# ESSAYS ON CROP DIVERSITY, FOOD SECURITY, AND LABOR MARKET DISCRIMINATION

By

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# ABSTRACT

Development strategies designed to enhance food security in developing nations often emphasize increasing agricultural productivity through input subsidies for staple crops. However, this focus can inadvertently reduce crop diversity, concentrating resources on staples and neglecting nutrient-rich traditional varieties, potentially impacting nutrition. Households may compensate by purchasing diverse foods, but this depends on their purchasing power and market access. Additionally, labor market discrimination can lead to long-term socio-economic consequences, such as unemployment, poverty, reduced investment in education, and perpetuating intergenerational poverty.

This dissertation delves into three interconnected essays focusing on crop diversity, food security, and labor market discrimination in developing countries, aiming to address critical challenges in these areas.

The first essay presents experimental evidence of labor market discrimination among college graduates in Bangladesh, focusing on high school backgrounds (general vs religious), gender, and religious attire. Using data from two consecutive correspondence experiments involving 8,288 fictitious resumes submitted to 1,036 job postings, the study finds significant discrimination against graduates from religious high schools, particularly against males. A second experiment reveals that this discrimination persists even for high-quality resumes, suggesting it is rooted in taste-based bias rather than statistical discrimination. While no significant gender-based discrimination is found overall, females receive more callbacks for low-paying jobs and positions requiring high client interaction.

The second essay explores the impact of input subsidies (specifically for fertilizer and seed) on crop diversity on family farms in Burkina Faso. While previous studies investigated either the impact of a fertilizer or a seed subsidy on targeted crops, few examined the effects of both subsidies

combined. Using a correlated random-effects model with a control function approach on nationally representative panel data, the study finds that the fertilizer subsidy leads to increased land allocation to targeted crops (rice, maize, cotton) and reduces crop diversity. Focusing on a minor crop with key agronomic and nutritional attributes, we conclude that land allocation to cowpea as the primary crop and intercrop declined with the fertilizer subsidy. However, the cowpea seed subsidy offsets this bias, enhancing diversity by promoting the cultivation of traditional micronutrient-rich crops like cowpea.

The third essay investigates the relative contributions of on-farm production diversity and commercialization of crops and livestock on food security among farm households in Mali. Employing a Conditional Mixed Process (CMP) with Instrumental Variables (IV) approach on the 2017 Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) General Household Survey data, the study finds that on-farm crops diversity has a statistically significant positive impact on food security. However, we do not observe a strong association between livestock diversity and crop or livestock commercialization with food security. Rather, livestock sales have a negative association with food security, suggesting that livestock sales may be driven by distress rather than strategic decision-making. Enhancing on-farm production diversity appears to be a more effective strategy for improving food security in farm households.

These essays provide valuable insights into critical economic issues, offering guidance for policymaking and development strategies in developing economies.

This dissertation is dedicated to the loving memory of my late mother, Firoza Begam. Her sacrifices and foresight laid the foundation for who I am today. No one would have been happier than she to see me reach this milestone.

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TABLE OF CONTENTS

CHAPTER 1

HIGH SCHOOL INSTITUTION AND LABOR MARKET DISCRIMINATION IN BANGLADESH

## 1.1 Introduction

Labor market discrimination refers to a situation in which a particular group experiences unequal (less favorable) treatment during various stages of employment, including recruitment, job allocation, compensation, performance evaluation, promotions, and dismissal, even when workers are assumed to have similar levels of productivity (Bertrand & Duflo, 2017; Neumark, 2018). This act of denying deserving opportunities has long-lasting social and economic consequences such as financial loss, unemployment, poverty, poor health and education outcomes, racial and regional disparities, lower investment in human capital, social exclusion, and the intergenerational transmission of poverty (Cain, 1986; Trenerry et al., 2012). Moreover, discrimination can result in the underutilization of human capital (Rafferty, 2020) and a lack of workplace diversity (Flabbi et al., 2019), hindering the effectiveness and growth of businesses (Thomas & Ely, 1996).

There are two prominent models of discrimination in the literature that explain the root causes of unequal treatment in the labor market and the cost of discrimination- taste-based bias and statistical discrimination. Taste-based discrimination arises from employer distaste or biases against certain groups based on non-economic factors like race, gender, or ethnicity rather than productivity. Employers may favor candidates similar to themselves or prioritize perceived "cultural fit" over objective qualifications, disadvantaging minority groups. This bias stems from prejudices, stereotypes, and preferences against a certain group, leading to refusal to hire, lower pay, or other unfavorable treatment (Becker, 1971). Essentially, employers who discriminate based on taste are willing to incur costs to maintain their biases, reflecting a preference for certain groups over others without regard to economic efficiency.

On the other hand, statistical discrimination arises when groups differ in their distribution of productive characteristics. Employers make predictions about a candidate's expected productivity based on average characteristics associated with the candidate's identity, aiming to minimize adverse selection due to imperfect information about individual-level characteristics (Arrow, 1973; Phelps, 1972). While taste-based discrimination stems from animosity or unreasonable stereotypes, statistical discrimination is theoretically efficient because it treats individuals according to their expected productivity. However, this model can still lead to unequal treatment. Although expected productivity and actual productivity would be equal on average within each group, individual actual productivity varies. Under the statistical discrimination model, job seekers are treated based on their group's average productivity. As a result, some candidates with lower expected group productivity may be treated less favorably or discriminated against even with higher individual productivity (Bertrand & Duflo, 2017).

Labor market discrimination based on various characteristics such as race, ethnicity, gender, age, religion, social class, disability status, nationality, location of residence, and other characteristics is a prevalent issue worldwide. Over the last few decades, a rich body of literature has attempted to identify and measure labor market discrimination using different methodologies. The first wave of discrimination studies focused on wage differentials between groups using a regression-based decomposition approach, as the relevant data are readily available (Blinder, 1973; Oaxaca, 1973). This method analyzed wage differentials by breaking them down into two components- composition and structural effects. However, it had limitations, including reliance on strong assumptions, sensitivity to the choice of reference groups, and other challenges (Neumark, 2004; Jann, 2008; Fortin, Lemieux, and Firpo, 2011).

In response to these limitations, the second wave of research utilized firm-level data, considering both wage differentials and workers' marginal productivity to uncover labor market discrimination (Altonji & Blank, 1999; Holzer, 1996). More recently, the third wave of studies has employed experimental audit or correspondence studies to unearth discrimination in the labor market (Bertrand & Mullainathan, 2004; Heckman, 1998; Riach & Rich, 2002).

Audit studies involve sending real testers with similar qualifications and racial identities to apply for jobs and face job interviews (Pager, 2003). However, they face criticisms as testers may vary in specific unobservable attributes such as appearance and interpersonal skills that may influence employers' hiring decisions (Heckman, 1998; Pager, 2007). Correspondence studies, on the other hand, send fictitious resumes to assess discrimination, eliminating direct interactions between candidates and employers. This approach mitigates biases arising from real testers' interaction in audit studies (Neumark, 2012).

This method has been convenient in assessing discrimination in labor (Bertrand & Mullainathan, 2004), credit (Alesina et al., 2013), and housing (Bosch et al., 2009; Hanson & Hawley, 2011) markets. A correspondence study is categorized as an experiment where researchers randomly control individual characteristics to assess their impact on outcome variables (e.g., employability). It can uncover discrimination that may be difficult to study otherwise, especially in assessing job market discrimination during hiring (Neumark, 2012). While explicitly focusing on the initial stage of recruitment, this method generates experimental, nonlaboratory evidence of labor market differentials based on factors such as race, gender, residential neighborhood, or other characteristics (Gaddis, 2019).

In a highly influential study on racial discrimination in the US job market, Bertrand and Mullainathan (2004) found that a candidate with an African American-sounding name needs to apply for 50 percent more jobs to receive similar callbacks compared to their white counterpart. Other studies have shown that black candidates receive fewer responses from employers and job offers with lower starting salaries than their white peers, even among high-quality candidates with degrees from top-ranked schools (Gaddis, 2015; Quillian et al., 2017). Moreover, (Pager, 2003) showed that a white candidate with a criminal history may receive more priority than an African American candidate with no criminal record. A recent correspondence study found that female college graduates in the Chinese job market are less likely to receive callbacks for interviews than male college graduates with similar productive characteristics (Zhang et al., 2021). Additionally, Phelps (1972) demonstrated that employers infer worker attributes based on applicant neighborhood characteristics, resulting in discrimination.

Religious identity and practices are also a significant source of labor market discrimination, particularly against religious minorities (Akbaba, 2023; Khattab, 2009). Experimental studies have delved into discrimination based on religious identity and practice, with a focus on minority Muslims and female Muslim candidates wearing headscarves. For instance, Drydakis (2010) revealed employment bias against religious minority groups in Athens, Greece. Studies conducted in the US demonstrated that Muslim candidates experience the highest discrimination among seven religious groups tested in the American South and New England regions (Wright *et al.*, 2013; Wallace, Wright, and Hyde, 2014). Acquisti and Fong (2020) also found that Muslim candidates receive 13 percent fewer callbacks than Christian candidates in the US. Valfort (2015) investigated discrimination based on religious practice in the French labor market and found that practicing Muslim candidates face higher discrimination compared to practicing Jews and Catholics.

Practicing Muslim candidates receive 10 percent of callbacks, Jews receive 16 percent, and Catholic candidates receive 21 percent from an equal number of submitted resumes, validating the findings of another study (Pierné, 2013).

While discrimination based on religious identity affects all members of a religious group, Muslim women who wear hijabs face a notably higher risk due to the visibility of their religious identity and practices. Research highlighting the challenges encountered by Muslim women wearing hijabs indicates that they are less likely to receive interview invitations and frequently encounter significant discrimination in Muslim minority countries (Fernández-Reino et al., 2022; Weichselbaumer, 2020). Recent anecdotal research also suggests the presence of Islamophobia in Muslim-majority countries (Bayraklı & Hafez, 2019). However, there remains a noticeable lack of experimental evidence regarding labor market discrimination based on religious attire or other religious affiliations, such as attending Islamic high schools in Muslim-majority countries.

In addressing this research gap, this study focuses on Bangladesh, a Muslim-majority country known for its racial, ethnic, religious, linguistic, and cultural homogeneity. Despite this homogeneity, Bangladesh offers a diverse array of high school education options, including general high schools, Islamic high schools or *Alia* Madrasahs, and vocational high schools in both Bangla and English-medium versions that follow national curricula, and international English-medium high schools that follow British or American curricula. General high schools and *Alia* Madrasahs represent the predominant streams of secondary education, available in both private and public sectors. While both streams follow the national curriculum, *Alia* Madrasahs include additional religious subjects such as Arabic, Islamic Studies, Quran, and Hadith. After completing their high school diplomas, students from both streams may pursue higher education through a competitive entrance examination. Notably, traditional unregistered religious educational institutions like *Qawmi* Madrasahs, whose diplomas are not recognized for college entry, are excluded from this discussion. These varied high school streams present a unique opportunity to examine whether college graduates with general high school or Madrasah backgrounds experience differential treatment in Bangladesh's labor market. Specifically, this study investigates whether systematic job market discrimination occurs during the initial recruitment phase for college graduates in Bangladesh based on their high school institute type, religious attire preferences, and gender. The study aims to answer the following research questions:

1. Are college graduate job candidates treated differently based on their high school background, gender, and preference for religious attire in the Bangladeshi job market? Religious attire refers to clothing or symbols worn to signify religious identity or fulfill religious obligations, such as hijabs for Muslim women or beards and caps for Muslim men.
2. If discrimination exists, what is its extent, and how does it vary across industries and job types?
3. What is the source of discrimination- taste-based bias or statistical discrimination?

To investigate these questions, we employ a theoretical framework based on (Neumark, 2012) to conceptualize the potential hiring discrimination process. The study utilizes an experimental correspondence test approach, a widely used technique for uncovering discrimination across various fields. We implemented two experiments: the first investigates the existence of discrimination, and the subsequent second experiment examines the source of the discrimination.

In the first experiment, a total of 3,248 fictitious resumes were submitted in response to 406 job openings in four sectors: IT, NGO, Media, and Corporate. These job openings were advertised on Bangladeshi online job sites, newspapers, and social media pages. The study reveals evidence of discrimination based on candidates' high school background, gender, and preference for religious attire. Candidates with Madrasah high school backgrounds receive significantly fewer callbacks than their counterparts across the industry, with male candidates experiencing the highest discrimination.

The extent of discrimination also varies across industries and job categories. While there is no overall gender-based callback differential against female candidates, they receive higher callbacks for low-paying jobs and positions requiring higher client interaction. Female candidates also receive slightly fewer callbacks for media industry jobs but significantly higher callbacks for NGO and IT jobs. Discrimination based on candidates' preference for religious attire is most pronounced in the media and corporate sectors and jobs involving higher client interaction. Candidates with Madrasah backgrounds receive significantly fewer callbacks for mid-level jobs than entry-level positions.

We conducted a second experiment to investigate discrimination against individuals with a Madrasah background and determine its nature—whether taste-based or statistical. We crafted eight fictitious resumes varying in high school background, gender, and resume quality (high vs. low). We craft high-quality resumes by including a high college GPA, higher voluntary and professional experience, additional training, and strong language and communication skills to indicate higher productivity than low-quality resumes. Our hypothesis posited that if discrimination is statistical, it would diminish for high-quality resumes. Suppose high-quality resumes from a discriminated-against group (e.g., resumes with excellent qualifications, skills, and experience) receive fewer callbacks or job offers than similar resumes from a non-discriminated group. In that case, it suggests that something beyond qualifications influences the decision and strongly indicates taste-based discrimination. Researchers use experiments with high-quality and low-quality resumes to isolate demographic effects (e.g., race, gender) on hiring outcomes. This method establishes causal links between demographic factors and discriminatory practices in hiring, offering critical insights into discrimination's scope and nature in the labor market.

In this second experiment, a total of 5,032 fictitious resumes were submitted to 629 job postings (eight resumes to each posting), mainly to corporate and NGO jobs—the two largest industries in terms of employment. These job postings encompassed jobs like Sales, Marketing, Management, Accounting, Finance, Front Desk/Receptionist, Computer Operator, Customer Service/Call Center, and others. We find that discrimination does not diminish with high-quality resumes, suggesting that discrimination is likely to be taste-based.

This study contributes to the literature on labor market discrimination in several ways. To the best of our knowledge, it is the first experimental study to investigate discrimination based on high school institutional choice, shedding light on an unexplored aspect of labor market discrimination. Secondly, it is the first experiment conducted in the Bangladeshi labor market context, attracting significant attention from researchers and policymakers as it provides experimental evidence. Thirdly, the study innovatively incorporates photographs to investigate differential treatment in the labor market— uncommon as most countries do not require photographs in resumes. Notably, it is the first study to examine discrimination against Muslim male candidates with religious symbols such as beards and caps. Lastly, this study is crucial in demonstrating how the signal of religiosity matters in the job market, serving as the first experiment to reveal the impact of Islamophobia on Muslims who explicitly (wearing religious attire) or implicitly (attending religious high school) display their religiosity in a Muslim-majority country setting.

## 1.2 Background

In Bangladesh, college graduates face significant challenges in the labor market, primarily due to a mismatch between available job openings (labor demand) and the growing number of graduates entering the job market each year (labor supply). Despite the country's sustained economic growth, unemployment remains a pressing issue, with an average national unemployment rate of 4.15 percent and a youth unemployment rate of 11.56 percent (World Bank, 2020). Notably, the unemployment rate among college graduates is even higher, reaching 38.6 percent (Murshid, Mahmood, and Shashi, 2019). This alarming statistic is compounded by two million youth joining the labor force annually, intensifying the imbalance between supply and demand. It is important to note that female labor force participation has increased significantly over the past two decades (Klasen, 2019).

In this context, securing employment after obtaining a master's degree is highly competitive, with an average waiting period of three years for graduates (Murshid, Mahmood, and Shashi, 2019). To illustrate the intense competition in the job market of Bangladesh, we take the Bangladesh Civil Service (BCS) recruitment process in 2018 as an example. There were 475,000 applicants for 2,135 positions, resulting in 222 applicants per job position.[1] The popular myth that "you cannot secure a good job without a powerful *mama-chacha* (powerful relatives)" highlights the difficulty in finding employment in Bangladesh.

A predominantly homogeneous population characterizes Bangladesh regarding race, religion, language, and ethnicity. However, there are multiple streams of high school education (Asadullah & Chaudhury, 2013). These include general high schools, government-approved

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[1] Source: The Daily Prothom Alo (https://en.prothomalo.com/youth/41st-BCS-applications-break-record-previous)

mainstream traditional Islamic schools (Alia Madrasah), vocational high schools, English medium schools following international curricula, an English version of general high schools and Madrasahs, and *Qawmi* Madrasah (a non-formal religious education). The two major streams among these are General High School and Alia Madrasah (commonly referred to as Madrasah). Students from Madrasah can switch to general school at any stage of their schooling from grade one to twelfth as both streams follow the same national curriculum till twelfth grade, except the fact that Madrasah incorporates additional religious subjects, such as Arabic and Islamic Studies (Kocaman and Uddin, 2021). Students in Bangladesh typically complete the Secondary School Certificate (SSC) examination in the 10th grade and the Higher Secondary School Certificate (HSC) examination in the 12th grade or their equivalents from any government-approved high school stream. After passing these examinations, students can enroll in college and pursue their desired disciplines.

