the outcomes of children from the same households associated with increasing the share of land by one percentage point.

I also examine the heterogeneous impacts of land cover by including in Equation 4.1 interactions between the land cover variable and variables of communes and households. The interactions allow the impacts of land cover on children to vary depending on household and commune characteristics.

4.4 . Results

4.4.1 . Main Results

I present the estimates of the effects of land cover on child education and labor outcomes from Table 4.4 to Table 4.9. Results show a negative impact of commune-level shares of cropland on child labor in agriculture, with common property, and household chores. I also find the negative effect of urban land child labor in agriculture and with common property in rural areas. However, I find no impact of land cover on school attendance and self-employment, which suggests that land cover is particularly important for child labor in agriculture and agriculture-related activities.

First, I investigate the impacts of land covers on education outcomes, shown in table Table 4.4. Only the coefficients of cropland cover are statistically significant when being evaluated alone. Specifically, Column 2 shows that a one percentage point increase in the share of cropland is associated with an increase in the probability of attending school by 0.33 percentage points. When considering both urban and cropland, the coefficients become statistically insignificant.

I then further explore the impacts of land cover on child labor, including agricultural activities within households, wage labor, self-employment, common property activities, and household chores. The estimates are shown in table Table 4.5 to table Table 4.9. The findings support the importance of land cover on child labor in agricultural activities within households, common property activities, and

housework. Table 4.7 shows that a one percentage point increase in the share of urban land decreases the probability of working in agriculture by 0.6. The magnitude increases to 2.6 percentage points when considering the cropland cover. Cropland cover affects child labor in agriculture in the same direction as urban land. A one percentage point increase in the share of cropland decreases the probability of working in agriculture by two percentage points. Taken together, urban land and cropland cover at the commune level reduces the probability of child labor in agricultural-related activities.

The findings from Table 4.7 provide the same pattern in the impacts of land cover on child labor in common property activities. However, urban land and cropland cover affect child household work in the opposite direction. When doing household chores is negatively affected by cropland cover at the commune level, the urban land cover increases the likelihood of child housework. I find little evidence favoring a link between land cover and child labor in wage jobs and self-employment.

Overall, these results lend credence to the need for further analyses of the impacts of land cover on child outcomes by household agricultural and economic activities.

Table 4.4: The impacts of urban land and cropland cover on child education

| | (1) | <i>School Attendance</i> (2) | (3) |
|------------------------|---------------------|-------------------------------------|---------------------|
| Share of urban land | -0.3254 (0.2134) | | -0.0392 (0.3429) |
| Share of cropland | | 0.3207* (0.1793) | 0.2929 (0.2872) |
| <i>Fixed-effects</i> | | | |
| Household fixed-effect | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| <i>Fit statistics</i> | | | |
| Observations | 10,660 | 10,660 | 10,660 |
| R ² | 0.50029 | 0.50033 | 0.50033 |
| Within R ² | 0.17391 | 0.17398 | 0.17398 |

Note: *Clustered (Household ID) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1* Table shows results from estimating Equation 4.1 via household fixed-effect regression. The dependent variable is school enrollment. All controls include child's age, child's age squared, and child gender, household head's age, household's head year of education, household head gender, income per capita, household size, proportion of female adults from 15 to 60 in households, proportion of female adults from 15 to 60 in households, proportion of members with upper-secondary degree, proportion of member with college/university, crop land area, living area per member, whether household has redbook, dummy for business household, population of commune, percentage of communes with electricity, percentage of communes with drinking water distribution, number of poor households in commune, number of enterprises in commune, distance from commune to mainroad, and whether commune has market. Fixed Effects include year, and household fixed effects.

Table 4.5: The impacts of urban land and cropland cover on wage labor

| | <i>Working for a wage</i> | | |
|------------------------|---------------------------|---------------------|---------------------|
| | (1) | (2) | (3) |
| Share of urban land | -0.2890 (0.1841) | | -0.1147 (0.2372) |
| Share of cropland | | 0.2589* (0.1415) | 0.1785 (0.1640) |
| <i>Fixed-effects</i> | | | |
| Household fixed-effect | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| <i>Fit statistics</i> | | | |
| Observations | 10,458 | 10,458 | 10,458 |
| R ² | 0.36462 | 0.36465 | 0.36466 |
| Within R ² | 0.07902 | 0.07906 | 0.07907 |

Note: *Clustered (Household ID) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1* Table shows results from estimating Equation 4.1 via household fixed-effect regression. The dependent variable is wage labor. All controls include child's age, child's age squared, and child gender, household head's age, household's head year of education, household head gender, income per capita, household size, proportion of female adults from 15 to 60 in households, proportion of female adults from 15 to 60 in households, proportion of members with upper-secondary degree, proportion of member with college/university, crop land area, living area per member, whether household has redbook, dummy for business household, population of commune, percentage of communes with electricity, percentage of communes with drinking water distribution, number of poor households in commune, number of enterprises in commune, distance from commune to mainroad, and whether commune has market. Fixed Effects include year, and household fixed effects.