There is a growing perception that candidates with a Madrasah high school background or those displaying explicit religiosity in their attire face discrimination when seeking job opportunities (Rahman, 2015). While substantial research evidence specifically addressing discrimination against candidates with a Madrasah high school background is lacking, anecdotal evidence from national mainstream media and social media suggests differential treatment of candidates based on their Madrasah high school background or religious attire (Ali et al., 2021; Rahman, 2015; Zaman et al., 2023).

Furthermore, despite successful investments in human capital and efforts to bridge the gender gap in school enrollment in Bangladesh, employment disparities persist. Women often face lower wages and are underrepresented in high-paying jobs and leadership positions compared to men. Numerous studies have identified gender wage differentials, consistently showing that women receive lower pay than their male counterparts, irrespective of qualifications and productivity (Ahmed & Maitra, 2010, 2015). However, despite these findings, there is a notable gap in research. No experimental study has been conducted to investigate gender discrimination during the primary selection process of hiring in the country.

In the Bangladeshi job market, applicants are required to include comprehensive details in their resumes, encompassing educational attainments, such as high school degrees (10th-grade and 12th-grade public examination results), along with demographic information and photographs, allowing employers to trace or verify candidates' backgrounds easily. Importantly, this unique aspect of including demographic information, high school education details, and the compulsory use of photographs in resumes provides an advantageous setting to investigate discrimination based on high school backgrounds, gender, and religious attire.

### 1.3 Conceptual Framework

We develop a theoretical framework based on Neumark (2012) to examine potential hiring discrimination. Assuming employers aim to maximize profits, they make hiring decisions based on expected productivity as perceived during the selection process. Productivity ($Q$) is a function of observable ($X^1$) and unobservable ($X^2$) individual characteristics of the employee, as well as firm characteristics ($F$) such as technology, management practices, and capital. Hence, the productivity function can be represented as $Q(X^1, X^2, F)$. In our study, since we use fictitious resumes and no candidates appear for an interview, we focus solely on observable characteristics, disregarding the influence of unobservable characteristics in the employer's primary selection process. This approach, known as a correspondence study, addresses the advantage Neumark (2012) highlighted in avoiding biases based on unobservable characteristics.

In the first-generation audit studies or matched pair tests, real testers with identical fictitious characteristics were used to attend interviews to identify discrimination by employers (Neumark, Bank, and Van Nort, 1996). However, this process has a severe limitation, as the employer may perceive some unobservable attributes of the testers, such as interpersonal skills, through the interview process. This limitation led to the development of correspondence studies. In correspondence studies, fictitious resumes with identical observable characteristics are submitted, ensuring that biases based on unobservable characteristics are eliminated (Neumark, 2012). In correspondence studies, the perceived productivity is thus a function of the observable characteristics revealed in the resume and firm characteristics, $Q(X, F)$, where $X$ represents individual observable characteristics specified in the resume.

The callback ($C$) from employers is influenced by the perceived productivity $Q(X, F)$ and the candidate's high school background ($B$), assuming high school background as the identity or the treatment category (which can be applied to the other two randomization levels too). We define discrimination as $C(Q(X,F)|B = 1) \neq C(Q(X,F)|B = 0)$ where $B = 1$ indicates a candidate with a Madrasah high school background and $B = 0$ implies a general high school background. Assuming the productivity and callback functions are additive, the callback rate for a group can be expressed as $C(Q(X,F), B) = Q(X,F) + \gamma B$. If the perceived productivity for both groups, based on observable characteristics in their resume, is equal, $Q_1^* = Q_2^* = Q^*$, the parameter $\gamma$ represents discrimination based on high school background. Consequently, the difference in callbacks between the two groups is $C(Q^*, 1) - C(Q^*, 0) = Q_2^* + \gamma - Q_1^* = \gamma$. The following equation is the basis for estimating this mean difference of callbacks:

$C_i(B) = \alpha + \gamma B_i + u_i,$

where $C_i$ represents the callback for candidate i, $B_i$ denotes the candidate's background or identity, $\gamma$ signifies the discrimination parameter, and $u_i$ is the error term. The significant and negative value of $\gamma$ implies discrimination against candidates when they have a religious high school background, $B = 1$.

## 1.4 Experimental Design

### 1.4.1 Identifying the Industry and Jobs

Determining the appropriate job categories and industries to target when sending fictitious resumes is crucial in investigating employment discrimination. It is important to consider the nature of the job postings and their suitability for a correspondence study. Some job openings, such as government jobs, require applicants to pay a fee and submit various documents, including academic transcripts and national identification cards. Recruiters of these positions, particularly in the public sector, have a legal obligation to call every applicant to the written test in the primary selection process, making sending fictitious resumes for such roles impractical. Therefore, as an initial criterion, we exclude public jobs from the selection.

In addition to government jobs, certain private sector positions, particularly in the service sector (e.g., private banks), may also require national ID cards and transcripts, similar to public sector roles. We have verified this information with HR personnel from a private bank. Consequently, we refrained from sending resumes to banking and other private sector jobs with comparable document requirements. Instead, we focus on job postings in the private sector that undergo primary screening based on resume evaluation and do not request additional documents apart from a resume and a cover letter.

Our strategy involves sending resumes to job postings in private companies and institutions open to college graduates. Aligned with the study's objectives and experimental plan, we have selected four sectors for the first experiment: corporate, NGO, media, and IT. The corporate sector represents the largest job market for university graduates. As non-profit organizations, NGOs are often perceived as women-friendly and non-discriminatory, contributing valuable insights into equal-opportunity practices. Media houses, known for potential bias against individuals with religious connections, provide a context to explore discrimination based on high school backgrounds or religious attire. Finally, the IT sector is a rapidly growing industry in Bangladesh, known for requiring specific software skills. We assume that self-identified equal-opportunity employers and IT firms adhere to non-discriminatory practices.

We also record employer and job-level characteristics, capturing essential information such as industry type (e.g., not-for-profit NGOs, corporations, media houses, and IT industries), required qualifications and skills, experience requirement (entry-level or mid-level), and the extent of customer interaction. To further refine our analysis, we distinguish between high-paying and low-paying positions. We categorize jobs that involve direct interaction with clients, such as sales jobs and call center executives, as well as positions that require face-to-face interactions, like front desk executives and receptionists, as high client-interaction jobs. We also consider jobs that involve frequent visits or field-level communication, such as field managers, and positions related to training and consultancy into that category. We define entry-level jobs as those with experience requirements of less than two years.

Furthermore, we classify jobs as low-paying based on each sector's median and mean salary. Specifically, if the median salary of a sector is equal to or less than the mean salary of that sector, then any job with a salary below the median salary is categorized as a low-paying job. Conversely, if a sector's mean salary is less than that sector's median salary, any job with a salary below the mean is categorized as a low-paying job; this happens for one industry. By dividing the sample into these distinct categories, we examine how callback rates vary across these categories for different groups of job applicants.

Industries such as IT and NGOs are assumed to be non-discriminatory, while NGOs are perceived to be women-friendly and non-discriminatory. Considering these employer and job-level characteristics, we aim to analyze discrimination across various dimensions and identify potential biases based on high school background, gender, and religious attire preferences.

In the second experiment, we chose two broad sectors- NGOs and corporations- as these are two of the largest employment sectors in Bangladesh, with frequent job openings compared to IT and media. Within these two broad sectors, we submitted resumes to different job categories: sales, marketing, admin, management, finance, accounting, receptionist, etc.

### 1.4.2 Sampling Design

To conduct the study on employment discrimination, we created four resumes for each high school background category: four from general high school and four from Madrasah. In the initial experiment, we randomized the four resumes in each category by gender, resulting in two resumes for female candidates and two for male candidates. This allows us to examine potential gender biases. Next, randomization is based on the preference of religious attire or symbols. Among the two female resumes, one includes a photograph with a headscarf (hijab), while the other does not. Among the two male resumes, one includes a photograph with a religious cap and beard, while the other does not feature a cap or beard. This randomization enables us to capture potential discrimination based on the preference for wearing religious attire. For a visual representation of the resume selection process, please refer to Figure A1 in the appendix.

In the second experiment, we employed randomization for the resumes based on gender, candidate quality, and high school background. Similar to the first experiment, we initially generated four resumes for each high school background category. Subsequently, we randomized the four resumes in each high school background category by gender, resulting in two resumes for male and two for female candidates. Finally, for each gender, we randomly paired one high-quality candidate resume with one low-quality one. For a visual representation of the resume selection process, please refer to Figure A2 in the appendix.

### 1.4.3 Fictitious Resumes and Identification Strategy

To conduct our study on employment discrimination, we created fictitious profiles of job candidates, incorporating relevant factors typically considered by employers. We use a standardized resume template tailored for each job, and the resume encompasses an objective statement, academic diplomas (including high school degrees), a list of computer and language skills, employment history, voluntary/internship experiences, and other pertinent information. When required, a cover letter was attached.

Following Bangladeshi customs for resumes, our experiments include demographic information and a photograph of candidates. It is worth noting that Bangladeshi application processes commonly require demographic information and a photograph. The requirement of this information allows us to randomize religious attire preferences in the first experiment. To ensure no bias arises from appearances, photographs of Bangladeshi college graduate youths with similar skin tones are included.

We strived to develop authentic and professional resumes that mirror what Bangladeshi college graduate job seekers typically submit for job applications. To eliminate biases related to candidates' marital status, especially for female candidates, no information regarding their marital status was included in the demographic section. Resumes consist of mailing addresses, email IDs, and phone numbers. Eight separate email addresses and phone numbers are employed to track callbacks systematically, with our male research assistant managing communication for male resumes and our female assistant managing female resumes.

To prevent any potential elite biases, mailing addresses are selected from similar middle-class residential locations in Dhaka city. Typical candidate names are used to avoid any perception of elite status. All resumes are consistent regarding college-level educational attainment, undergraduate major, college category, high school quality, high school GPA, experiences, leadership and computer skills, and language skills.

While maintaining consistency across all eight resumes sent for a given job, each resume is tailored to meet specific job requirements. This customization ensures that the experiences and skills presented in the resumes are appropriate for the specific job while avoiding categorization as overqualified or underqualified. Additionally, all eight resumes sent for a particular job are similar in terms of the quality of candidates in the first experiment but categorized into high- and low-quality resumes in the second experiment.

In the resume preparation process, we employed three stages of randomization. First, resumes were randomized based on two types of high school backgrounds: Islamic high school (*Alia* Madrasah or Madrasah) and general high school, as previously mentioned. For this study, we specifically focused on general high school and Alia Madrasah. We excluded English medium schools following British/American curricula, English version general schools, or Madrasahs following national curricula to prevent biases related to assumed English proficiency and elite status. Additionally, we excluded vocational stream high schools due to somewhat different curricula from general schools and Madrasah, as well as non-formal Qawmi Madrasah education, as they do not provide formal high school certification. Regarding high school institutional quality, we chose reputed high schools in Dhaka City for both general schools and Madrasahs.

Second, we prioritized consistency within a candidate's high school profile. If a candidate obtained their SSC equivalent degree (10th-grade public examination) from a Madrasah, we maintain a consistent profile by keeping their HSC degree (12th grade) from a Madrasah, and vice versa. Mixed high school profiles, where the types of high schools differ, were intentionally excluded to maintain a consistent approach.

Third, we consider three major areas of study in high schools: science, business, and humanities. The science group focuses on Physics, Chemistry, Biology, and Mathematics, while the humanities group includes General Science, Political Science, Economics, and Sociology. The business group focuses on business-related classes. Acknowledging that some employers may prefer candidates with a science high school background due to perceived talent, we maintained consistency within the high school academic majors, either science or humanities. We exclude the commerce major in high school given its unavailability in the Madrasah curriculum. To ensure a consistent approach, we avoid scenarios where candidates change their high school majors between SSC and HSC (e.g., Science in SSC but humanities in HSC). Additionally, we ensure that high school GPAs fall within a close range to guarantee similarity between both groups.

Fourth, although we keep the SSC and HSC GPAs the same (e.g., GPA 5 out of 5) for all candidates, there are potential concerns about the evaluation quality in both streams. One might ask whether the results genuinely indicate an equivalent level of achievement. However, regardless of high school background, all students undergo the same university entrance test for admission to public universities. Students can select specific majors based on their performance, securing close merit positions in the entrance test. This standardized approach helps eliminate biases related to high school GPAs, as the university entrance test is uniform for all students, and they subsequently pursue similar or closely related majors in college.

Fifth, it is essential to maintain consistency in selecting universities, majors, and other qualifications across all the resumes. Specifically, the University of Dhaka was utilized for bachelor's or master's degrees in 98% and 100% of the cases in experiments 1 and 2, respectively. There are several reasons for this choice. The University of Dhaka is widely recognized as the premier university in the country, renowned for its rigorous admission process and academic excellence. By using this university consistently, we aim to ensure uniformity and comparability in the educational background of the candidates presented in the resumes. Lastly, it is noteworthy that when including a master's degree in the resume, whether due to job requirements or for the sake of consistency, we ensure that all resumes sent for a particular job reflect the presence of a master's degree. This approach is implemented to uphold standardization in the resumes and maintain uniformity across the application process.

Appendix Table A 1.1a and Table A 1.1b displays the results of the balance test for resume characteristics between the general high school and Madrasah groups in the first and second experiments. The objective is to ensure no significant differences in individual attributes—such as college GPA, work experience, computer literacy, leadership/volunteer experience, training, language skills, and other individual characteristics—between the two groups. The balance test aims to verify that resumes in each group are similar regarding these important factors, enabling a fair and unbiased comparison when examining the impact of high school background on callback rates.

### 1.4.4 Jobs Search, Sending Resumes, and Communication

Research assistants actively search for job openings on popular online platforms, including BDjobs.com and ProthomAloJobs.com, as well as in relevant social media groups. Specifically targeting positions accessible to college graduates, the search focuses on administrative, sales, marketing, management, finance, accounting, data analysis, web development, receptionist, or other entry-level to mid-level positions.

We create eight customized resumes for each job posting by aligning them with the specific requirements outlined in the job description. Our templates are meticulously adjusted to ensure that the resumes reflect the desired qualifications and skills specified by the employers. Subsequently, we submit these resumes to the employers, adhering to their preferred submission method, commonly involving email or the organization's online application system.

We carefully match the profiles of our fictitious candidates with the job requirements for each posting. In the first experiment, eight resumes were submitted for each job, maintaining consistency in high school background, gender, and religious attire preference within each set of resumes. As a result, 3248 resumes were submitted to 406 job postings. In the second experiment, the resumes are consistent in terms of high school, gender, and resume quality within each set of resumes. A total of 5,032 resumes were submitted to 629 job openings (8 resumes for each opening).

Two research assistants conducted job searches, submitted resumes between September 2021 and April 2022, and tracked callbacks until June 2022 for the first experiment. The second experiment spanned from August 2022 to June 2023. In Bangladesh, the response process from employers varies. Email communication for interviews was uncommon, and voicemail services were not widely used. Typically, employers directly contact selected candidates via phone, especially smaller ones. However, there were instances when employers used both email and phone calls.

Research assistants diligently recorded the callbacks for interviews or written tests to track the employer's responses. They were responsible for managing communications related to the resumes, with clear instructions to keep their cell phones on at all times to avoid missing any calls from potential employers. In the event of a missed call, the research assistants promptly followed up to confirm whether it was a callback. They also monitored their email inboxes, including spam folders, to ensure no callbacks were overlooked.

To ensure smooth communication and avoid confusion, we assign specific roles to our research assistants based on gender. Our male research assistant handles the four male resumes, while our female research assistant handles the call for the four female resumes. This approach ensures that when employers reach out to schedule interviews or discuss job opportunities over the phone, there is no confusion regarding the candidates' gender. By having dedicated research assistants for each gender group, we minimize biases or misperceptions that may arise due to differences in voice or gender. This method ensures a fair and accurate representation of the candidates and helps maintain consistency in the interactions between employers and our fictitious job applicants. Both research assistants are trained to handle these communications professionally and follow the established protocols. They are well-prepared to respond to inquiries, provide information, and facilitate the interview scheduling process, all while maintaining the anonymity and integrity of the study. If the employer calls for an interview, our research assistants politely decline by stating, “I have already accepted another position” or “I am no longer interested in this position.”

Callbacks were documented in an Excel spreadsheet, capturing key details such as the method of communication (email or phone call), the date of the callback, and the specific job and resume associated with it. In the rare cases where an employer sends a hard copy response via the postal service, we provide mailing addresses where we have a contact to facilitate effective tracking and documentation.