Table 4.6: The impacts of urban land and cropland cover on agricultural labor

| | (1) | <i>Working in Agriculture</i> (2) | (3) |
|------------------------|-----------------------|--|-----------------------|
| Share of urban land | -0.6509** (0.2789) | | -2.600*** (0.6964) |
| Share of cropland | | -0.1730 (0.3917) | -1.996*** (0.6577) |
| <i>Fixed-effects</i> | | | |
| Household fixed-effect | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| <i>Fit statistics</i> | | | |
| Observations | 10,458 | 10,458 | 10,458 |
| R ² | 0.48523 | 0.48498 | 0.48639 |
| Within R ² | 0.12425 | 0.12382 | 0.12621 |

Note: *Clustered (Household ID) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1* Table shows results from estimating Equation 4.1 via household fixed-effect regression. The dependent variable is labor in agriculture within household. All controls include child's age, child's age squared, and child gender, household head's age, household's head year of education, household head gender, income per capita, household size, proportion of female adults from 15 to 60 in households, proportion of female adults from 15 to 60 in households, proportion of members with upper-secondary degree, proportion of member with college/university, crop land area, living area per member, whether household has redbook, dummy for business household, population of commune, percentage of communes with electricity, percentage of communes with drinking water distribution, number of poor households in commune, number of enterprises in commune, distance from commune to mainroad, and whether commune has market. Fixed Effects include year, and household fixed effects.

Table 4.7: The impacts of urban land and cropland cover on self-employment

| | (1) | <i>Being self-employed</i> (2) | (3) |
|------------------------|---------------------|---------------------------------------|---------------------|
| Share of urban land | -0.0214 (0.1361) | | -0.1574 (0.2172) |
| Share of cropland | | -0.0289 (0.1141) | -0.1393 (0.1763) |
| <i>Fixed-effects</i> | | | |
| Household fixed-effect | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| <i>Fit statistics</i> | | | |
| Observations | 10,458 | 10,458 | 10,458 |
| R ² | 0.38579 | 0.38580 | 0.38585 |
| Within R ² | 0.03773 | 0.03774 | 0.03783 |

Note: *Clustered (Household ID) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1* Table shows results from estimating Equation 4.1 via household fixed-effect regression. The dependent variable is self-employment. All controls include child's age, child's age squared, and child gender, household head's age, household's head year of education, household head gender, income per capita, household size, proportion of female adults from 15 to 60 in households, proportion of female adults from 15 to 60 in households, proportion of members with upper-secondary degree, proportion of member with college/university, crop land area, living area per member, whether household has redbook, dummy for business household, population of commune, percentage of communes with electricity, percentage of communes with drinking water distribution, number of poor households in commune, number of enterprises in commune, distance from commune to mainroad, and whether commune has market. Fixed Effects include year, and household fixed effects.

Table 4.8: The impacts of urban land and cropland cover on labor in common property

| | (1) | <i>Working with common property</i> (2) | (3) |
|------------------------|--------------------|--|---------------------|
| Share of urban land | 0.0295 (0.1069) | | -1.266* (0.7037) |
| Share of cropland | | -0.4389 (0.2950) | -1.326* (0.7102) |
| <i>Fixed-effects</i> | | | |
| Household fixed-effect | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| <i>Fit statistics</i> | | | |
| Observations | 10,458 | 10,458 | 10,458 |
| R ² | 0.45910 | 0.45946 | 0.46013 |
| Within R ² | 0.04625 | 0.04688 | 0.04807 |

Note: *Clustered (Household ID) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1* Table shows results from estimating Equation 4.1 via household fixed-effect regression. The dependent variable is labor in common property. All controls include child's age, child's age squared, and child gender, household head's age, household's head year of education, household head gender, income per capita, household size, proportion of female adults from 15 to 60 in households, proportion of female adults from 15 to 60 in households, proportion of members with upper-secondary degree, proportion of member with college/university, crop land area, living area per member, whether household has redbook, dummy for business household, population of commune, percentage of communes with electricity, percentage of communes with drinking water distribution, number of poor households in commune, number of enterprises in commune, distance from commune to mainroad, and whether commune has market. Fixed Effects include year, and household fixed effects.

Table 4.9: The impacts of urban land and cropland cover on housework

| | (1) | <i>Doing housework</i> (2) | (3) |
|------------------------|----------------------|-----------------------------------|----------------------|
| Share of urban land | 0.8913** (0.4000) | | 0.0371 (0.6336) |
| Share of cropland | | -0.9007*** (0.3097) | -0.8747* (0.4808) |
| <i>Fixed-effects</i> | | | |
| Household fixed-effect | Yes | Yes | Yes |
| Year | Yes | Yes | Yes |
| <i>Fit statistics</i> | | | |
| Observations | 10,458 | 10,458 | 10,458 |
| R ² | 0.37218 | 0.37238 | 0.37238 |
| Within R ² | 0.07135 | 0.07165 | 0.07165 |

Note: *Clustered (Household ID) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1* Table shows results from estimating Equation 4.1 via household fixed-effect regression. The dependent variable is housework. All controls include child's age, child's age squared, and child gender, household head's age, household's head year of education, household head gender, income per capita, household size, proportion of female adults from 15 to 60 in households, proportion of female adults from 15 to 60 in households, proportion of members with upper-secondary degree, proportion of member with college/university, crop land area, living area per member, whether household has redbook, dummy for business household, population of commune, percentage of communes with electricity, percentage of communes with drinking water distribution, number of poor households in commune, number of enterprises in commune, distance from commune to mainroad, and whether commune has market. Fixed Effects include year, and household fixed effects.

4.4.2 . Heterogeneity Analyses

To examine the heterogeneous impacts on child outcomes by household agricultural and economic activities, I include the interactions between land cover and economic characteristics in the regressions of Equation 4.1. In each regression, I include land cover variables and their interaction with an interacted variable and control for the child, household, and commune-level characteristics as presented in the primary model from Table 4.4 to Table 4.9. In Table 4.10, I present only the estimated coefficient of land cover variables and the interactions. Shares of urban land and cropland interacted with four household-level variables representing dependence on agriculture, livestock ownership, crop production, and non-farm, non-wage, non-forestry, or non-aquaculture businesses. There are thus four regressions whose results are presented in four panels in Table 4.10.

First, I explore whether the impacts of land cover differ by the household's level of dependence on agriculture. Households depend highly on agriculture if half of their annual income comes from agriculture. According to the results reported in panel A of Table 4.10, cropland has a significant negative effect on school attendance of children from households who highly depend on agriculture. While the impacts on domestic child labor, including agricultural jobs, and housework, tend to be weaker for children from these households, the impact on wage labor seems more vital. The effect of urban land does not vary significantly by the household's dependence on agriculture. This finding implies that rural children from households that depend more on agriculture might be more sensitive and vulnerable to the change in land cover.

I additionally examine whether children from households with livestock ownership are affected differentially by land cover change. We find a positive and significant difference in the effect of the commune-level share of urban land and cropland on

child labor. In particular, the impact of cropland on the probability of working in agriculture, forestry, and aquaculture for children in households owning livestock is significantly lower than the impact on those from households without livestock. The opposite effects of cropland on wage labor and agriculture labor can be explained by substituting these two labor in rural children in Vietnam. I also observe that the negative impact of urban land on the probability of using common property to generate income for households is weaker if households own any livestock. Urban land also tends to reduce these children's chore activities.

Similarly, I explore the heterogeneous impact by crop production. Panels C of Table 4.10 provide estimates for children from households with and without crop production. The results suggest that children from households with crop production are less impacted by cropland change than children without crop production. The impacts of cropland depend on crop production only for agriculture labor and self-employment. Nevertheless, the impacts of urban land do not differ significantly between the two groups.

I finally examine whether children from households with non-farm, non-wage, non-forestry, and non-aquaculture businesses are affected differentially by land cover. It is evident from Panel D of Table 4.10 that children from households with businesses are more affected by urban land than those from non-business households. Notably, for children from business households, urban land has more significant negative effects on child labor, evidenced by a lower probability of working in agriculture, using common property to generate income, and doing housework. Regarding cropland, household enterprise reduces the magnitude of negative impact on working with common property and self-employment. These results suggest that household business amplifies urban land's effects but counteracts cropland's consequences on child labor.

The heterogeneous analysis shows that child labor of households that are less dependent on agriculture and have fewer agricultural activities are differently affected by cropland. The heterogeneous analysis shows that the agricultural labor of children from households that are less dependent on agriculture and have fewer agricultural activities are less affected by cropland cover. However, they are more likely to work for wages outside the household. Regarding urban land, household enterprise magnifies the impacts on child labor. Overall, land cover change from rural to urban land conversion can lead to different outcomes for rural children depending on their economic background. These different outcomes can worsen inequality among rural children.

Table 4.10: Interaction terms between drought variable and household variables in commune fixed-effects regressions

| | School Atten- dance | Working for a wage | Working in Agri- culture | Being self- employed | Working with common property | Doing house- work |
|---|---------------------------|----------------------------|--------------------------------|----------------------------|---------------------------------------|---------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: Dependence on Agriculture | | | | | | |
| Share of ur- ban land | 0.0360 (0.3484) | -0.1073 (0.2409) | - 2.560*** (0.6997) | -0.1553 (0.2192) | -1.286* (0.7030) | 0.0342 (0.6374) |
| Share of cropland | -0.2859 (0.2904) | 0.1877 (0.1650) | - 2.008*** (0.6601) | -0.1369 (0.1768) | -1.329* (0.7089) | - 0.8850* (0.4768) |
| Share of urban land × Depen- dence on Agriculture | 0.0975 (0.2492) | 0.0769 (0.2073) | -0.5791 (0.4295) | -0.0128 (0.0626) | 0.1490 (0.1258) | -0.2219 (0.4484) |
| Share of cropland × Depen- dence on Agriculture | - 0.0344** (0.0163) | - 0.0486*** (0.0123) | 0.0503* (0.0283) | 0.0018 (0.0084) | 0.0118 (0.0176) | 0.0582* (0.0301) |
| Panel B: Livestocks | | | | | | |
| Share of ur- ban land | -0.0060 (0.3462) | -0.1243 (0.2443) | - 2.575*** (0.6921) | -0.1660 (0.2239) | -1.309* (0.7056) | 0.2733 (0.6533) |
| Share of cropland | -0.3006 (0.2882) | 0.1982 (0.1673) | - 2.036*** (0.6563) | -0.1362 (0.1769) | -1.309* (0.7130) | - 0.8942* (0.4774) |
| Share of ur- ban land × Livestock | 0.1153 (0.1494) | 0.0395 (0.1524) | -0.1361 (0.2741) | 0.0310 (0.0847) | 0.1575** (0.0686) | - 0.7770** (0.3302) |
| Share of cropland × Livestock | 0.0115 (0.0132) | - 0.0272** (0.0108) | 0.0447** (0.0219) | 0.0002 (0.0074) | -0.0173 (0.0126) | 0.0111 (0.0266) |
| Panel C: Crops | | | | | | |
| Share of ur- ban land | 0.2665 (0.3626) | -0.1954 (0.2686) | - 2.436*** (0.7083) | 0.0305 (0.3120) | -1.296* (0.7015) | -0.5519 (0.8015) |