### 1.4.5 Sample Size

Appropriate sample size is crucial in any experimental study, including correspondence experiments focused on detecting discrimination in labor markets. Prior studies using the correspondence approach have demonstrated a range of sample sizes, from less than 100 (Neumark, Bank, and Van Nort, 1996) to over 1500 experimental units (Wright et al., 2013). Statistical power calculation is important in determining the appropriate sample size. Guided by a power calculation suggested by Lahey and Beasley (2009) and Vuolo, Uggen, and Lageson (2016), G*Power software was used to determine an appropriate sample size based on the recommended significance level, power, and effect size.

Given the absence of prior studies specifically examining employment discrimination based on high school background, we refer to related correspondence studies focusing on various aspects, such as religious affiliation (Wallace et al., 2014; Wright et al., 2013), race (Bertrand & Mullainathan, 2004), caste (Banerjee et al., 2009), gender (Zhang et al., 2021). These studies suggest an average effect size ranging from .15 to .30. We have chosen the desired effect size of 0.15 with 5% significance level ($\alpha = 0.05$) and the probability of correctly rejecting the null hypothesis when it is false (power, $1 - \beta$) is set at 0.80. A power calculation suggests an appropriate sample size of 277 experiment units to achieve this effect size. However, considering our industry-wise variability, we intentionally increased our sample size to include 406 experimental units (3248 resumes) in the first experiment, and 629 experiment units (5032 resumes) in the second experiment. Additionally, the relatively low cost of implementing the experiment allowed us to significantly expand the sample size beyond our initial design.

### 1.4.6 Ethical consideration

While audit or correspondence experiments are valuable for revealing labor market discrimination, concerns have been raised regarding their ethical implications, particularly the potential burden of sending additional fictitious resumes to employers. Through informal consultations with human resource professionals and a review of existing literature, it has been suggested that the impact of adding eight resumes is relatively minor. In Bangladesh, HR professionals typically receive an average of 100-150 resumes for a position.

Moreover, insights from similar experiments conducted in contexts like India further support the viability of using a similar number of resumes. For example, (Banerjee et al., 2009) employed a similar number of resumes (eight to twelve for each employer) in Delhi, India. Given the significance of addressing discrimination allegations in the Bangladeshi labor market, it is crucial to generate evidence and shed light on this issue. This approach is balanced by careful consideration of ethical concerns and industry norms.

This study received approval from the Institutional Review Board (IRB) of Michigan State University. Additionally, we used photographs of real individuals who volunteered and provided written consent for their use. These photographs were incorporated into fictitious resumes created for our experiment, which aimed to test hiring discrimination by sending these resumes to employers. The consent letter template is included in the appendix.

## 1.5 Empirical Method

The outcome variable in this study is the binary response of receiving a callback for an interview or written test. To ensure comparability among candidates, we control individual characteristics such as college GPA, work experience, computer literacy, leadership/volunteer experience, training, language skills, and high school background. Job-level fixed effects were controlled to account for Job-level or employer-level heterogeneity.

For estimating the likelihood of receiving a callback, we employed a linear probability model to estimate the likelihood of getting a callback, as it is easy to interpret and equally valid for this analysis and sometimes a better alternative to logit estimation, especially when the posting fixed effects are included (Huang, 2022). In the first experiment, we utilize model I and model II to identify the discrimination, and in the second experiment, we employ model III to explore the source of discrimination.

The callback for a resume i, $y_i = \beta_0 + \beta_1 M_i + \beta_2 F_i + \beta_3 A_i + a_j + u_i$ (I)

Where $M_i$ is a dummy variable for high school background; 1 for Madrasah and 0 otherwise. $F_i$= 1 if female, 0 for male; $A_i$ is capturing whether the candidate has any religious symbol or attire, equal to 1 if a candidate has religious attire, zero otherwise. $a_j$ captures the job-level heterogeneity and $u_i$ is the error terms. Standard errors are clustered at the job level.

The hypothesis posits that candidates with a Madrasah high school background will likely receive fewer callbacks than candidates from general high schools, holding all other factors constant. $(\beta_1 < 0)$. Regarding gender discrimination, we expected that it would decrease over time in Bangladesh's labor markets, so $\beta_2$ could be zero or negative. However, there might be exceptions, with a possibility of a positive $\beta_2$ for NGOs and the media industry, which is perceived as women-friendly. The hypothesis for religious attire is negative $(\beta_3 < 0)$, particularly in the media industry.

The experiment is structured as an eight-armed treatment, with randomization occurring at three stages: high school, gender, and attire. The eight treatment groups are as follows: Madrasah-male-beard, Madrasah-male-no-beard, Madrasah-female-hijab, Madrasah-female-no-hijab, School-male-beard, School-male-no-beard, School-female-hijab, and School-female-no-hijab. Among all these groups, we choose the resume for a male candidate with a general high school background and no beard as the base category.

The second model aims to estimate the difference in callbacks for each treatment group compared to the base category. More specifically, the second model can be specified as below:

$$y_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + \beta_7 X_{7i} + a_j + u_i \qquad \text{(II)}$$

Where $y_i$ is the callback and $X_{1i}$ to $X_{7i}$ represents a dummy for the seven treatment groups. $X_{0i}$ is the base category which is not in the model. The estimated value of $\alpha$ implies the callback rates for the base category, and other estimator shows the difference of callbacks for a particular group compared to the base category.

Furthermore, analysis was conducted for both models on subsamples categorized by job characteristics, including distinctions such as entry-level or mid-level positions, high-paying or low-paying jobs, the level of client interactions, industry-wise breakdowns, and gender. This analysis allows us to explore the potential variations in discrimination patterns across job types, levels of pay, and gender.

In the second experiment, we introduce high-quality and low-quality resumes to investigate the source of discrimination (we explain it in detail in section 1.6.4). Moreover, we decided not to randomize based on religious attire for two reasons. First, introducing a new randomization based on resume quality necessitates increasing the number of resumes to sixteen to cover four levels of randomization. This increase is not feasible due to ethical concerns about sending numerous fictitious resumes to employers. Second, both religious high school background and religious attire indicate religious affiliation. Therefore, we chose to focus solely on high school background, which signifies religious affiliation in a less overt manner. The experimental design randomly assigns some observable productive attributes that employers usually get a signal for, such as higher college GPA, leadership experience, and other skills, in addition to randomizing at high school and gender levels. We include the interaction of a Madrasah high school background and high-quality resume in the model to examine the source of discrimination, whether the prevailing discrimination is statistical or taste based. Here is the model III:

The callback for a resume i, $y_i = \beta_0 + \beta_1 M_i + \beta_2 F_i + \beta_3 HQ_i + \delta M_i * HQ_i + u_i$ (III)

Where $HQ_i$ represents a high-quality resume. $\delta$ is the variable of interest, which is how callback varies with high-quality resumes for candidates with Madrasah high school backgrounds. A negative coefficient of $\delta$ will indicate that employers may have taste against candidates with a Madrasah high school background even when qualifications are similar.

## 1.6 Results

### 1.6.1 Summary Statistics of Jobs

After conducting our job search, a total of 3,248 resumes to 406 job positions in the first experiment were submitted, with each job receiving eight resumes. We exclude approximately 150 job postings that explicitly indicated a gender preference (i.e., some night-duty focused positions explicitly express their preference for only male candidates, or some receptionist positions prefer only females), focusing instead on job positions open to all applicants. The distribution of resumes across industries varied, with the media industry receiving the lowest number of resumes (560 resumes for 70 jobs) due to fewer job openings in that sector. NGO, corporate, and IT sectors had relatively higher openings than the media sector, and we submitted 960, 976, and 752 resumes to these sectors in the first experiment. In the second experiment, we sent 2512 and 2520 resumes to NGO and Corporate sectors, breaking 944 resumes to administrative jobs, 1192 to sales jobs, 1624 to management jobs, and 1272 to other jobs.

The overall callback rate for the submitted resumes is 9.36% and 10.75%, respectively, in the first and second experiments, consistent with other studies (Banerjee et al., 2009; Bertrand & Mullainathan, 2004). In the first experiment, among the different industries, the media industry had the highest callback rate at 12.5 percent, while the NGO sector had the lowest callback rate at 6.88 percent. Most job positions (73%) are located in the capital city, Dhaka. However, it is important to note that around 60% of the NGO jobs are located outside of Dhaka, which aligns with the nature of NGO work in rural areas. Regarding experience requirements, 32% of the positions are categorized as entry-level, requiring less than two years of work experience, while the remaining positions require mid-level experience of two to five years. The educational requirements vary across industries; more than half of the corporate and NGO jobs require a master's degree, while the IT and media industries accept applicants with an undergraduate degree. Approximately half of the jobs fall under the category of high client interaction. Detailed information about the job characteristics of the first experiment can be found in Appendix Table A 1.2a.

In the second experiment, the corporate sector has a 12.36% callback rate, whereas NGO jobs receive 9.16% of callbacks. 56% of jobs were located in Dhaka city. 47% of jobs are entry-level and require less than two years of experience, and the remaining 53% require two to five years of experience. 41% of jobs require a master's degree, whereas 38% of positions prefer specific majors. 49% of the positions are considered as high client interaction jobs. Detailed information about the job characteristics of the second experiment can be found in Appendix Table A 1.2b.

### 1.6.2 Average Callback Rates

All three panels of Table 1.1a provide insights into the average callback rates in the first experiment based on factors such as high school backgrounds, gender, and attire. In each panel, the lower section presents callback differentials across various industries. It is important to note that each employer received the same set of eight resumes with similar characteristics randomized at the high school, gender, and attire level.

Panel A of Table 1.1a reveals a significant differential in callbacks between candidates from general and Madrasah high school backgrounds, with Madrasah candidates experiencing a 40% lower callback rate overall. This disparity is even more pronounced among male candidates, as they need to apply for 96% more jobs than their counterparts with general high schools to receive similar callbacks, given that they all graduated from the University of Dhaka, majoring in similar disciplines. These findings highlight the considerable disadvantage faced by Madrasah candidates across industries. On the other hand, no significant difference is observed among female candidates from Madrasahs or general schools.

Panel B of Table 1.1a highlights the mean callback differences based on religious attire. Female candidates wearing hijabs did not experience any significant differences in callbacks. However, the disparity in callbacks for male candidates with and without a beard and cap is substantial, with male candidates with religious symbols (beards and caps) receiving 89% fewer callbacks. Notably, male candidates with Madrasah backgrounds who wore religious attire received fewer callbacks than their peers from general high school backgrounds. However, within the general high school group, there was a significant difference in callbacks for candidates with and without a beard. The media industry, followed by the corporate sector, exhibited the highest bias against candidates with religious attire. Candidates wearing religious attire had to apply to

69% more jobs to receive a callback than those without religious attire in the media industry. On the other hand, no significant differences were observed in callbacks based on religious attire for NGO and IT jobs.

Panel C of Table 1.1a provides insights into the mean callback differences based on gender. On average, female candidates receive higher callbacks compared to male candidates. Female candidates experience significantly higher callback rates in NGO jobs, indicating a favorable response from employers in this sector. However, female candidates receive slightly fewer callbacks in the media industry, although the difference is not statistically significant. Notably, male candidates from Madrasah backgrounds receive significantly lower callbacks than their female counterparts. In contrast, there is no significant difference in callback rates between male and female candidates from general high school backgrounds.

Table 1.1b shows the average callback differences in the second experiment based on high school, resume quality, and gender in panels A, B, and C, respectively. Panel A shows that candidates with a Madrasah high school background receive fewer callbacks than candidates with general high school backgrounds, irrespective of industry or job categories. Male candidates face higher discrimination compared to female candidates. The differences become wider for the high-quality resume than the differences between the two high school groups in the case of low-quality resumes. Panel B shows the callback differential between high- and low-quality resumes. High-quality resumes receive more callbacks. High-quality female resumes receive twice as many callbacks as low-quality female resumes, while the increase for males is 44 percent. A similar pattern is observed for resumes from general versus Madrasah high schools. The difference between high- and low-quality resumes is more pronounced for candidates with a general high school background, while Madrasah candidates, regardless of the resume quality, do not attract as much employer interest. Panel C indicates that callback rates are similar for male and female candidates overall. However, male candidates from general high schools receive more callbacks compared to their female counterparts. Conversely, female candidates with Madrasah high school backgrounds are favored over males.

### 1.6.3 Effects of High School, Gender, and Attire on Callback

Table 1.2 exhibits the regression results of the likelihood of receiving a callback, controlling for firm-level heterogeneity using job-fixed effects. Column (1) shows the results for the total sample, while columns (2) to (5) present industry-wise results. The coefficients for Madrasah candidates are consistently negative and statistically significant across all columns, indicating a lower likelihood of receiving a callback for candidates from Madrasah backgrounds. The coefficient for the religious attire variable reveals that the media sector exhibits the highest discrimination against candidates wearing hijabs or having a beard. In contrast, the IT sector shows a significant positive coefficient for candidates with religious attire. Among female candidates, only those applying to NGO jobs receive a statistically significant five-percentage-point increase in callbacks. The coefficient plot in panel A of Figure 1.1 visualizes these findings.

Table 1.3 focuses on the likelihood of a callback based on different job categories. Columns (1) and (2) show the likelihood of callback differential based on the level of client interaction- high vs. low. In both cases, coefficients for the Madrasah variable are negative, indicating lower callback rates than their general school counterparts. The coefficient for religious attire is insignificant for low-interaction jobs while significantly negative for high-interaction jobs, suggesting that employers have a preference against candidates with religious attire in positions that require direct customer dealings. Female candidates are preferred for high client-interaction jobs, while the coefficient is insignificant for low-interaction jobs. The coefficient plot in panel B of Figure 1.1 visualizes these results.

Columns (3) and (4) of Table 1.3 examine the regression results for high-paying and low-paying jobs, respectively, with panel C of Figure 1.1 displaying the corresponding coefficient plot. The coefficients for Madrasah candidates are negative and statistically significant in both cases, indicating a lower likelihood of receiving a callback for candidates from Madrasah backgrounds. Columns (5) and (6) of Table 1.3 investigate the impact of Madrasah, gender, and attire on entry-level and mid-level jobs, and panel D of Figure 1.1 presents the coefficient plot. The coefficients for Madrasah candidates are negative and significant across both job levels. Regarding religious attire, candidates receive fewer callbacks in mid-level jobs. Female candidates receive nearly a six-percentage-point increase in callbacks for low-paying jobs, suggesting a positive bias towards female candidates in this category, consistent with the findings of (Bidisha, Faruk, and Mahmood, 2022).

Table 1.4 presents the regression results for Model II, which includes the eight treatment arms. The base category is the male candidate with a general high school background and having no religious attire serves as the base category. The constant term in the regression table represents the callback rate for the base category, while the seven other coefficients indicate the differences in callbacks for each treatment arm compared to the base category. Column (1) displays the results for the total sample, and columns (2) to (5) provide industry-wise results.

The base category receives a callback rate of 16%. The base category receives the highest preference in the job market. It allows us to break down the discrimination between groups. Treatment Group 1, which differs from the base category by having religious attire only, experiences a significant decrease of 9.9 percentage points compared to the base category. The base category receives the highest callback rate in the media industry, at 32.9%. The media industry exhibits discrimination against nearly all other treatment groups, with the highest discrimination observed against male candidates with religious attire. Although we find no significant gender-based discrimination in model I, model II unearths the gender discrimination issue. Female candidates from general schools with no religious attire receive 7.1 percentage points lower callbacks than their male counterparts from general schools with no religious attire. Female candidates in the media industry also face significant discrimination, with callback rates 24 percentage points lower than the base category. However, the NGO sector generally shows non-discriminatory behavior, except for candidates from Madrasah backgrounds. To unlock the mystery of gender-based discrimination, we investigate gender discrimination by splitting the sample into subsamples in Table 1.5. The findings reveal gender-based discrimination against women when comparing two similar groups from general high school backgrounds without any religious signals. Model I shows no significant overall discrimination against women because women with religious signals, such as a religious high school background or religious attire, receive preference over those without any religious signals. Female candidates from Madrasah backgrounds still receive fewer callbacks than those from general schools if they wear religious attire. It indicates discrimination based on Madrasah high school background for both male and female candidates, with a higher extent for male candidates. However, women wearing hijabs are preferred by some employers over those without hijabs, while men experience substantial discrimination for having religious attire. One explanation for this could be that a hijab or headscarf has become normalized or preferred attire for female employees, while a beard and cap for male employees have not.

### 1.6.4 Test for the Type of Discrimination

Two workhorse models of labor market discrimination are taste-based and statistical. Taste-based discrimination occurs when employers hold prejudices or stereotypes about specific groups, leading to biased treatment. This form of discrimination is rooted in irrational preferences or biases unrelated to productivity (Becker, 1971). It can stem directly from employers' animosity towards a particular group or may be influenced by existing employees or customers who may be uncomfortable interacting with specific groups. On the other hand, statistical discrimination arises when groups differ in their distribution of productive characteristics. Employers make predictions about a candidate's productivity based on average characteristics associated with the candidate's identity, aiming to minimize adverse selection due to imperfect information about individual-level characteristics (Arrow, 1973; Phelps, 1972).