| | | | | | | |
|--|---------------------|---------------------|----------------------------|-----------------------|----------------------|---------------------------|
| Share of cropland | -0.2880 (0.2898) | 0.1996 (0.1674) | - 2.134*** (0.6608) | -0.1795 (0.1756) | -1.361* (0.7064) | - 0.8977* (0.4748) |
| Share of urban land × Crops | -0.2882 (0.2011) | 0.0980 (0.1627) | -0.2026 (0.2502) | -0.2378 (0.2135) | 0.0349 (0.1158) | 0.7411 (0.5556) |
| Share of cropland × Crops | -0.0034 (0.0272) | -0.0211 (0.0271) | 0.1535*** (0.0394) | 0.0339** (0.0160) | 0.0287 (0.0266) | 0.0559 (0.0574) |
| Panel D: Household Enterprise | | | | | | |
| Share of urban land | -0.0846 (0.3562) | -0.4780 (0.2522) | - 2.258*** (0.7084) | -0.0970 (0.2185) | -1.154 (0.7070) | 0.5514 (0.6239) |
| Share of cropland | -0.2963 (0.2878) | 0.1786 (0.1654) | - 1.997*** (0.6610) | -0.1545 (0.1819) | -1.332* (0.7145) | - 0.8501* (0.4790) |
| Share of urban land × Household enterprise | 0.2368 (0.1479) | -0.2205 (0.1444) | - 0.6957*** (0.2236) | -0.0844 (0.1143) | - (0.0810) | - 1.039*** (0.2820) |
| Share of cropland × Household enterprise | -0.0156 (0.0183) | -0.0077 (0.0132) | 0.0445 (0.0272) | 0.1078*** (0.0140) | 0.0403** (0.0182) | 0.0226 (0.0317) |
| <i>All Controls</i> | Yes | Yes | Yes | Yes | Yes | Yes |
| <i>Fixed-effects</i> | | | | | | |
| Commune | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |

Note: *Clustered (Household ID) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.* In each panel, each column represents the coefficients in a separate regression. The column headings indicate dependent variables. Robust standard errors are clustered at household level. See the note under Table 4.4 for more details.

4.5 . Conclusion

In Vietnam, land has been massively converted from rural or agricultural to urban or non-agricultural purposes. Rural-to-urban land conversion changes the livelihood

of rural and agricultural households and leads to a rapid transformation of land cover in the neighborhood. This chapter contributes to the literature about the impact of urbanization and the branch of studies focusing on the impact of physical environments on child outcomes.

By exploiting the variation in the change of share of cropland and urban land cover within local communes, I found that both shares of urban land and cropland affect child labor in the same direction. While expansion in urban land cover is significantly associated with a decrease in child labor in household agricultural activities, a fall in cropland in the neighborhood leads to higher participation of children in these activities. The magnitude is more substantial for urban land cover, suggesting the overall negative effect of the land cover change resulting from rural to urban land conversion.

I show that while cropland cover has stimulating effects on the education and labor outcomes of children from agricultural households, children from business households are more responsive to the change in urban land cover. The impacts of cropland cover on rural households whose income is heavily dependent on agriculture or who have agricultural activities are significantly weaker for domestic labor but more vital for wage labor outside the household. In contrast, children from business households are more likely to reduce the probability of working when the share of urban land in the commune increases. The disproportionate impacts of land cover on rural children require further research to clarify the pathway through which land cover change affects child outcomes. Effective land-use policy strongly needs this evidence to avoid inequality aggravation among rural children.

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A - First Appendix

A.1 . Summary statistics of outcome variables

Table A.1: Summary statistics of outcome variables

| | (1) | (2) | (3) |
|--|--------------------------------|------------------------------|-----------------------------|
| | Age 8 | Age 12 | Age 15 |
| | | Mean (SD) [N] | |
| <i>Panel A: Cognitive Skills</i> | | | |
| Mathematics | 301.142 (14.463) [1,749] | 0.048 (0.890) [1,759] | 0.025 0.917 [1,740] |
| Language | 304.465 (10.487) [1,654] | 0.059 (0.855) [1,759] | 0.048 0.904 [1,740] |
| <i>Panel B: Non-cognitive Skills</i> | | | |
| Self-esteem | | 0.001 (0.823) [1,705] | 0.007 0.795 [1,695] |
| Self-efficacy | | 0.015 (0.839) [1,705] | 0.014 0.850 [1,701] |
| <i>Panel C: Educational Attainment</i> | | | |
| Highest grade achieved | | 5.766 (0.689) [1,732] | 8.703 (0.609) [1,691] |
| <i>Panel D: Parental Investment</i> | | | |
| Number of hours of extra-classes | 6.845 (5.976) [1,752] | 5.217 (5.202) [1,722] | 4.911 (5.821) [1,734] |
| <i>Panel E: Health</i> | | | |
| Height-for-age z-score | −1.039 (1.047) [1,748] | −0.994 (1.125) [1,713] | −0.987 0.904 [1,739] |
| Weight-for-age z-score | −1.078 (1.318) [1,744] | | |

Table A.1: Summary statistics of outcome variables

| | (1) | (2) | (3) |
|---------------------|------------------------------|------------------------------|----------------------------|
| | Age 8 | Age 12 | Age 15 |
| | Mean (SD) [N] | | |
| BMI-for-age z-score | −0.645 (1.424) [1,740] | −0.576 (1.286) [1,713] | −0.530 1.186 [1,739] |
| Stunting | 0.208 (0.460) [1,748] | 0.215 (0.490) [1,713] | 0.127 0.375 [1,738] |
| Underweight | 0.271 (0.524) [1,743] | | |
| Thinness | 0.132 (0.388) [1,737] | 0.154 (0.415) [1,713] | 0.116 0.376 [1,738] |