In the first experiment, we estimate $\gamma$ from this equation, $C_i(B) = \alpha + \gamma B_i + u_i$ , where $\gamma$ signifies the discrimination, the significant and negative value of $\gamma$ implies discrimination against candidates with Madrasah high school backgrounds, $B = 1$. However, $\gamma$ does not confirm the source of discrimination, whether the bias against candidates with a Madrasah high school background is taste-based or statistical. Taste or prejudice-based discrimination usually does not vary with the candidates' observable characteristics. It persists at all levels as the biases are deeply ingrained and influenced by various factors unrelated to productivity.

On the other hand, since incomplete information about productive characteristics leads to statistical discrimination, signals of higher productivity through observable attributes might mitigate this type of discrimination. To distinguish the high-category resume from the low-category resume, we use a high GPA, high voluntary and leadership experience, training, and skills as a proxy for a higher productivity signal in the high-quality resume. We implement a second correspondence experiment with a hypothesis that if the existing discrimination is statistical, it should be lessened for high-quality resumes. Interaction terms of high school background and high-quality resume signify how the callback rate changes with high-quality resumes for different high school background groups.

Table 1.6 and Table 1.7 present the results from the second experiment of the study with the interaction of Madrasah High School and high-quality resumes included in the regression. Tables 1.6 and 1.7 illustrate the likelihood of a callback disaggregating sample industry-wise job category-wise based on job types considering the level of interaction, level of pay, and experience requirement. In contrast, Table 1.8 shows the likelihood of a callback disaggregating data based on resume quality. Tables 1.6 and 1.7 show that candidates with Madrasah backgrounds receive lower callbacks than the general high school group, high-quality resumes are preferred over low-quality resumes, and there is no significant gender-based discrimination overall except for management jobs. Table 1.8 shows that the callback differential increases for high-quality resumes with higher perceived productive characteristics. The negative coefficient for the interaction term in Tables 1.6 and 1.7 indicates that higher resume quality does not reduce the discrimination against candidates with a Madrasah high school background. This finding is inconsistent with the theory of statistical discrimination, suggesting that the existing discrimination in the Bangladeshi labor market is based on taste or prejudice.

## 1.7 Conclusion and Policy Implications

Discrimination in hiring has far-reaching implications for individuals and businesses, undermining meritocracy and perpetuating inequality. The correspondence studies provide compelling evidence of discrimination during the hiring process. Discrimination can also happen in other stages of employment, such as promotion, job allocation, compensation, performance evaluation, promotions, and dismissal, which might be higher than the initial screening stage. However, investigating discrimination in those stages is beyond the purview of correspondence study. The two experiments this study utilizes to investigate labor market discrimination in Bangladesh reveal significant discrimination based on candidates' high school backgrounds, gender, and attire preferences. The first experiment reveals that differential treatment exists in the labor market of Bangladesh, with males encountering a higher degree of discrimination for having a Madrasah high school background or religious attire. The second experiment shows that discrimination based on the type of high school institution a candidate attended is substantial even after adding higher perceived productive characteristics and callback differential increase for high-quality resumes. It indicates that observed labor market discrimination against candidates with Madrasah high school backgrounds lies in taste-based biases. However, there are some limitations to using correspondence experiments to investigate labor market discrimination. This method can only detect discrimination during the initial selection process, not in subsequent stages such as work assignments, performance evaluations, promotions, or dismissals. Additionally, this study cannot control the individual employees involved in the primary hiring decisions. As a result, it does not definitively determine whether the observed discrimination is due to the employer as a whole or a specific human resource manager.

The findings of this study shed light on the importance of addressing discriminatory practices in the early stages of recruitment. Policymakers can leverage these insights to develop targeted interventions to eliminate biases in the labor market. One potential approach could involve removing demographic information and high school diplomas from resumes and discouraging the inclusion of photographs for college graduates to address the biases in the primary screening process. Such measures can help reduce selection bias and promote a fairer, more inclusive hiring environment.

By combatting labor market discrimination, policymakers can create a more equitable society where individuals are judged based on their skills, qualifications, and potential rather than extraneous factors. The findings of this study serve as a call to action for policymakers, employers, and other stakeholders to work collaboratively toward eradicating discrimination and ensuring equal opportunities for all individuals in the labor market.

## TABLES AND FIGURES OF CHAPTER ONE

Table 1.1a: Mean callback rates based on school type, attire, and gender (Experiment #1)

| | N | All | General | Religious | Ratio | difference | p-value |
|---|---|---|---|---|---|---|---|
| **Panel A: School** | | | | | | | |
| Total Sample | 3248 | 0.094 | 0.109 | 0.078 | 1.40 | 0.031 | 0.00 |
| Female | 1624 | 0.103 | 0.107 | 0.100 | 1.07 | 0.008 | 0.63 |
| Male | 1624 | 0.084 | 0.111 | 0.057 | 1.96 | 0.054 | 0.00 |
| Male with no beard | 812 | 0.110 | 0.160 | 0.059 | 2.71 | 0.101 | 0.00 |
| Male with Beard | 812 | 0.058 | 0.062 | 0.054 | 1.14 | 0.008 | 0.65 |
| Female with no hijab | 812 | 0.092 | 0.089 | 0.096 | 0.92 | -0.008 | 0.72 |
| Female with hijab | 812 | 0.115 | 0.126 | 0.104 | 1.21 | 0.022 | 0.32 |
| NGO | 960 | 0.069 | 0.079 | 0.059 | 1.35 | 0.021 | 0.20 |
| Corporate | 976 | 0.096 | 0.115 | 0.078 | 1.47 | 0.037 | 0.05 |
| Media | 560 | 0.125 | 0.143 | 0.107 | 1.34 | 0.036 | 0.20 |
| IT | 752 | 0.098 | 0.115 | 0.083 | 1.39 | 0.032 | 0.14 |
| **Panel B: Attire** | N | All | Regular | Religious | Ratio | difference | p-value |
| Total Sample | 3248 | 0.094 | 0.101 | 0.086 | 1.17 | 0.015 | 0.15 |
| Female | 1624 | 0.103 | 0.093 | 0.115 | 0.81 | -0.022 | 0.14 |
| Male | 1624 | 0.084 | 0.110 | 0.058 | 1.89 | 0.052 | 0.00 |
| General School | 1624 | 0.109 | 0.125 | 0.094 | 1.33 | 0.031 | 0.05 |
| Madrasah | 1624 | 0.078 | 0.078 | 0.079 | 0.98 | -0.001 | 0.93 |
| NGO | 960 | 0.069 | 0.069 | 0.069 | 1.00 | 0.000 | 1.00 |
| Corporate | 976 | 0.096 | 0.117 | 0.076 | 1.54 | 0.041 | 0.03 |
| Media | 560 | 0.125 | 0.157 | 0.093 | 1.69 | 0.065 | 0.02 |
| IT | 752 | 0.098 | 0.080 | 0.117 | 0.68 | -0.037 | 0.09 |
| **Panel C: Gender** | N | All | Male | Female | Ratio | difference | p-value |
| Total Sample | 3248 | 0.094 | 0.084 | 0.104 | 0.81 | -0.020 | 0.05 |
| General School | 1624 | 0.109 | 0.111 | 0.107 | 1.04 | 0.004 | 0.81 |
| Madrasah | 1624 | 0.078 | 0.057 | 0.100 | 0.57 | -0.043 | 0.00 |
| NGO | 960 | 0.069 | 0.042 | 0.096 | 0.43 | -0.054 | 0.00 |
| Corporate | 976 | 0.096 | 0.092 | 0.101 | 0.92 | -0.008 | 0.66 |
| Media | 560 | 0.125 | 0.129 | 0.122 | 1.06 | 0.007 | 0.80 |
| IT | 752 | 0.098 | 0.093 | 0.104 | 0.90 | -0.011 | 0.63 |

Source: Authors, based on experimental data. The p-value indicates the significance level of the callback difference between the two groups.

Table 1.1b: Mean callback rates based on school type, resume quality, and gender (Experiment #2)

| | N | All | General | Religious | Ratio | difference | p-value |
|---|---|---|---|---|---|---|---|
| **Panel A: School** | | | | | | | |
| Total Sample | 5032 | 0.108 | 0.120 | 0.096 | 1.25 | 0.024 | 0.010 |
| Female | 2516 | 0.105 | 0.113 | 0.097 | 1.16 | 0.016 | 0.190 |
| Male | 2516 | 0.110 | 0.127 | 0.094 | 1.35 | 0.033 | 0.010 |
| High-Quality CV | 2516 | 0.131 | 0.149 | 0.114 | 1.31 | 0.035 | 0.010 |
| Low-Quality CV | 2516 | 0.084 | 0.091 | 0.077 | 1.18 | 0.014 | 0.220 |
| NGO | 2512 | 0.092 | 0.104 | 0.080 | 1.30 | 0.024 | 0.040 |
| Corporate | 2520 | 0.123 | 0.136 | 0.111 | 1.22 | 0.025 | 0.060 |
| Administrative | 944 | 0.094 | 0.104 | 0.085 | 1.23 | 0.020 | 0.320 |
| Sales | 1192 | 0.111 | 0.126 | 0.096 | 1.32 | 0.031 | 0.100 |
| Management | 1624 | 0.108 | 0.125 | 0.093 | 1.35 | 0.032 | 0.040 |
| Others Job | 1272 | 0.113 | 0.120 | 0.107 | 1.12 | 0.013 | 0.480 |
| **Panel B: CV Quality** | N | All | High | Low | Ratio | difference | p-value |
| Total Sample | 5032 | 0.108 | 0.131 | 0.084 | 1.63 | 0.047 | 0.000 |
| Female | 2516 | 0.105 | 0.140 | 0.070 | 2.00 | 0.070 | 0.000 |
| Male | 2516 | 0.110 | 0.130 | 0.090 | 1.44 | 0.040 | 0.010 |
| General School | 2516 | 0.12 | 0.149 | 0.091 | 1.67 | 0.058 | 0.000 |
| Madrasah | 2516 | 0.10 | 0.114 | 0.077 | 1.38 | 0.037 | 0.000 |
| NGO | 2512 | 0.092 | 0.120 | 0.070 | 1.71 | 0.050 | 0.000 |
| Corporate | 2520 | 0.123 | 0.150 | 0.100 | 1.50 | 0.050 | 0.000 |
| Administrative | 944 | 0.094 | 0.110 | 0.080 | 1.38 | 0.030 | 0.150 |
| Sales | 1192 | 0.111 | 0.140 | 0.080 | 1.75 | 0.060 | 0.000 |
| Management | 1624 | 0.108 | 0.140 | 0.080 | 1.75 | 0.060 | 0.000 |
| Others Job | 1272 | 0.113 | 0.120 | 0.100 | 1.20 | 0.020 | 0.220 |
| **Panel C: Gender** | N | All | Male | Female | Ratio | difference | p-value |
| Total Sample | 5032 | 0.108 | 0.110 | 0.105 | 1.10 | 0.005 | 0.550 |
| General School | 2516 | 0.12 | 0.127 | 0.113 | 1.18 | 0.014 | 0.300 |
| Madrasah | 2516 | 0.10 | 0.094 | 0.097 | 0.90 | -0.007 | 0.790 |
| NGO | 2512 | 0.092 | 0.100 | 0.090 | 1.11 | 0.010 | 0.330 |
| Corporate | 2520 | 0.123 | 0.120 | 0.120 | 1.00 | 0.000 | 0.950 |
| Administrative | 944 | 0.094 | 0.080 | 0.110 | 0.73 | -0.030 | 0.150 |
| Sales | 1192 | 0.111 | 0.110 | 0.110 | 1.00 | -0.010 | 0.710 |
| Management | 1624 | 0.108 | 0.120 | 0.100 | 1.20 | 0.030 | 0.080 |
| Others Job | 1272 | 0.113 | 0.120 | 0.110 | 1.09 | 0.010 | 0.480 |

Note: The p-value indicates the level of significance of the callback difference between the two groups.

Table 1.2: Likelihood of receiving a callback- overall and by sector of employment (Experiment #1)

| | Total Sample | Corporate | IT | Media | NGO |
|---|---|---|---|---|---|
| Madrasah (α) | -.031*** | -.037*** | -.032* | -.036* | -.021** |
| | (.007) | (.013) | (.018) | (.021) | (.008) |
| Religious Attire (β) | -.015* | -.041*** | .037** | -.064** | 0 |
| | (.008) | (.012) | (.018) | (.025) | (.01) |
| Female (γ) | .02 | .008 | .011 | -.007 | .054** |
| | (.016) | (.029) | (.034) | (.04) | (.027) |
| Constant | .107*** | .131*** | .09*** | .179*** | .052*** |
| | (.01) | (.018) | (.024) | (.032) | (.015) |
| N | 3248 | 976 | 752 | 560 | 960 |
| R-squared | .352 | .4 | .336 | .249 | .419 |
| Job FE | Yes | Yes | Yes | Yes | Yes |
| Test for α=β (p-value) | 0.0001 | 0.0405 | 0.0004 | 0.0369 | 0.0155 |

*Note:* The dependent variable- callback is a binary variable with outcome {0,1}, and all regressions include job-fixed effects. Standard errors are in parenthesis and clustered at the job level. *, **, and *** denote statistically significant at 10%, 5%, and 1%.

Table 1.3: Likelihood of a callback for different job categories (Experiment #1)

| | Level of interaction | | Level of pay | | Experience required | |
|---|---|---|---|---|---|---|
| | High | Low | High | Low | Entry | Mid-level |
| Madrasah (α) | -.041*** | -.021** | -.022** | -.038*** | -.029** | -.031*** |
| | (.009) | (.01) | (.009) | (.011) | (.013) | (.008) |
| Religious Attire ((β) | -.039*** | .007 | -.015 | -.015 | .002 | -.022** |
| | (.011) | (.011) | (.009) | (.012) | (.016) | (.009) |
| Female (γ) | .044* | -.002 | -.025 | .059** | .026 | .017 |
| | (.022) | (.022) | (.02) | (.024) | (.03) | (.018) |
| Constant | .107*** | .106*** | .097*** | .115*** | .109*** | .105*** |
| | (.014) | (.016) | (.013) | (.016) | (.02) | (.012) |
| N | 1552 | 1696 | 1512 | 1736 | 1024 | 2224 |
| R-squared | .358 | .354 | .366 | .345 | .358 | .348 |
| Job FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Test for α=β (p-value) | 0.0000 | 0.0840 | 0.0384 | 0.0007 | 0.0777 | 0.0005 |

Note: The dependent variable- callback is a binary variable with outcome {0,1}. Standard errors are in parenthesis and clustered at the job level. *, **, and *** denote statistically significant at 10%, 5%, and 1%.

Table 1.4: Likelihood of a callback: regression results with job fixed effects (Experiment #1)

| | Total Sample | Corporate | IT | Media | NGO |
|---|---|---|---|---|---|
| School Male Beard | -.099*** | -.09*** | -.064** | -.3*** | -.017 |
| | (.016) | (.026) | (.03) | (.056) | (.021) |
| School Female No Hijab | -.071*** | -.074* | -.085** | -.243*** | .042 |
| | (.022) | (.041) | (.042) | (.063) | (.034) |
| School Female Hijab | -.034 | -.066 | .011 | -.2*** | .058 |
| | (.023) | (.042) | (.047) | (.07) | (.036) |
| Madrasah Male No Beard | -.101*** | -.107*** | -.096*** | -.229*** | -.025* |
| | (.015) | (.028) | (.031) | (.051) | (.014) |
| Madrasah Male Beard | -.106*** | -.123*** | -.064** | -.271*** | -.025 |
| | (.016) | (.03) | (.03) | (.058) | (.019) |
| Madrasah Female No Hijab | -.064*** | -.041 | -.096** | -.214*** | .025 |
| | (.022) | (.043) | (.043) | (.068) | (.032) |
| Madrasah Female Hijab | -.057** | -.107*** | -.011 | -.171** | .025 |
| | (.023) | (.037) | (.052) | (.071) | (.032) |
| Constant | .16*** | .172*** | .149*** | .329*** | .058*** |
| | (.015) | (.026) | (.028) | (.048) | (.02) |
| N | 3248 | 976 | 752 | 560 | 960 |
| R-squared | .361 | .407 | .348 | .304 | .42 |
| Job FE | Yes | Yes | Yes | Yes | Yes |

Note**:** Standard errors are in parenthesis and clustered at the job level. The dependent variable callback is a binary variable with outcome {0,1}. A male candidate with no beard from general school is the base category. *, **, and *** denote statistically significant at 10%, 5%, and 1%.

Table 1.5: Likelihood of a callback: regression results with job fixed effects (Experiment #1)

| | Total Sample | Corporate | IT | Media | NGO |
|---|---|---|---|---|---|
| Panel A | CVs with Gen. high school background, no religious attire | | | | |
| Female | -.072*** | .042 | -.074* | -.243*** | -.086** |
| | (.022) | (.034) | (.041) | (.063) | (.042) |
| Constant | .16*** | .058*** | .172*** | .329*** | .15*** |
| | (.011) | (.017) | (.02) | (.031) | (.021) |
| N | 811 | 240 | 244 | 140 | 187 |
| R-squared | .554 | .52 | .574 | .59 | .571 |
| Job FE | Yes | Yes | Yes | Yes | Yes |
| Panel B | CVs with general high school background and religious attire | | | | |
| Female | .064*** | .075** | .025 | .1** | .075 |
| | (.02) | (.034) | (.038) | (.046) | (.049) |
| Constant | .062*** | .042** | .082*** | .029 | .085*** |
| | (.01) | (.017) | (.019) | (.023) | (.025) |
| N | 811 | 240 | 244 | 140 | 187 |
| R-squared | .504 | .533 | .498 | .492 | .492 |
| Job FE | Yes | Yes | Yes | Yes | Yes |
| Panel C | CVs with Madrasah high school background, no religious attire | | | | |
| Female | .037** | .05* | .066* | .014 | 0 |
| | (.018) | (.029) | (.036) | (.052) | (.031) |
| Constant | .059*** | .033** | .066*** | .1*** | .053*** |
| | (.009) | (.014) | (.018) | (.026) | (.015) |
| N | 811 | 240 | 244 | 140 | 187 |
| R-squared | .549 | .556 | .55 | .515 | .577 |
| Job FE | Yes | Yes | Yes | Yes | Yes |
| Panel D | CVs with Madrasah high school background, religious attire | | | | |
| Female | .049*** | .05* | .016 | .1* | .054 |
| | (.018) | (.029) | (.029) | (.051) | (.044) |
| Constant | .054*** | .033** | .049*** | .057** | .085*** |
| | (.009) | (.014) | (.014) | (.025) | (.022) |
| N | 811 | 240 | 244 | 140 | 187 |
| R-squared | .55 | .556 | .547 | .541 | .551 |
| Job FE | Yes | Yes | Yes | Yes | Yes |
| Panel E | CVs of female candidates with religious attire | | | | |
| Madrasah | -.022 | -.033 | -.041 | .029 | -.021 |
| | (.015) | (.024) | (.027) | (.046) | (.026) |
| Constant | .126*** | .117*** | .107*** | .129*** | .16*** |
| | (.007) | (.012) | (.014) | (.023) | (.013) |
| N | 812 | 240 | 244 | 140 | 188 |
| R-squared | .789 | .818 | .719 | .71 | .875 |
| Job FE | Yes | Yes | Yes | Yes | Yes |

Note: Standard errors are in parenthesis and clustered at the job level. The dependent variable callback is a binary variable with outcome {0,1}. *, **, and *** denote statistically significant at 10%, 5%, and 1%.

Table 1.6: Likelihood of a callback with high and low-quality resumes (Experiment #2)

| | Total Sample | Industry | | Job Category | | | |
|---|---|---|---|---|---|---|---|
| | | Corporate | NGO | Admin | Sales | Management | Others |
| Madrasah | -.014** | -.016* | -.011 | -.025* | -.02** | -.015 | .003 |
| | (.006) | (.008) | (.007) | (.013) | (.008) | (.01) | (.012) |
| High Quality CV | .058*** | .056*** | .061*** | .021 | .077*** | .081*** | .038** |
| | (.009) | (.014) | (.013) | (.019) | (.019) | (.018) | (.019) |
| Female | -.005 | .001 | -.011 | .028 | .007 | -.027* | -.013 |
| | (.01) | (.014) | (.014) | (.022) | (.018) | (.016) | (.024) |
| Madrasah*HighCV | -.021*** | -.017 | -.025** | .013 | -.02 | -.034** | -.031* |
| | (.008) | (.012) | (.011) | (.014) | (.015) | (.017) | (.017) |
| Constant | .093*** | .108*** | .079*** | .079*** | .084*** | .097*** | .107*** |
| | (.007) | (.011) | (.009) | (.015) | (.014) | (.011) | (.017) |
| N | 5032 | 2520 | 2512 | 944 | 1192 | 1624 | 1272 |
| R-squared | .535 | .561 | .499 | .57 | .567 | .53 | .498 |
| Job FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Note: Standard errors are in parentheses* and clustered at the job level. **** p<.01, ** p<.05, * p<.1*

Table 1.7: Likelihood of a callback based on job categories with high- and low-quality resumes (Experiment #2)

| | Level of Interaction | | Level of Pay | | Experience Required | |
|---|---|---|---|---|---|---|
| | High | Low | High | Low | Entry | Midlevel |
| Madrasah | -.019*** | -.008 | -.017** | -.01 | -.014 | -.013* |
| | (.007) | (.008) | (.009) | (.007) | (.008) | (.007) |
| High Quality CV | .058*** | .058*** | .067*** | .05*** | .051*** | .064*** |
| | (.013) | (.014) | (.014) | (.013) | (.014) | (.013) |
| Female | -.007 | -.003 | .004 | -.013 | -.016 | .004 |
| | (.015) | (.013) | (.013) | (.015) | (.015) | (.013) |
| Madrasah*HighCV | -.015 | -.028** | -.022** | -.021* | -.036*** | -.009 |
| | (.011) | (.012) | (.011) | (.012) | (.013) | (.01) |
| Constant | .102*** | .085*** | .077*** | .107*** | .115*** | .074*** |
| | (.011) | (.009) | (.01) | (.01) | (.011) | (.009) |
| N | 2480 | 2552 | 2328 | 2704 | 2360 | 2672 |
| R-squared | .552 | .516 | .541 | .53 | .553 | .517 |
| Job FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Note: Standard errors are in parentheses* and clustered at the job level. *** *p<.01*, ** *p<.05*, * *p<.1*

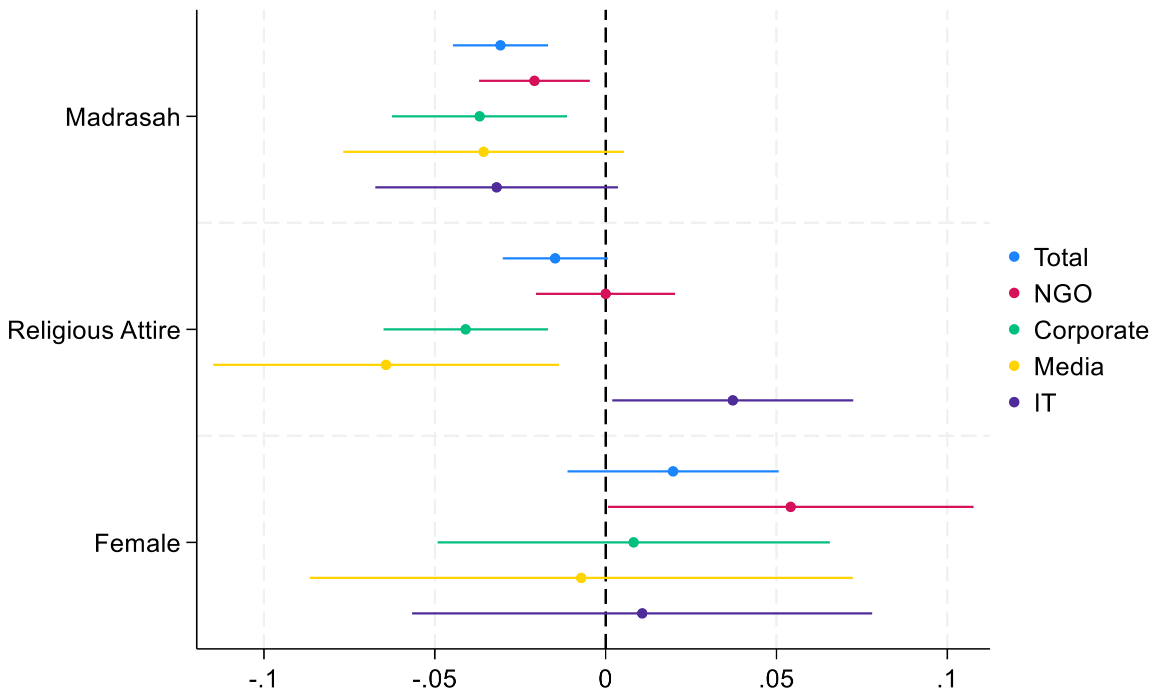
Table 1.8: Likelihood of a callback based on high- and low-quality resumes (Experiment #2)

| | Total Sample | Resume Quality | |
|---|---|---|---|
| | | Low | High |
| Madrasah | -.024*** | -.014** | -.035*** |
| | (.006) | (.006) | (.009) |
| Female | -.005 | -.018 | .008 |
| | (.011) | (.012) | (.015) |
| Constant | .122*** | .1*** | .145*** |
| | (.006) | (.007) | (.009) |
| N | 5032 | 2516 | 2516 |
| R-squared | .529 | .641 | .635 |
| Job FE | Yes | Yes | Yes |

*Note: Standard errors are in parentheses* and clustered at the job level. **** p<.01, ** p<.05, * p<.1*

Figure 1.1: Coefficient plots for Model I: Discrimination across industries and job categories

Panel A: Total sample and industry-wise




Panel B: Level of client interaction

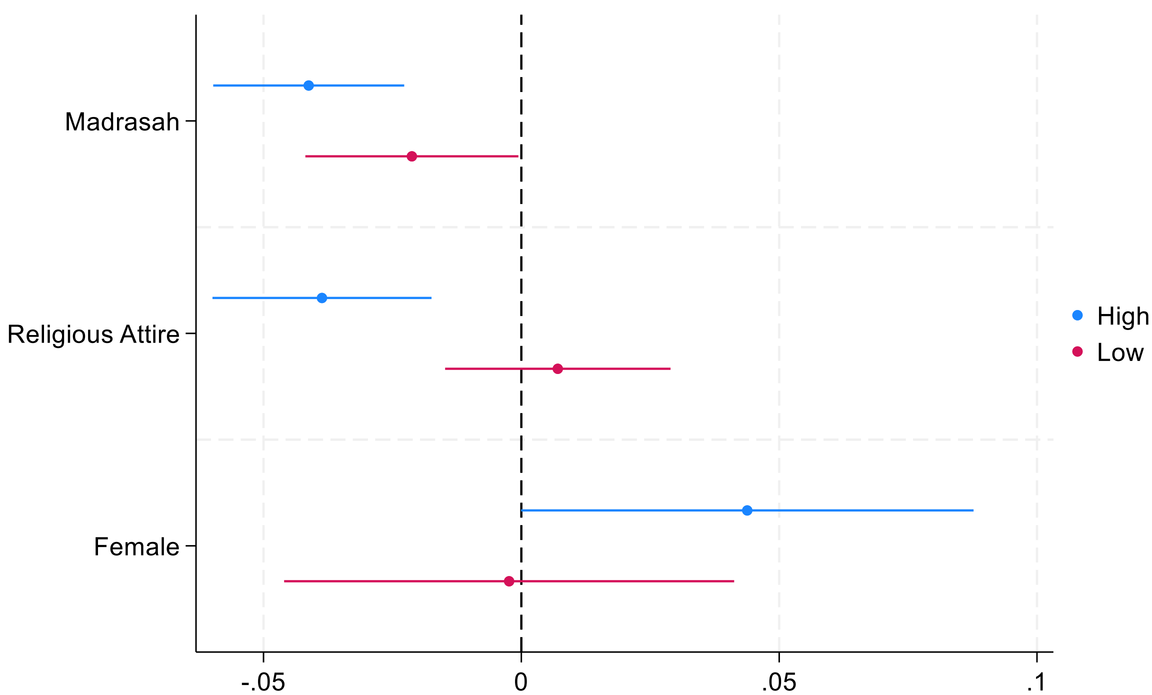
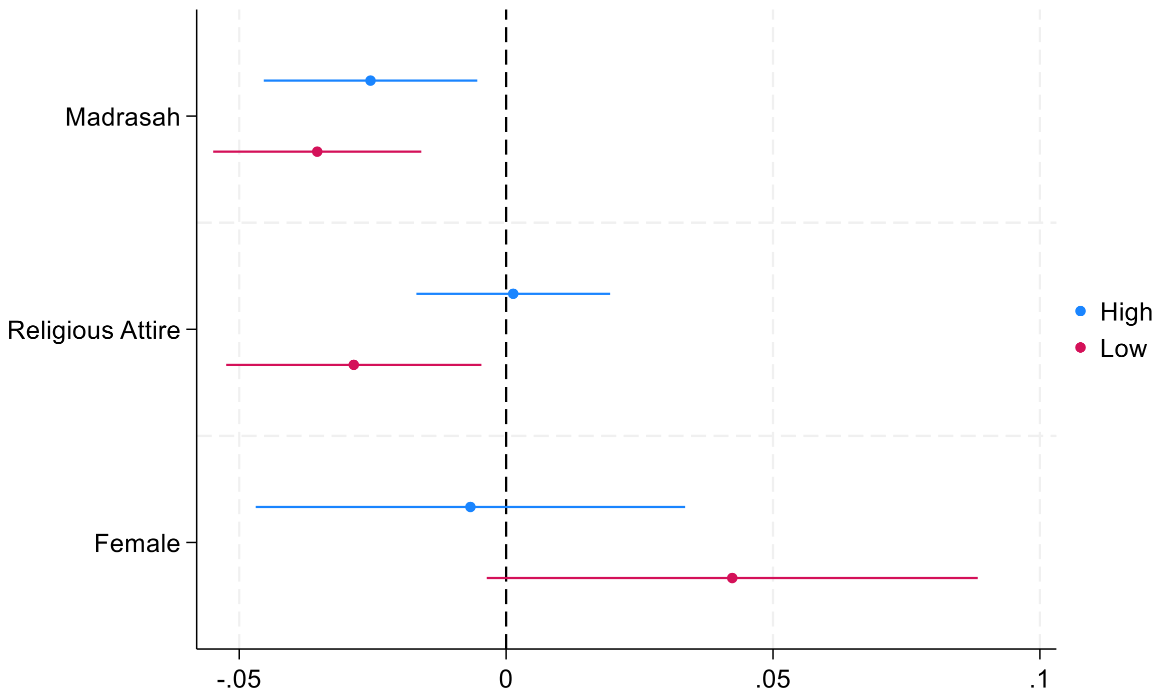
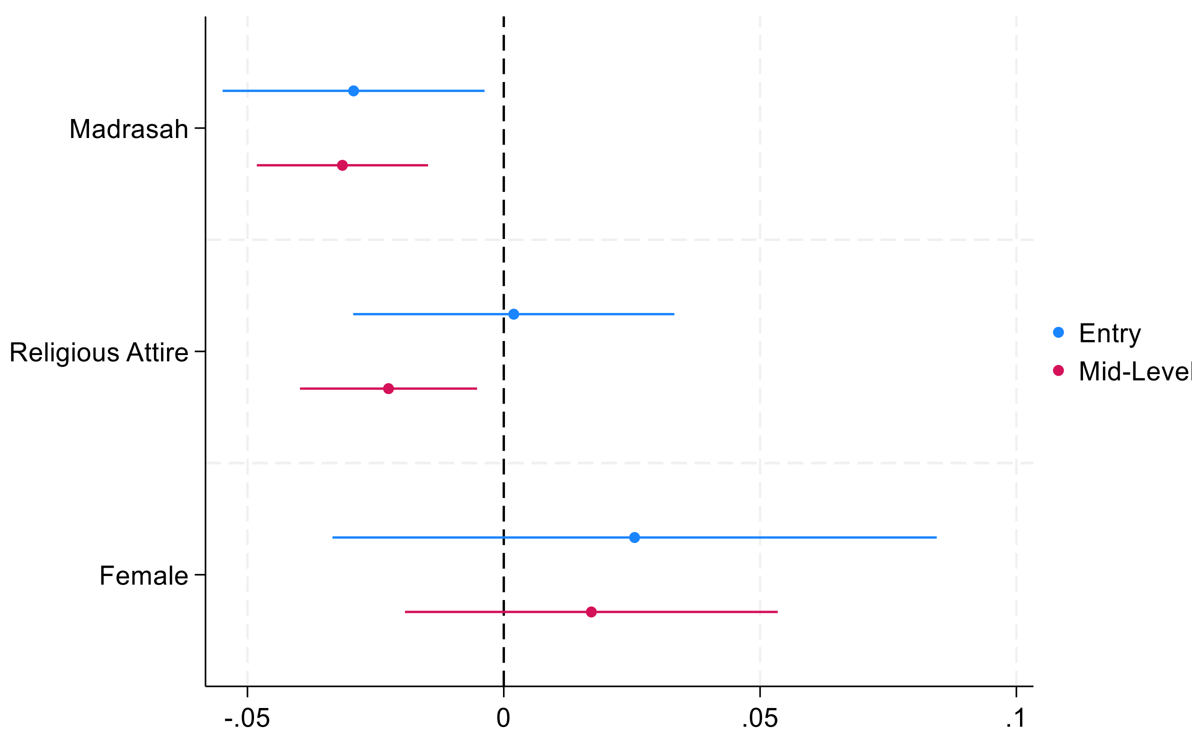


Figure 1.1 (cont'd)

Panel C: Level of Pay




Panel D: Based on experience-required



CHAPTER 2
INPUT SUBSIDIES AND CROP DIVERSITY ON FAMILY FARMS IN BURKINA FASO

## 2.1 Introduction

In developing agricultural economies, the increasing use of modern inputs, such as chemical fertilizer, has been associated with higher agricultural productivity, especially when combined with improved seed varieties and/or adequate provision of moisture through irrigation infrastructure (Erisman et al., 2008; Morris et al., 2007; Smil, 2002). Historically, as a reflection of infrastructural impediments, such as sparse road networks and distance from ports, farmers in Sub-Saharan Africa have used fertilizer at substantially lower rates than farmers in Asia and Latin America (Heisey & Norton, 2007). Although average fertilizer usage in Sub-Saharan Africa grew by 8% annually in the early 2000s (Ariga et al., 2019) and almost doubled from 2008 (12 kg/hectare) to 2018 (20 kg/hectare), use rates are still well below the international average of 136 kg/hectare (AFAP, 2020; World Bank, 2019).