A.2 . Summary statistics of control variables

Table A.2: Summary statistics of control variables

| Variable | Mean | N | Mean | St. Dev. |
|---|-------------|-------|--------|----------|
| <i>Age 5</i> | | | | |
| Child's sex (male = 1, female = 0) | Binary | 1,763 | 0.512 | 0.500 |
| Ethnic minorities (Ethnic minorities = 1, Kinh = 0) | Binary | 1,763 | 0.121 | 0.327 |
| BMI-for-age z-score at age 1 | Continuous | 1,758 | −0.412 | 0.983 |
| Height-for-age z-score at age 1 | Continuous | 1,758 | −1.102 | 1.311 |
| Weight-for-age z-score at age 1 | Continuous | 1,758 | −0.956 | 1.088 |
| Father's age | Discrete | 1,704 | 30.006 | 5.861 |
| Father's education | Discrete | 1,697 | 6.478 | 4.112 |
| Mother's age | Discrete | 1,759 | 27.092 | 5.680 |
| Mother's education | Discrete | 1,749 | 5.914 | 4.106 |
| Average working days per week of care-giver | Discrete | 1,648 | 1.257 | 0.538 |
| Age order of siblings in the household | Categorical | 1,761 | | |
| <i>Index child is the eldest</i> | | 5 | | |
| <i>Index child is the youngest</i> | | 925 | | |

Table A.2: Summary statistics of control variables

| Variable | Mean | N | Mean | St. Dev. |
|--|-------------|-------|--------|----------|
| <i>Index child has no siblings in the household</i> | | 831 | | |
| Number of sisters in the household | Discrete | 1,763 | 0.437 | 0.762 |
| Number of brothers in the household | Discrete | 1,763 | 0.332 | 0.516 |
| Number of males aged 0-5 | Discrete | 1,763 | 0.138 | 0.365 |
| Number of males aged 6-12 | Discrete | 1,763 | 0.208 | 0.460 |
| Number of males aged 13-17 | Discrete | 1,763 | 0.079 | 0.292 |
| Number of males aged 18-60 | Discrete | 1,763 | 1.268 | 0.694 |
| Number of males aged 61+ | Discrete | 1,763 | 0.111 | 0.316 |
| Number of females aged 0-5 | Discrete | 1,763 | 0.163 | 0.387 |
| Number of females aged 6-12 | Discrete | 1,763 | 0.268 | 0.571 |
| Number of females aged 13-17 | Discrete | 1,763 | 0.101 | 0.357 |
| Number of females aged 18-60 | Discrete | 1,763 | 1.353 | 0.720 |
| Number of females aged 61+ | Discrete | 1,763 | 0.163 | 0.377 |
| Wealth index | Continuous | 1,763 | 0.461 | 0.217 |
| Housing quality index | Continuous | 1,763 | 0.584 | 0.303 |
| Access to services index | Continuous | 1,763 | 0.436 | 0.271 |
| Consumer durables index | Continuous | 1,763 | 0.364 | 0.208 |
| Access to safe drinking water | Binary | 1,763 | 0.102 | 0.302 |
| Access to sanitation | 1,763 | 0.524 | 0.50 | |
| Access to electricity | 1,763 | 0.873 | 0.333 | |
| Access to adequate fuels for cooking | 1,763 | 0.245 | 0.430 | |
| Number of groups caregiver is a member of | Discrete | 1,763 | 0.387 | 0.728 |
| Number of groups from which the caregiver has received support | Discrete | 1,763 | 0.254 | 0.591 |
| Number of other sources from which the caregiver has received support | Discrete | 1,763 | 2.776 | 1.151 |
| Number of household members who support child financially | Discrete | 1,762 | 2.462 | 1.052 |
| Number of household members who care for the child | Discrete | 1,762 | 2.886 | 1.431 |
| Creche enrollment in first year | Binary | 1,763 | 0.064 | 0.245 |
| Child care help from outside household | Binary | 1,763 | 1.657 | 0.475 |
| Level of formal education caregiver want the child to complete | Discrete | 1,738 | 15.100 | 1.914 |
| At age caregiver expects the child to start earning money to support household | Discrete | 1,731 | 21.376 | 6.240 |
| Caregiver expects the child lives close when grown-up | Categorical | 1,752 | | |
| <i>Not at all</i> | | 351 | | |

Table A.2: Summary statistics of control variables

| Variable | Mean | N | Mean | St. Dev. |
|---|-------------|-------|------|----------|
| <i>A little</i> | | 227 | | |
| <i>Somewhat</i> | | 375 | | |
| <i>Quite a lot</i> | | 562 | | |
| <i>A lot</i> | | 237 | | |
| Caregiver expects the child provides financial assistance to younger siblings when grown-up | Categorical | 1,735 | | |
| <i>Not at all</i> | | 134 | | |
| <i>A little</i> | | 240 | | |
| <i>Somewhat</i> | | 586 | | |
| <i>Quite a lot</i> | | 616 | | |
| <i>A lot</i> | | 159 | | |
| Caregiver expects the child helps you with housework when grown-up | Categorical | 1,761 | | |
| <i>Not at all</i> | | 224 | | |
| <i>A little</i> | | 355 | | |
| <i>Somewhat</i> | | 600 | | |
| <i>Quite a lot</i> | | 477 | | |
| <i>A lot</i> | | 105 | | |
| Caregiver expects the child provides financial assistance when grown-up | Categorical | 1,757 | | |
| <i>Not at all</i> | | 245 | | |
| <i>A little</i> | | 229 | | |
| <i>Somewhat</i> | | 478 | | |
| <i>Quite a lot</i> | | 645 | | |
| <i>A lot</i> | | 160 | | |
| Caregiver expects the child cares for you she/he is old | Categorical | 1,761 | | |
| <i>Not at all</i> | | 32 | | |
| <i>A little</i> | | 75 | | |
| <i>Somewhat</i> | | 134 | | |
| <i>Quite a lot</i> | | 895 | | |
| <i>A lot</i> | | 625 | | |
| Caregiver expects the child provides emotional support | Categorical | 1,761 | | |
| <i>Not at all</i> | | 11 | | |
| <i>A little</i> | | 19 | | |
| <i>Somewhat</i> | | 64 | | |
| <i>Quite a lot</i> | | 727 | | |
| <i>A lot</i> | | 940 | | |