Increasing the use of modern inputs has been a policy aim in many countries of Sub-Saharan Africa since their independence. Low fertilizer use has been considered a key contributing factor to lagging agricultural productivity growth in Sub-Saharan Africa (Morris et al., 2007). High fertilizer prices, often reflecting substantial transport costs in landlocked countries such as Burkina Faso, and limited access to credit are key reasons for low fertilizer use (Gro Intelligence, 2016; Morris et al., 2007). The first generation of government-managed subsidy programs resulted in unsustainable fiscal burdens dismantled during the 1990s as part of the World Bank's structural adjustment programs. However, since the Abuja Declaration on Fertilizer in 2006, "smart" input subsidies have proliferated in Sub-Saharan Africa (Jayne et al., 2018). From 2007 to 2012, many Sub-Saharan African countries (e.g., Burkina Faso, Ethiopia, Ghana, Kenya, Mali, Malawi, Nigeria, Tanzania, Zambia) introduced fertilizer subsidy programs, and some other countries introduced subsidized credit for fertilizer (e.g., Rwanda) (FAO, 2019).

In 2008, Burkina Faso launched a fertilizer subsidy program to increase farm output and income and improve food availability. Although this subsidy is universal in the sense that it does not target any specific group of beneficiaries, it primarily targets rice, maize, and cotton crops because of their importance to the agricultural economy (S. H. Haider, 2018; M. V. T. Smale & Thériault, 2019; Wanzala-Mlobela et al., 2013). Eligible farms cultivating target crops can access subsidized fertilizer proportional to the hectares of land they anticipate devoting to the crop (Wanzala-Mlobela, Fuentes, and Mkumbwa, 2013). In addition to the fertilizer subsidy program, the government of Burkina Faso introduced a seed subsidy program for cowpeas in 2014 (Ministère de l'Agriculture et de la Sécurité Alimentaire, 2014). Besides cereals, cowpea is an important crop in Burkina Faso because it provides essential nutrients, fixes nitrogen, matures quickly, and generates cash in local markets.

While previous studies of the impact of input subsidies have investigated either the impact of fertilizer or seed subsidy on the land allocation among targeted or non-targeted crops, few have examined the effects of both subsidies combined. Several investigated the impact of both fertilizer and seed subsidies but focused on the target crop (i.e., maize). Chibwana, Fisher, and Shively (2012) studied the cropland allocation effects of both fertilizer and improved seed subsidies to maize and tobacco in Malawi and found a positive association between subsidy program participation and land allocation to maize and tobacco- the targeted crops. Karamba's (2013) study found a substantial decrease in the share of land allocation to maize and an increase in land allocation to tobacco in Malawi, suggesting that raising the productivity of maize enables farmers to reallocate land to a cash crop and earn more income. In Kenya, Mason *et al.* (2017) reported a land allocation bias toward maize as a result of fertilizer and improved seed subsidy programs that targeted maize. Other two studies examined the effect of the maize input subsidy program (fertilizer and improved seed) on a legume crop and found that farmers reallocate land towards maize from other crops like groundnuts (Mason, Jayne and Mofya-Mukuka, 2013; Zulu, Kalinda, and Tembo, 2014). The only study we learned about investigated the effect of a legume seed subsidy on land allocation and found that the subsidy increases the area planted for legumes (M. Khonje et al., 2021).

Land reallocation changes crop diversity on farms. Theriault and Smale (2021) found that the fertilizer subsidy in Mali distorts the land allocation in favor of targeted crops and reduces the spatial equality of land allocation among crops. Adjimoti *et al.* (2017) investigated the impact of fertilizer and seed policies on crop diversification and found that access to fertilizer and seed negatively affects crop diversity and leads to crop specialization.

Our analysis adds new evidence by testing the impact of both fertilizer and seed subsidy programs in Burkina Faso on land allocation as well as crop diversity. Unlike previous studies, we investigate the impact of the two different input subsidies together that address different groups of crops—a fertilizer subsidy on staple grains and cotton (typical target crops) and a seed subsidy on cowpea (a minor crop). On the one hand, the fertilizer subsidy can encourage farmers to allocate larger area shares to fertilizer-targeted crops. On the other hand, by raising target crop productivity, the fertilizer subsidy may encourage farmers to reallocate land to other desirable crops. We hypothesize that the fertilizer subsidy may either increase or decrease the area share of cowpeas, but the cowpea seed subsidy should increase the area share of cowpeas. Building on Theriault and Smale (2021), we apply a two-year household panel to examine the individual and interacting effects of the fertilizer and cowpea seed subsidy on crop area shares. To our knowledge, our study is the first to explore the impact of both a fertilizer and a seed subsidy on various targeted crops, including a minor crop, cowpea.

We utilize a nationally representative panel dataset collected by the General Research and Sectoral Statistics Department (Direction Générale des Études et des Statistiques Sectorielles (DGESS)) of the Ministry of Agriculture and Food Security (Ministère de l'Agriculture et de la Sécurité Alimentaire (MASA)) of Burkina Faso for the years 2015 and 2017. We apply a control function approach (CFA) with correlated random effects (CRE) to estimate the impact of the input subsidy programs on land allocation and crop diversity. According to the construction of the outcome variables, we use Tobit, Poisson, or OLS estimators. We use instrumental variables to address and control the potential endogeneity of participating in the subsidy.

Next, we summarize the key features of the fertilizer and cowpea seed subsidy programs in Burkina Faso. Then, we describe the importance of crop diversity on farms and the important roles played by cowpeas. We then present a conceptual framework and econometric strategy and interpret regression results. We draw conclusions and policy implications in the final section.

## 2.2 Input Subsidies in Burkina Faso

The government of Burkina Faso initiated the fertilizer subsidy program in 2008 after the food price shocks in 2007-08, intending to increase fertilizer use, raise agricultural productivity, and combat food and nutrition insecurity. The fertilizer subsidy favors specific farming systems and farm types, with farm households producing maize, rice, and cotton being able to claim subsidized fertilizer proportional to their anticipated land allocation to these crops (Wanzala-Mlobela, Fuentes, and Mkumbwa, 2013). In addition, to encourage fertilizer use and minimize the possibility of diversion of fertilizer from cotton to cereal plots, cotton farmers can receive subsidized fertilizer on credit for both cotton and cereal crops, with the fertilizer credit being deducted from the farmer's cotton payment (Maître d'Hôtel & Issoufou, 2018; Theriault & Serra, 2014). Lack of access to credit has been found to negatively affect land allocation to cotton and maize in Burkina Faso (Porgo et al., 2017). Recently, the fertilizer subsidy program has expanded to include other staple crops, such as millet and sorghum (Maître d'Hôtel & Issoufou, 2018; Ministère de l'Agriculture des Aménagements Hydro-Agricoles et de la Mécanisation (MAAHAM), 2021), even though they have much lower yield responses to fertilizer (H. Haider et al., 2018). Our analysis focuses on the primary crops (cotton, maize, and rice) targeted by the fertilizer subsidy since its launch and during the 2015 and 2017 cropping seasons.

The Burkina Faso national fund, rather than donor funds, pays for the subsidy. With a limited government budget, government priority areas change from year to year. About 17 percent of total fertilizer use in Burkina Faso is supplied from the government-subsidized fertilizer source; the remainder comes from other channels (Wanzala-Mlobela et al., 2013). Therefore, a farming household may not receive a fertilizer subsidy every year due to changing priorities and management.

Since 2014, the government of Burkina Faso has also distributed small quantities of certified seeds of selected crops at a subsidized price (Ministère de l'Agriculture et de la Sécurité Alimentaire, 2014). Beneficiaries are identified at the administrative level of the commune by a committee composed of representatives of local technical assistance services and government.[2] Within communes, villages are divided into three groups, with inputs distributed in a three-year rotation. Within beneficiary villages, farming households are selected similarly by local agents and administrators, with a representative from the private sector also participating as an observer.

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[2] Specifically, the Head of the Zone d'Appui Technique, mayor, and representative of the Chambre Régionale d'Agriculture.

The program directions state that seed distribution should be given priority to smallholder farming households and women farmers who have adopted good practices but fall short of providing concrete recommendations for implementation. Concerning subsidized fertilizer, only the cultivation of targeted crops and the use of good practices are mentioned.

**2.3 The Importance of Crop Diversity on Farms**

Crop diversity helps maintain crop productivity, adapt to changing growing conditions, control plant pests and diseases, and address nutritional needs and dietary preferences. Diversification among and within crops is often viewed as a means of coping with rainfall risk and climate change (Di Falco and Chavas, 2008; Asfaw, Pallante, and Palma, 2018; Bellon *et al.*, 2020; Bozzola and Smale, 2020), and can also reduce exposure to price fluctuations (Mulwa et al., 2017). Maggio and Sitko (2021) describe two ways that diversification supports the productivity and stability of agroecological systems: 1) greater diversity increases the chances that the most well-adapted crop species will survive (the 'sampling effect'), and 2) more diverse systems exploit the fact that different species have different resource use patterns, such as nitrogen and moisture requirements (the 'complementarity effect').

By improving biological control in farming systems, crop species diversification can reduce dependence on insecticides (Redlich, Martin, and Steffan-Dewenter, 2018) and conventional inputs (Isbell et al., 2017)- especially where such inputs are scarce and expensive, as in Burkina Faso. Finally, crop diversity supports farmers' livelihoods through farm production for consumption and creating options for sales revenues (Bellon et al., 2020; Kozicka et al., 2020; Pingali & Rosegrant, 1995). In Ethiopia, Michler and Josephson (2017) found that crop diversity reduces poverty, although Khonje *et al.* (2022) found a negative relationship between crop diversity and the nutritional status of children and adolescents in Tanzania and Uganda.

A particular focus of our study is cowpea, locally known as *niébé*. An indigenous grain legume of West Africa, cowpea is known as a "lost" crop of Africa, recently "found" again by agricultural researchers and policymakers (National Research Council, 2006). Burkina Faso is the third country after Nigeria and Niger in cowpea production (FAO, 2020) and also exports the crop to sub-regional markets of Ghana, Ivory Coast, Togo, Benin, and Nigeria. Cowpea matures early in dryland production systems, provides essential nutrients to the diets of both humans and livestock, helps fix nitrogen in the soil and control erosion, and generates revenues for farming families—and especially women (Langyintuo et al., 2003; M. Smale & Thériault, 2021).

**2.4 Conceptual Framework**

Rice, maize, and cowpea are food and cash crops for smallholder farming families in Burkina Faso. Cotton has been a cash crop with a strong, vertically integrated supply chain and a major earner of export revenues (Kaminski, 2011).

The members of extended family households in rural Burkina Faso are typically involved in joint agricultural production over numerous plots operated simultaneously. The household head, most often a senior male, provides overall supervision, including land and input allocation, while individual family members contribute their labor. The head carries a particular obligation to provide for the staple food needs of the household on the common plot (Kazianga & Wahhaj, 2013). Family members work together unpaid to produce the cereals and cotton to meet the family's food and cash needs. Other family members may also have their 'private plots' distributed by the household head to produce whatever they want independently in their remaining time. They can spend their earnings or contribute to overall family expenses when necessary (Thorsen, 2002).

We view land allocation decisions in the context of the non-separable model of the household farm, where the labor of household members is organized to maximize utility over the consumption of goods and leisure (Singh, Squire, and Strauss, 1986). In the non-separable case, market failures and imperfections drive the simultaneity of consumption and production decisions (De Janvry, Fafchamps, and Sadoulet, 1991; Bardhan and Udry, 1999). Households produce agricultural goods for consumption and sale and also consume goods purchased at local markets. They use production inputs sourced from their homes and those purchased from markets, working as unpaid labor on their farms and as laborers on other farms or in off-farm employment. In this region, markets for hired labor are poorly developed (Kazianga & Wahhaj, 2013; Mbaye & Gueye, 2018).

Cash constraints faced by farming households inhibit their investment in agricultural inputs since the credit markets are poorly developed in Burkina Faso. Farm sales and off-farm employment of family members only partially relax these constraints. When consumption decisions cannot be separated from production decisions, shadow prices are endogenous. Capital endowments, including human capital, affect demand for inputs such as fertilizer and seed through their influence on transaction costs and consumption preferences. On the one hand, subsidized inputs can reduce production costs for crops targeted by the subsidy, which can incentivize reallocating land across targeted and non-targeted crops. On the other hand, higher productivity due to subsidized inputs can create the possibility of producing food needs in smaller areas, releasing land for other nutrient-rich or high-value crops.

Our conceptual framework builds on LaFave, Peet, and Thomas (2013) and Benin *et al.* (2004). Households optimize utility over a vector of consumption goods and leisure conditioned on the observed ($\mu$) and unobserved (e) household characteristics that shape their preferences. Consumption goods comprise both produced farm goods ($c_f$) and goods purchased from the market ($c_m$). Variable farm inputs ($X$) include fertilizer and seed primarily in combination with the services of some farm equipment. These are allocated across multiple crops produced simultaneously on various plots of different sizes, soils, and elevation, primarily with the labor of household members. The time endowment includes work on the family farm ($L^F$), off-farm ($L^O$) or leisure ($l$).

$$\max_{c_f, c_m, l} \left[u(c_m, c_f, l; \mu, e)\right] \tag{1}$$

Subject to:

$$Q = Q(\alpha, X;\ Z) \tag{2}$$

$$\text{E} = L^F + L^O + l \tag{3}$$

$$p_f Q(\alpha, X; Z) - \sum_{m=1}^{M} r_m x^m + w\ (L^F + L^O) + \gamma_0 = p_f c_f + p_m c_m \tag{4}$$

Area shares ($\alpha$) of total cropland *A*, which is fixed in each season, are distributed among N crops. The choice of area shares among different crops implies farm outputs, and the sum of area shares to *N* crops is equal to 1; $\sum_{i=1}^{N} \alpha_i = 1$. Production output ($Q$) is conditioned on the farm's physical characteristics *Z* (such as the location of plots, which is correlated with soil types and quality in this region (Udry, 1996) and agroforestry practices). Household characteristics such as human capital and livestock assets affect consumption preferences, access to markets, and production. $r_m$ is a vector of input prices or opportunity costs (e.g., fertilizer price, rent), and *p* with subscripts *f* and *m* are output prices of farm goods and market goods, respectively.

The household produces *N* crops using *M* factors of production and chooses to consume farm produce $c_f$ or sells $Q - c_f$ from total farm outputs subject to the constraints of production technology that depends on input use, labor, and land allocation, given the farm's physical characteristics *Z*. The utility function (1) can also be expressed as

$$\max_{\alpha_1, \ldots, \alpha_N \geq 0; c_f, c_m, \ X, L} V(c_f, c_m, l; \mu, e) \tag{5}$$

A total family time endowment constrains labor and leisure. Total farm income is derived from net profits, labor earnings, and exogenous earnings. $\gamma_0$ (transfers such as remittances from migrant household members, pensions received, and the value of crop stocks carried from one season to the next).

In the particular case of perfect markets, the production and consumption decisions made by the farm household are separable. Farm profits $\pi_i = p_i q_i - \sum_{m=1}^{M} r_m x_m^i$ ; $i = 1, 2, \ldots, N$ motivate decisions regarding the quantity produced of each good ($q_i$ ), in response to the exogenous market price $p_i$ , and given $r_m$ , the price or opportunity cost of the input m and $x_m^i$ is the amount of input m used in the production of goods $i$. The optimal consumption and production choices will be a function of the market wage rate, input prices, and output prices.