A.3 . Items included in factor analysis of non-cognitive skills

Table A.3: Items included in factor analysis of non-cognitive skills

| Skills | Statements | |
|---------------|---|---|
| | Round 3 | Round 4 |
| Self-esteem | <p>Overall, I have a lot to be proud of</p> <p>I can do things as well as most people</p> <p>Other people think I am a good person</p> <p>A lot of things about me are good</p> <p>I do lots of important things</p> <p>When I do something, I do it well</p> | <p>I'm as good as most other people</p> <p>Overall, I have a lot to be proud of</p> <p>I can do things as well as most people</p> <p>Other people think I am a good person</p> <p>A lot of things about me are good</p> <p>I do lots of important things</p> <p>When I do something, I do it well</p> |
| Self-efficacy | <p>When I am confronted with a problem, I can usually find several solutions</p> <p>If I am in trouble, I can usually think of a solution.</p> <p>I am confident that I could deal efficiently with unexpected events.</p> <p>I can always manage to solve difficult problems if I try hard enough.</p> <p>It is easy for me to stick to my aims and accomplish my goals.</p> <p>I can remain calm when facing difficulties because I can rely on my coping abilities.</p> <p>I can usually handle whatever comes my way.</p> | <p>When I am confronted with a problem, I can usually find several solutions</p> <p>I am confident that I could deal efficiently with unexpected events.</p> <p>It is easy for me to stick to my aims and accomplish my goals.</p> <p>I can remain calm when facing difficulties because I can rely on my coping abilities.</p> <p>I can usually handle whatever comes my way.</p> <p>Thanks to my resourcefulness, I know how to handle unforeseen situations.</p> |

Table A.3: Items included in factor analysis of non-cognitive skills

| Skills | Statements | |
|-----------------------|---|---|
| | Round 3 | Round 4 |
| Parent-child relation | Thanks to my resourcefulness, I know how to handle unforeseen situations. | |
| | I can solve most problems if I invest the necessary effort. | |
| | I like my parents | I like my parents |
| | My parents like me. | My parents like me. |
| | My parents and I spend a lot of time together | My parents and I spend a lot of time together |
| | I get along well with my parents | I get along well with my parents |
| | My parents understand me | My parents understand me |
| | If I have children of my own, I want to bring them up like my parents raised me | If I have children of my own, I want to bring them up like my parents raised me |
| | My parents are easy to talk to | My parents are easy to talk to |
| | My parents and I have a lot of fun together | My parents and I have a lot of fun together |
| Peer relation | I make friends easily | I make friends easily |
| | I am popular with kids of my own age | I am popular with kids of my own age |
| | Most other kids like me | Most other kids like me |
| | Other kids want me to be their friend | Other kids want me to be their friend |
| | I have more friends than most other kids | I have more friends than most other kids |
| | I have lots of friends | I have lots of friends |
| | I am easy to like | I am easy to like |
| | I get along with other kids easily | |

B - Second Appendix

B.1 . Drought in Vietnam from 2010 to 2018



Figure B.1: Drought in Vietnam in years of survey

B.2 . Descriptive statistics of the sample

Table B.1: Descriptive statistics of the sample

| Variable | Mean | N | Mean | St. Dev. | |
|---|--------|--------|-------|----------|-----|
| Number of times using outpatient services | 40,492 | 0.798 | 2.121 | 0 | 120 |
| Number of times using inpatient services | 40,492 | 0.069 | 0.468 | 0 | 31 |
| Working for economic activities (yes = 1, no = 0) | 40,492 | 0.154 | 0.361 | 0 | 1 |
| Highest grade achieved | 40,492 | 5.611 | 3.553 | 0 | 12 |
| Attending school (yes = 1, no = 0) | 40,492 | 0.661 | 0.473 | 0 | 1 |
| Age | 40,492 | 12.024 | 3.757 | 6 | 18 |

Table B.1: Descriptive statistics of the sample

| Variable | Mean | N | Mean | St. Dev. | |
|---|--------|--------|--------|----------|-------|
| Gender (male = 1, female = 0) | 40,492 | 0.515 | 0.500 | 0 | 1 |
| Household head's years of education | 40,492 | 1.715 | 2.051 | 0 | 12 |
| Age of household head | 40,492 | 45.349 | 11.721 | 11 | 104 |
| Gender of household head | 40,492 | 0.812 | 0.391 | 0 | 1 |
| Poor household (poor = 1, non-poor = 0) | | | | | |
| Per capita living area (m2) | 40,468 | 79.917 | 48.990 | 5 | 750 |
| Area (urban = 1, rural = 0) | 40,492 | 0.257 | 0.437 | 0 | 1 |
| Household size | 40,492 | 4.764 | 1.445 | 1 | 15 |
| Ethnic minorities (Ethnic minorities = 1, Kinh = 0) | 40,492 | 0.237 | 0.425 | 0 | 1 |
| Proportion of male under 5 in households | 40,492 | 0.030 | 0.074 | 0.000 | 0.500 |
| Proportion of female under 5 in households | 40,492 | 0.028 | 0.073 | 0.000 | 0.500 |
| Proportion of male from 5 to 15 in households | 40,492 | 0.160 | 0.156 | 0.000 | 0.750 |
| Proportion of female from 5 to 15 in households | 40,492 | 0.151 | 0.156 | 0.000 | 1.000 |
| Proportion of male from 15 to 60 in households | 40,492 | 0.280 | 0.148 | 0.000 | 1.000 |
| Proportion of female from 15 to 60 in households | 40,492 | 0.297 | 0.139 | 0.000 | 1.000 |
| Proportion of members with upper-secondary degree | 40,492 | 0.360 | 0.296 | 0.000 | 1.000 |
| Proportion of member with college/university | 40,492 | 0.036 | 0.114 | 0.000 | 0.800 |
| Drought severity | 39,466 | 0.125 | 0.177 | 0.000 | 1.000 |

B.3 . Robustness check to alternative way of measuring drought

Table B.2: Estimated effect of drought severity on child outcomes, using an alternative measure of drought

| | Attending school | Highest grade achieved | Working for economic activities | Number of times using out-patient services | Number of times using inpatient services |
|-----------------------|---------------------|------------------------|---------------------------------|--|--|
| | (1) | (2) | (3) | (4) | (5) |
| Drought months | -0.0069 (0.0046) | 0.0021 (0.0089) | 0.0053*** (0.0020) | - 0.0604*** (0.0154) | -0.0006 (0.0032) |
| <i>Fixed-effects</i> | | | | | |
| Commune | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes |
| <i>Fit statistics</i> | | | | | |
| Observations | 39,284 | 39,284 | 39,284 | 39,284 | 39,284 |
| R ² | 0.24664 | 0.88852 | 0.41667 | 0.26274 | 0.21700 |
| Within R ² | 0.05131 | 0.86668 | 0.23873 | 0.01909 | 0.00255 |

Clustered (commune) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Each column represents the coefficients in a separate regression. The column headings indicate dependent variables. All Controls include household head's age, household's head highest diploma, household head gender, household size, proportion of female adults from 15 to 60 in households, proportion of female adults from 15 to 60 in households, ethnic minorities, proportion of members with upper-secondary degree, proportion of member with college/university, living area, whether the household resides in a rural area, whether the household is classified as poor, child's age, child's age squared, and male child indicator. Fixed Effects include year, and commune fixed effects.

Table B.3: Estimated effect of drought severity on child outcomes, using logistic regression

| | Attending school | Working for economic activities |
|-----------------------|---------------------|---------------------------------|
| | (1) | (2) |
| Drought months | -0.0400 (0.0268) | 0.0589* (0.0319) |
| <i>Fixed-effects</i> | | |
| commune | Yes | Yes |
| year | Yes | Yes |
| <i>Fit statistics</i> | | |
| Observations | 35,657 | 26,701 |

| | | |
|-----------------------|---------|---------|
| Squared Correlation | 0.20760 | 0.52122 |
| Pseudo R ² | 0.16917 | 0.49952 |

Clustered (commune) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Each column represents the coefficients in a separate logistic regression. The column headings indicate dependent variables. All Controls include household head's age, household's head highest diploma, household head gender, household size, proportion of female adults from 15 to 60 in households, proportion of female adults from 15 to 60 in households, ethnic minorities, proportion of members with upper-secondary degree, proportion of member with college/university, living area, whether the household resides in a rural area, whether the household is classified as poor, child's age, child's age squared, and male child indicator. Fixed Effects include year, and commune fixed effects.