In our case, consumption decisions cannot be separated from those that affect production. Labor is provided primarily by household members, and the fertilizer subsidy is a policy effort to address the underdevelopment of commercial fertilizer markets; seed for staple food crops is often saved on farms rather than purchased. Households' own valuation of crops (shadow prices) determines input allocation and production decisions. Prices are influenced by the costs of market transactions, which in turn are a function of household-specific characteristics ( $\mu, e$ ) and market characteristics ($\Omega_{\mathrm{M}}$). The optimal choice $\hat{h}$ (a vector of land allocation $\hat{\alpha}_i$, consumption $\hat{c}_f$ and $\hat{c}_m$, input demand $\hat{X}$, and labor $\hat{L}$) can be expressed as a function of exogenous income ($\gamma_0$), farm size (A), market characteristics ($\Omega_{\mathrm{M}}$), and physical farm characteristics (Z):

$$\hat{h} = F(A, \gamma_0, Z, \Omega_{\mathrm{M}}). \qquad (6)$$

We assume these factors are the determinants of crop diversity and land allocation in utility-maximizing farm households. Equation (6) is the basis for econometric estimation of crop diversity (*D*):

$$D = D(\alpha_i(A, \gamma_0, Z, \Omega_{\mathrm{M}})). \quad (7)$$

The effects of the fertilizer and seed subsidies are the focus of our analysis. We can express the demand for inorganic fertilizer as $[x_j = x_j(r_{j1}, r_{j2}, w_a, A;\ Z)]$ where $r_{j1}$ is the subsidized price and $r_{j2}$ is the regular market price of inorganic fertilizer ($r_{j1} < r_{j2}$). A household can buy fertilizer at market price and/or subsidized price. $x_{j1}$ and $x_{j2}$ are the amounts of inorganic fertilizer at subsidized and market prices. Seed demand can also be shown similarly.

## 2.5 Empirical Strategy

### 2.5.1 Data source

We utilize a nationally representative household-level panel dataset from the Continuous Farm Household Survey (Enquête Permanente Agricole (EPA)) of Burkina Faso. Data were collected by the General Research and Sectoral Statistics Department (Direction Générale des Études et des Statistiques Sectorielles (DGESS)) of the Ministry of Agriculture and Food Security (Ministère de l'Agriculture et de la Sécurité alimentaire (MASA)). The 2006 Population Census was the basis for the sampling frame of the EPA survey. The EPA is used to estimate farm production area, input use, production, and yield of crops. Rural households also provide limited information on livestock holdings, credit, and off-farm employment in these years. This analysis uses data for the 2015 and 2017 cropping seasons, including 4249 and 4249 household farms across all 45 provinces, respectively. Around 11 percent and 8 percent of households benefitted from subsidized fertilizer in 2015 and 2017, respectively, though only 2 percent received subsidized fertilizer in both periods. About 9 percent and 8 percent of households benefitted from cowpea seed subsidies in 2015 and 2017, respectively, and only 1.2 percent of households participated in both periods. Data outliers were treated by windsorizing these variables at 1% and 99%.

### 2.5.2 Outcome variables

Here, we measure crop diversity as counts and shares over farmer-recognized crop - species. We define four outcome variables, of which three are fractional variables with outcomes of [0, 1]. These three outcome variables are the household's share of farmland planted to the fertilizer subsidy target crops, the household's share of farmland allocated to cowpeas as a primary crop, and the intercrop area share of cowpeas. We measure intercrop area share to cowpea by taking the ratio of intercrop area devoted to cowpea to the total area of farmland used for intercrop for every household. We employ the count of all crops produced by the household as an indicator of crop species richness. The maximum number of crop species a farm household grows is 12, with an average of 5. Crop count is the most straightforward and often used richness indicator. A well-known limitation of crop count is that it does not account for farm size, which we expect to be positively related to the number of crops grown. Another limitation is that it does not consider the "weight" or area allocated to each crop. Table 2.1 illustrates the summary statistics of the outcome variables for the entire sample.

### 2.5.3 Estimation strategy

We specify the following linear model with additive unobserved heterogeneity:

$$y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 F_{it} + \beta_3 S_{it} + \delta F_{it} * S_{it} + \eta_t + c_i + u_{it}$$

Where $y_{it}$ is the outcome variable, $X_{it}$ is the set of observed covariates that may change across household i only, or across household i and time t, $F_{it}$ is the potentially endogenous variable representing participation in the fertilizer subsidy program, $S_{it}$ is the potentially endogenous variable representing participation in the cowpea seed subsidy program, $F_{it} * S_{it}$ is the interaction term of both fertilizer and seed subsidy, $\eta_t$ is the time dummy variable, $c_i$ is the time-invariant household-specific omitted factors (unobserved heterogeneity) correlated with $S_{it}$, $F_{it}$, and $u_{it}$ is the idiosyncratic error.

For the fractional outcome variables, $0 \leq y_{it} \leq 1$, where outcome at the endpoints, zero and one, $y_{it}$ follows a two-limit Tobit model. For the count outcome variables, $y_{it}$ follows a Poisson model.

Household-level, time-invariant unobserved heterogeneity that may be correlated with other covariates may cause selection bias in panel data. In linear models, we usually apply the fixed effect estimation technique to control unobserved heterogeneity, but this approach creates an incidental parameters problem when the model is non-linear, and the time period is small. The correlated random effects (CRE) approach is better suited for non-linear models (J M Wooldridge, 2008; Jeffrey M Wooldridge, 2005). The CRE estimation technique addresses the unobserved heterogeneity issue by controlling for the averages of all time-varying exogenous variables. The household-level mean value of $x_{it}$ captures any correlation between exogenous variables and time-invariant unobserved heterogeneity (J. Wooldridge, 2012).

Participation in input subsidy programs may be endogenous because beneficiaries are not selected randomly. For example, self-selection may mean that households with better networks might have more access to the subsidy (i.e., $cov(S_{it}, v_{it}) \neq 0$ and $cov(F_{it}, v_{it}) \neq 0$ where $v_{it} = c_i + u_{it}$ ) so unobserved household characteristics may affect the likelihood of participation. We use the control function approach (CFA) to address the potential endogeneity issue, which both tests for and corrects the endogeneity (Jeffrey M Wooldridge, 2015) (Appendix shows the details of how CFA deals with endogeneity).

The control function approach requires appropriate instrumental variables (IV), which should be correlated with the household's access to the subsidized fertilizer (i.e., $cov(F_{it}, z_{it}) \neq$

$0$ ) but not directly related to the outcome variables of land allocation and crop diversity (i.e., $cov(F_{it}, z_{it}) = 0$ ). The same applies to the seed subsidy and the interaction of fertilizer and seed subsidies. We tested several potential instruments. These included: 1) how long the household has lived in the village, proxied by the year of acquisition of the oldest plot (Bezu et al., 2014); 2) the number of household members who served as a leader in any farmer organization (Mason & Smale, 2013), 3) the number of days that household members received any training during last year, 4) the number of household members with secondary education or higher, 5) the number of household members received any training during last ten years, 6) the number of household members involved in non-crop organizations, and 7) two village level variables- number of people who are members of any organizations, and number of people involved with non-crop organizations. Among these, we find that the number of household members who received any training during the last ten years is a strong IV for fertilizer subsidy, the number of household members involved with any non-crop organizations as a member is a strong IV for seed subsidy, and their interaction for the interaction variable of fertilizer and seed subsidy (see on-line appendix Table A 2.1). Logically, attending training programs or membership in non-crop organizations opens the door to networking and connections that help households access subsidized inputs, but we see no direct association with crop species diversity metrics or cropland allocation among crops. The fertilizer subsidy program in Burkina Faso began in 2008, and we are working with panel data from 2015 and 2017. Farmers have been attending training when the subsidy program is in effect. The higher number of household members attending training programs during the last ten years implies the higher social network opportunities that allow them to access subsidized fertilizer or seed using that network. Although there is a chance that people may learn agricultural practices from the training, it is very marginal and not necessarily about crop diversity. There are a variety of training sessions on environmental issues, gender issues, business skills, agricultural practices, health, and nutrition for people to attend organized by government, national, or international NGOs. At the same time, membership in a non-plant organization teaches nothing about crops. However, it opens the door for networking with people who might help access subsidized inputs through sharing information or helping directly.

Households were asked about the sources of their inorganic fertilizer and seed, including the subsidy programs, gifts from others, retailers, or commercial dealers. Households collecting any positive subsidized amount of NPK or urea are considered participants, and any positive subsidized amount of cowpea seed indicates participation in the seed subsidy. Both variables are binary.

In the first stage of regressions, the subsidy variables are regressed on the instrumental variables along with other covariates. The reduced-form CFA-CRE probit estimation helps to control the factors affecting participation in the subsidy program. The generalized residual for participation in the fertilizer and seed subsidy programs and their interaction terms (grF, grS grFS), which depends on the inverse Mills ratio, is predicted from the reduced form models. Then, we use these generalized residuals in the second stage regression as additional regressors to test the null hypothesis of exogeneity. The instruments are also plausible in satisfying the exclusion restriction since training or membership in non-crop organizations has no direct relation with crop species diversity or land allocation between targeted and non-targeted crops.

We use the CFA-CRE Tobit and OLS estimation for the model with the fractional outcome with the limit at 0 and 1, CFA-CRE Poisson, and OLS for the discrete dependent variables. We report the bootstrapped standard error for both first and second-stage regressions, and since the source of variation is within-household participation in the subsidy programs, standard errors are clustered at the household level. We also report the regression results from the fixed effect (FE) with instrumental variables estimation in Appendix Table A 2.2.

### 2.5.4 Explanatory variables

We control for a set of relevant variables broadly categorized in plot, market, and household characteristics that may affect both access to subsidies and spatial crop diversity, selected based on our theoretical framework and past empirical literature on the determinants of crop diversity (Benin et al., 2004; Naylor, 2006; Van Dusen & Taylor, 2005). Table 2.2 shows the summary statistics of the covariates for the entire sample.

Plots managed collectively under the stewardship of the senior head typically provide the basis of staple food production for the family, whereas plots managed by individual household members are most often used to produce legumes and other crops (Kazianga & Wahhaj, 2013). Thus, the existence and proportion of individual plots in a farm household become an important determinant of producing diversified crops, reflected in the percentage of individually managed plots.

Similarly, the topographical location of plots is associated with soil types in this region, where lowland plots are more suitable for rice production because they retain moisture. Dryland cereals are typically grown on the plain. We consider steep land a base category among plain, lowland, and steep land types. Agroforestry has been promoted to protect plots from wind and soil erosion, and in some cases, trees have included nitrogen-fixing species; plots without agroforestry are the base category of the binary variable here.

With the main cereal crops, households often produce cowpea or other legumes as an intercrop. A household with more intercropped plots may also have more crop diversity.

Market characteristics such as distances to the nearest retailers and markets are unavailable in the EPA data. To reflect these, we use the incidence of off-farm employment, which suggests proximity to towns and urban areas and access to credit in the year preceding the survey. Access to credit reduces the cash constraint that might affect the decision to participate in the subsidy program and investment in agricultural production.

We expect that household capital endowments, including human capital and household assets proxied by livestock ownership, may affect access to subsidized fertilizer and seed and also their land allocation decisions. Human capital includes physical labor availability proxied by the adult male and female members as well as labor quality expressed in education. The number of adult women also raises the chances of receiving the cowpea seed subsidy. Other things being equal, a larger farm increases the likelihood and extent of land allocation to targeted crops but also increases the likelihood that other crops may be grown. The use of organic manure is often considered a substitute for mineral fertilizer and acts on soil structure to complement the nutrients provided by mineral fertilizer. The number of children in the household is expected to strongly shape food requirements. A female-headed household may produce more micronutrient-rich traditional crops in addition to cereals.

## 2.6 Results and Discussion

### 2.6.1 Relevance of the Instruments

Coefficients suggest a statistically significant relationship between the instruments and the endogenous variables in the CRE probit, first-stage regressions of fertilizer subsidy, cowpea seed subsidy, and their interaction term (Appendix Table A 2.1). These findings imply that the instrumental variables—the number of household members who received training during the last ten years, the number of household members involved with non-crop organizations, and the interaction of both subsidy participations—satisfy the relevance assumption.

### 2.6.2 Effects of fertilizer and seed subsidy on land allocation to targeted crops

The statistical significance of the coefficients of generalized residuals leads us to reject the exogeneity of the household's participation in the subsidy program (Table 2.3). Considering the variables of fertilizer subsidy, seed subsidy, and their interaction, the marginal effect of the fertilizer subsidy is: $\frac{\partial y_{it}}{\partial F_{it}} = \beta_f + \delta\ S_{it}$ where $\beta_f$ is the coefficient of the fertilizer subsidy variable, and $\delta$ is the coefficient of the interaction term. Similarly, the effect of the seed subsidy is: $\frac{\partial y_{it}}{\partial S_{it}} = \beta_s + \delta\ F_{it}$. A negative sign on the coefficient of the interaction term indicates the offsetting effect of seed subsidy when $S_{it} = 1$ (household also participated in seed subsidy). Statistical significance of the fertilizer subsidy demonstrates that participation in the fertilizer subsidy program increases the farm area share allocated to crops targeted by the fertilizer subsidy (rice, maize, and cotton), consistent with the findings of (Theriault & Smale, 2021). The statistically significant, negative coefficient on the seed subsidy variable implies that participation in the cowpea seed subsidy reduces the area share to crops targeted by the fertilizer subsidy, which aligns with our hypothesis. The extent and sign of the coefficient of the interaction term of the subsidy variables indicate that participation in both subsidies together offsets the bias of fertilizer subsidy toward targeted crops (rice, maize, and cotton).

Other results are of interest. The number of lowland plots positively impacts the area share of the target crops, reflecting that lowlands are a better fit for rice production. Access to credit during the last 12 months positively affects area shares in targeted crops. The number of intercrop plots and the number of household members in off-farm work contribute negatively to the area share to target crops. Female-headed households tend to allocate less farmland share to rice, maize, and cotton. Chi-square statistics shown in the table attest to the joint significance of the covariates.

### 2.6.3 Effect of fertilizer and cowpea seed subsidy on crop diversity

Table 2.4 shows the impact of participation in the subsidy programs on the total crop count. Again, the significance of the coefficients of the generalized residuals indicates endogeneity. Household participation in either the fertilizer or the seed subsidy program has a negative impact on the total crop count. The coefficient of the interaction term of the subsidies is positive, which means that participating in both subsidy programs offsets the negative effect of the individual subsidy on the total crop count.

The percentage of total plots managed by an individual household member has a statistically significant, positive impact on total crop count, which suggests that a greater concentration in common plots managed by the head on behalf of the family leads to greater crop diversity and vice versa. The number of intercropped plots, lowland or plain land plots, access to credit, and female-headed households are positively and significantly associated with the total crop count.

### 2.6.4 Effect of fertilizer and cowpea seed subsidy on land allocation to cowpea

Table 2.5 reports the effect of participation in the subsidy program on the area share of cowpeas both as a primary crop and intercrop. Results show that the individual effect of the fertilizer subsidy is negative on the area share intercropped with cowpea, whereas the seed subsidy, perhaps surprisingly, has no significant impact. The positive coefficient of interaction term implies that participation by a household in both subsidy programs offsets the negative effect of the individual fertilizer subsidy, increasing land allocation to cowpeas.

### 2.7 Conclusions and Policy Implication

Input subsidies have numerous known drawbacks and can be a budgetary burden for countries like Burkina Faso, but they have been justified based on the argument that they can offset market failures. Since 2008, the fertilizer subsidy program in Burkina Faso has targeted rice, maize, and cotton to extend and intensify the use of mineral fertilizer and improve agricultural productivity in crops of major economic importance. Compared with other programs in Sub-Saharan Africa, this type of subsidy is labeled "universal" because it does not target any specific population group, such as agricultural households operating smaller farm sizes or headed by women. Any farming household can access the subsidy in proportion to the hectares of land they plan to devote to cultivating target crops, although government implementation documents recommend "good farming practices."

While previous studies investigated the impact of fertilizer or seed subsidy on target crops, we analyzed household panel data to explore the impact of both fertilizer and seed subsidies combined. We contribute to the literature by exploring how participation in the input subsidy programs affects cropland allocation and crop diversity. We also investigate the effect of the subsidy on the production of a minor crop that is economically significant in Burkina Faso - cowpea. To our knowledge, this is the first study to explore the effects of both fertilizer and seed subsidies on various targeted crops, including a minor crop.

We use the control function approach with a correlated random effects model to address the potential endogeneity due to self-selection into the programs and individual heterogeneity. We use crop diversity indices to assess the effects of the subsidies on crop diversity along with the measure of land share to targeted and non-targeted crops. We apply our models to a nationally representative two-year panel data set collected by the General Research and Sectoral Statistics Department of the Ministry of Agriculture and Food Security of Burkina Faso.