C - Third Appendix

C.1 . Land cover in Vietnam from 2008 to 2016

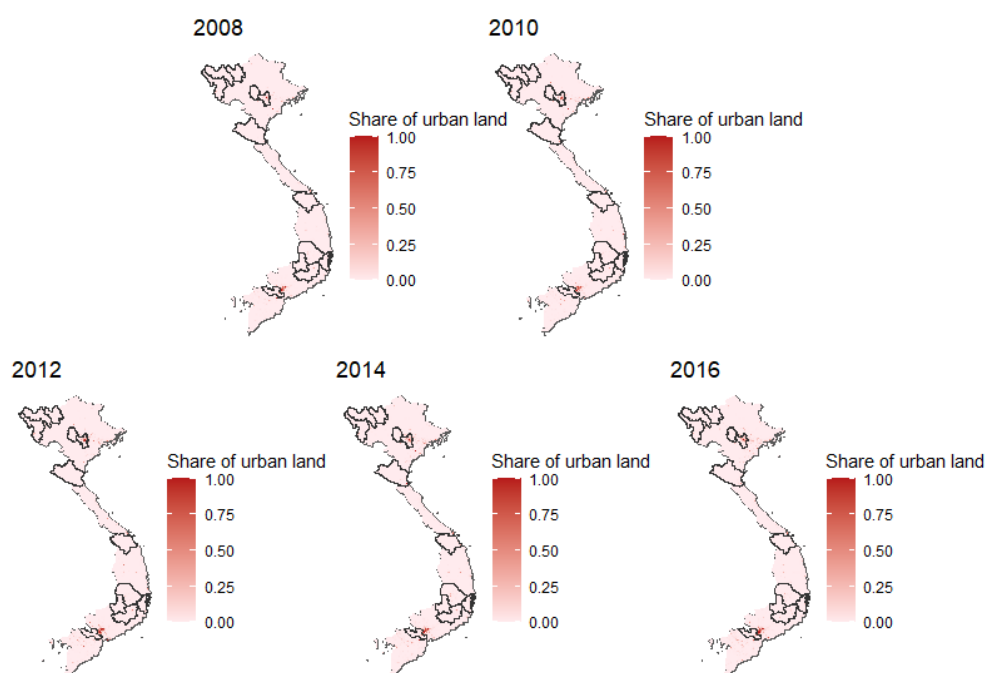


Figure C.1: Urban land cover in Vietnam in years of survey

C.2 . Descriptive statistics of the sample

Table C.1: Descriptive statistics of the sample

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|--------|--------|----------|-----|-----|
| Ethnic minorities (Ethnic minorities = 1, Kinh = 0) | 11,177 | 0.309 | 0.462 | 0 | 1 |
| Gender of household head | 11,177 | 0.851 | 0.356 | 0 | 1 |
| Household head's years of education | 11,177 | 6.597 | 3.722 | 0 | 12 |
| Age of household head | 11,177 | 46.753 | 12.059 | 18 | 93 |
| Household size | 11,177 | 5.273 | 1.643 | 1 | 14 |
| Number of female from 15 to 60 in households | 11,172 | 1.582 | 0.810 | 0 | 6 |

Table C.1: Descriptive statistics of the sample

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|--------|-----------|-----------|-------|---------|
| Number of male from 15 to 60 in households | 11,174 | 1.507 | 0.860 | 0 | 6 |
| Number of female from 5 to 15 in households | 11,172 | 0.812 | 0.870 | 0 | 5 |
| Number of male from 5 to 15 in households | 11,174 | 0.836 | 0.823 | 0 | 5 |
| Number of female under 5 in households | 11,172 | 0.105 | 0.338 | 0 | 3 |
| Number of male under 5 in households | 11,174 | 0.109 | 0.329 | 0 | 3 |
| Proportion of members with upper-secondary degree | 11,177 | 0.463 | 0.266 | 0.000 | 1.000 |
| Proportion of member with college/university | 11,177 | 0.017 | 0.072 | 0.000 | 0.800 |
| Cropland (ha) | 11,177 | 7.681 | 13.472 | 0.000 | 325.000 |
| Per capita living area (m2) | 11,177 | 15.606 | 10.811 | 1.000 | 150.000 |
| Share of commune having electricity | 10,857 | 91.357 | 20.077 | 0.000 | 100.000 |
| Share of commune with drinking water | 10,877 | 22.069 | 34.565 | 0.000 | 100.000 |
| Population of commune | 10,886 | 7,787.973 | 3,907.393 | 0 | 25,131 |
| Commune has market (yes = 1, no = 0) | 10,861 | 0.581 | 0.493 | 0 | 1 |
| Distance to the main road | 10,871 | 3.931 | 25.954 | 0.000 | 500.000 |
| Number of poor households | 10,874 | 259.248 | 471.668 | 0 | 22,211 |
| Number of enterprises in commune | 10,863 | 13.937 | 64.360 | 0 | 1,200 |

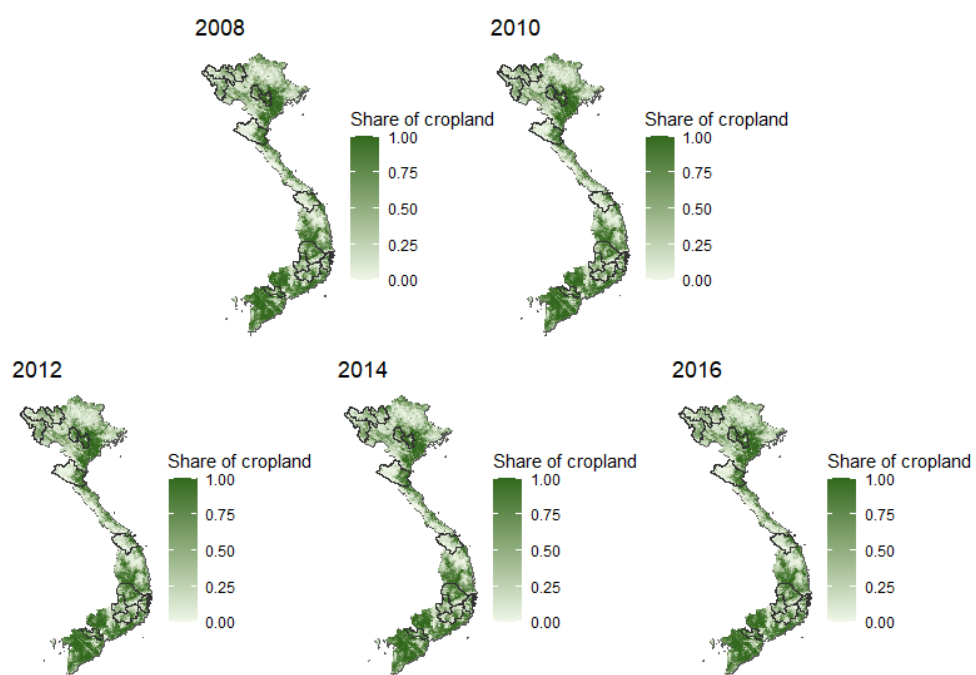


Figure C.2: Cropland cover in Vietnam in years of survey