We find that benefiting from the fertilizer subsidy on targeted crops increases the land share allocated to the target crops (maize, cotton, and rice) compared to non-targeted crops also reduces crop diversity on household farms. However, the subsidy on improved cowpea seed has an offsetting effect. We find that the fertilizer subsidy reduces the land allocation to cowpea in terms of land allocation to cowpea both as a primary crop and intercrop. The combination of fertilizer and cowpea seed subsidy partially offsets that effect.

The fertilizer subsidy may indeed increase the yield of cereals such as maize (S. H. Haider, 2018), address caloric deficits, and enable farming households to sell more and purchase additional food groups with cash if these are available in local markets. At the same time, the fertilizer subsidy appears to negatively affect the production of cowpea and other non-target crops, some of which may be high-value crops or provide essential micronutrients to rural and urban consumers. Achieving caloric sufficiency at the cost of diet quality is not a win-win strategy, especially considering the challenges of addressing the health needs of Burkinabe women of reproductive age and young children. Together, our results highlight the importance of adopting a more integrated farming system approach in designing and implementing the input subsidy program to boost agricultural production and productivity and eventually improve food security.

## TABLES AND FIGURES OF CHAPTER TWO

Table 2.1: Definitions and summary statistics of outcome variables, 2015 and 2017

| Variables | Definition | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Share area target | Ratio of land allocated to subsidized fertilizer targeted crops to total farmland | .27 | .31 | 0 | 1 |
| Share area cowpea | Ratio of land allocated to cowpea to total farmland | .04 | .09 | 0 | 1 |
| Share intercrop area cowpea | The ratio of land allocated to cowpea to total intercropped farmland | .62 | .44 | 0 | 1 |
| Crops count | Total crop count | 5.03 | 1.91 | 1 | 12 |

N=8498

Table 2.2: Definitions and summary statistics of explanatory variables, 2015 and 2017

| Variables | Definition | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Plot Characteristics | | | | | |
| Percentage of individual plots | Percentage of plots on the farm managed by individual member | 36.43 | 28.39 | 0 | 100 |
| Plot plainland | Plots located on the plain land | 8.43 | 6.22 | 0 | 67 |
| Plot lowland | Lowland plots | .71 | 1.63 | 0 | 22 |
| Plot with tree | Agroforestry plots | 6.16 | 4.9 | 0 | 64 |
| Intercrop plot | Intercropped plots | 2.62 | 3.37 | 0 | 33 |
| Market characteristics | | | | | |
| Non-farm employment | HH members working off-the farm | .18 | .71 | 0 | 11 |
| Credit | HH members received credits in last 12 months | .28 | .69 | 0 | 12 |
| Household characteristics | | | | | |
| Area total | Farm size (ha) | 4.86 | 4.27 | .335 | 23.12 |
| Livestock | HH members owning livestock | 3.00 | 2.20 | 0 | 27 |
| Higher education | HH member with secondary or higher education | .39 | .86 | 0 | 14 |
| Male adult per ha | Male adults per hectare | .77 | .96 | 0 | 17.93 |
| Female adult per ha | Female adult members per hectare | .94 | 1.07 | 0 | 20.92 |
| child | Number of children | 5.80 | 3.96 | 0 | 34 |
| Head female | Female household head | .05 | .22 | 0 | 1 |
| Manure use per ha | Manure usea (kg/ha) | 534.77 | 1142.59 | 0 | 7542.19 |
| Treatment variables (potentially endogenous) and instrumental variable | | | | | |
| Sub_Fer | =1 if received subsidized fertilizer | .1 | .3 | 0 | 1 |
| Sub_Seed | =1 if received subsidized seed | .09 | .28 | 0 | 1 |
| Sub_ferseed | Interaction term of Sub_fer and Sub_seed | .05 | .21 | 0 | 1 |
| Member to non-crop association | Number of HH members involved with any non-crop organization | 4.40 | 2.99 | 0 | 31 |
| Training in 10 years | The number of HH members received training during the last ten years | .51 | 1.01 | 0 | 20 |
| Interaction of IVs | Interaction of training 10 years and non-crop member | .20 | 1.04 | 0 | 40 |

N=8498

Source: Authors, based on EPA data 2015 and 2017.

Table 2.3: Effect of participation in the subsidy programs on the area share to fertilizer targeted crops

| | Coeff (Tobit) | APE (Tobit) | OLS |
|---|---|---|---|
| Fertilizer subsidy (yes/no) | 0.48*** | 0.48*** | 0.45*** |
| | (0.09) | (0.09) | (0.08) |
| Seed subsidy (yes/no) | -0.28*** | -0.28** | -0.09 |
| | (0.10) | (0.12) | (0.09) |
| Interaction of both subsidy | -0.41*** | -0.41*** | -0.38*** |
| | (0.13) | (0.14) | (0.13) |
| Generalized residual (Fertilizer) | -0.10* | -0.10** | -0.10** |
| | (0.05) | (0.05) | (0.04) |
| Generalized residual (Seed) | 0.19*** | 0.19*** | 0.09* |
| | (0.05) | (0.06) | (0.05) |
| Generalized residual (interaction of both) | 0.13* | 0.13** | 0.12** |
| | (0.07) | (0.06) | (0.06) |
| Percentage of individual plots | -0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) |
| Plot plainland | 0.00*** | 0.00*** | -0.00 |
| | (0.00) | (0.00) | (0.00) |
| Plot lowland | 0.00 | 0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) |
| Plot with tree | -0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) |
| Intercrop plot | -0.01*** | -0.01*** | -0.01*** |
| | (0.00) | (0.00) | (0.00) |
| Area total (ha) | -0.00* | -0.00 | -0.00* |
| | (0.00) | (0.00) | (0.00) |
| Non-farm employment | -0.02*** | -0.02*** | -0.01** |
| | (0.00) | (0.01) | (0.00) |
| Credit | 0.03*** | 0.03*** | 0.03*** |
| | (0.01) | (0.01) | (0.01) |
| Livestock | -0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) |
| Higher education | 0.01** | 0.01** | 0.01** |
| | (0.01) | (0.01) | (0.00) |
| Male adult per ha | 0.01 | 0.01 | 0.01 |
| | (0.01) | (0.01) | (0.01) |
| Female adult per ha | 0.01 | 0.01 | 0.01 |
| | (0.01) | (0.01) | (0.01) |

Table continued to the next page

Table 2.3 (cont'd)

| | Coeff (Tobit) | APE (Tobit) | OLS |
|---|---|---|---|
| Child | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) |
| Head female | -0.06*** | -0.06*** | -0.04*** |
| | (0.02) | (0.02) | (0.01) |
| Manure use per ha | 0.00* | 0.00 | 0.00* |
| | (0.00) | (0.00) | (0.00) |
| Mean (time-varying variables) | Yes*** | Yes*** | Yes*** |
| Year 2017 | 0.04*** | 0.04*** | 0.03*** |
| | (0.00) | (0.01) | (0.00) |
| Constant | 0.18*** | | 0.22*** |
| | (0.02) | | (0.01) |
| N | 8498 | 8498 | 8498 |
| r2_p | 0.39 | 0.39 | |
| chi2 | 12071.63 | 12071.63 | 13335.38 |
| p | 0.00 | 0.00 | 0.00 |

Source: Authors based on EPA 2015 and 2017. APEs denote average marginal effects. Bootstrapped Standard errors are in the parentheses. The dependent variable- the share of total farmland devoted to fertilizer targeted crops is a fractional variable with outcome [0,1]. *, **, and *** denote statistically significant at 10%, 5%, and 1%.

Table 2.4: Effect of participation in the subsidy programs on the total count of crops

| | Total Count (OLS) | Total Count (Poisson) |
|---|---|---|
| Fertilizer subsidy (yes/no) | -0.93*** | -0.14* |
| | (0.36) | (0.08) |
| Seed subsidy (yes/no) | -0.97 | -0.56*** |
| | (0.64) | (0.12) |
| Interaction of both subsidy | 1.55** | 0.41*** |
| | (0.67) | (0.12) |
| Generalized residual (Fertilizer) | 0.32* | 0.04 |
| | (0.19) | (0.04) |
| Generalized residual (Seed) | 0.86*** | 0.35*** |
| | (0.32) | (0.06) |
| Generalized residual (interaction of both) | -0.61** | -0.16*** |
| | (0.31) | (0.06) |
| Percentage of individual plots | 0.00 | 0.00** |
| | (0.00) | (0.00) |
| Plot plainland | 0.13*** | 0.02*** |
| | (0.01) | (0.00) |
| Plot lowland | 0.14*** | 0.02*** |
| | (0.02) | (0.00) |
| Plot with tree | 0.02*** | 0.00*** |
| | (0.01) | (0.00) |
| Intercrop plot | 0.12*** | 0.02*** |
| | (0.01) | (0.00) |
| Area total (ha) | 0.02** | 0.01*** |
| | (0.01) | (0.00) |
| Non-farm employment | -0.03* | -0.01** |
| | (0.02) | (0.01) |
| Credit | 0.10** | 0.01 |
| | (0.04) | (0.01) |
| Livestock | -0.01 | -0.00 |
| | (0.01) | (0.00) |
| Higher education | -0.04 | -0.00 |
| | (0.03) | (0.01) |
| Male adult per ha | 0.04 | 0.01 |
| | (0.03) | (0.01) |
| Female adult per ha | -0.09*** | -0.03*** |
| | (0.03) | (0.01) |

Table continued to the next page

Table 2.4 (cont'd)

| | Total Count (OLS) | Total Count (Poisson) |
|---|---|---|
| Child | -0.02 | -0.00 |
| | (0.01) | (0.00) |
| Head female | $0.17^{**}$ | $0.03^{**}$ |
| | (0.08) | (0.02) |
| Manure use per ha | 0.00 | 0.00 |
| | (0.00) | (0.00) |
| Year 2017 | $-0.10^{***}$ | $-0.03^{***}$ |
| | (0.03) | (0.00) |
| Mean (time-varying variables) | Yes*** | Yes*** |
| Constant | $3.92^{***}$ | $1.46^{***}$ |
| | (0.07) | (0.02) |
| N | 8498 | 8498 |
| r2 | 0.49 | |
| chi2 | 9494.89 | 11851.72 |
| p | 0.00 | 0.00 |

Source: Authors' calculation based on EPA 2015 and 2017. Bootstrapped Standard errors are in parentheses. The dependent variables are the total count of crops. *, **, and *** denote statistically significant at 10%, 5%, and 1%.

Table 2.5: Effect of participation in the subsidy program on area share to the cowpea as a primary crop and as an intercrop

| | Coeff (Tobit): Primary Crop | APE(Tobit): Primary Crop | Coeff (Tobit): Intercrop | APE(Tobit): Intercrop |
|---|---|---|---|---|
| Fertilizer subsidy (yes/no) | -0.06 | 0.48*** | -1.57** | -1.57** |
| | (0.08) | (0.09) | (0.61) | (0.61) |
| Seed subsidy (yes/no) | -0.10 | -0.28** | -0.51 | -0.51 |
| | (0.06) | (0.12) | (0.56) | (0.56) |
| Interaction of both subsidy | 0.11 | -0.41*** | 2.70*** | 2.70*** |
| | (0.08) | (0.14) | (0.72) | (0.72) |
| Generalized residual (Fertilizer) | -0.01 | -0.10** | 0.30 | 0.30 |
| | (0.04) | (0.05) | (0.30) | (0.30) |
| Generalized residual (Seed) | 0.08*** | 0.19*** | 0.26 | 0.26 |
| | (0.03) | (0.06) | (0.28) | (0.28) |
| Generalized residual (interaction of both) | -0.00 | 0.13** | -0.74** | -0.74** |
| | (0.04) | (0.06) | (0.32) | (0.32) |
| Percentage of individual plots | -0.00 | -0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Plot plainland | 0.01*** | 0.00*** | -0.01 | -0.01 |
| | (0.00) | (0.00) | (0.01) | (0.01) |
| Plot lowland | 0.00* | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.02) | (0.02) |
| Plot with tree | 0.00*** | -0.00 | -0.01 | -0.01 |
| | (0.00) | (0.00) | (0.01) | (0.01) |
| Intercrop plot | -0.00** | -0.01*** | -0.03*** | -0.03*** |
| | (0.00) | (0.00) | (0.01) | (0.01) |
| Area total (ha) | -0.00 | -0.00 | 0.01 | 0.01 |
| | (0.00) | (0.00) | (0.01) | (0.01) |
| Non-farm employment | -0.01** | -0.02*** | -0.03 | -0.03 |
| | (0.00) | (0.01) | (0.03) | (0.03) |
| Credit | -0.01 | 0.03*** | -0.07** | -0.07** |
| | (0.00) | (0.01) | (0.03) | (0.03) |
| Livestock | -0.00 | -0.00 | -0.01 | -0.01 |
| | (0.00) | (0.00) | (0.02) | (0.02) |
| Higher education | 0.01* | 0.01** | 0.01 | 0.01 |
| | (0.00) | (0.01) | (0.03) | (0.03) |

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Table 2.5 (cont'd)

| | Coeff (Tobit): Primary Crop | APE(Tobit): Primary Crop | Coeff (Tobit): Intercrop | APE(Tobit): Intercrop |
|---|---|---|---|---|
| Male adult per ha | -0.00 | 0.01 | 0.00 | 0.00 |
| | (0.01) | (0.01) | (0.04) | (0.04) |
| Female adult per ha | -0.02** | 0.01 | 0.03 | 0.03 |
| | (0.01) | (0.01) | (0.03) | (0.03) |
| Child | -0.00 | 0.00 | 0.02 | 0.02 |
| | (0.00) | (0.00) | (0.01) | (0.01) |
| Head female | 0.02* | -0.06*** | 0.01 | 0.01 |
| | (0.01) | (0.02) | (0.10) | (0.10) |
| Manure use per ha | 0.00 | 0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Year 2017 | 0.03*** | 0.04*** | -0.02 | -0.02 |
| | (0.00) | (0.01) | (0.03) | (0.03) |
| Mean (time-varying variables) | Yes*** | Yes*** | Yes*** | Yes*** |
| Constant | -0.10*** | | 0.68*** | |
| | (0.01) | | (0.08) | |
| N | 8498 | 8498 | 5720 | 5720 |
| r2_p | 0.26 | 0.26 | 0.043 | 0.043 |
| chi2 | 2591.01 | 2591.01 | 1261.47 | 1261.47 |
| p | 0.00 | 0.00 | 0.00 | 0.00 |

Source: Authors, based on EPA 2015 and 2017. APEs denote average marginal effects. Bootstrapped Standard errors are in parentheses. The dependent variables area shares of cowpea as a primary crop and as an intercrop. *, **, and *** denote statistically significant at 10%, 5%, and 1%.

# CHAPTER 3
# CROP AND LIVESTOCK DIVERSITY, COMMERCIALIZATION, AND FOOD SECURITY ON HOUSEHOLD FARMS IN MALI

## 3.1 Introduction

Food security, which refers to physical and economic access to sufficient, safe, and nutritious food that meets dietary needs and food preferences for an active and healthy life (Barrett, 2010; World Food Summit, 1996), remains a critical challenge in developing countries, particularly Africa. In 2023, 282 million people, or 21.5% of the population across 59 countries and territories, faced severe food insecurity, with African countries experiencing the highest prevalence of severe food and nutrition insecurity (FSIN and Global Network Against Food Crises, 2024). While the UN's Sustainable Development Goals (SDGs) aim to eradicate hunger by 2030, recent statistics indicate that this target may be difficult to achieve, especially in Sub-Saharan Africa (SSA) due to high population growth rates, challenges in food production, economic shocks, and conflicts (FSIN and Global Network Against Food Crises, 2024; Furman et al., 2021).

The development priority of raising incomes and reducing prices by boosting agricultural production is undisputed (Reardon, Delgado, and Matlon, 1992; Dawe, 2007; Jayne, Mather, and Mghenyi, 2010). However, demonstrating empirical linkages between agricultural productivity and food security has remained elusive (Mozumdar, 2012; Muzari, 2016; Ogundari & Awokuse, 2016; Wiebe, 2003). Measuring the observable effects of agricultural interventions aimed at improving food security is beset by methodological challenges, such as data availability and quality, endogeneity, counterfactuals or comparison groups, measurement indicators or indices, and context dependence (Masset et al., 2012; Reardon & Barrett, 2000; Saint Ville et al., 2019; UNICEF & WHO, 2017).

Both on-farm production diversity and commercialization have the potential to contribute to diet diversity and food security. Crop and livestock diversity can enhance food security by providing a more varied and nutritious diet. Crop diversity ensures a range of essential nutrients are available, while livestock diversity provides animal-source foods rich in protein and micronutrients. Additionally, diverse production systems can mitigate pests, diseases, and climate variability risks, ensuring more stable food supplies (Jones, Shrinivas, and Bezner-Kerr, 2014). On-farm production diversity has emerged as a critical factor in enhancing food security, as evident in a growing body of literature (Anderzén et al., 2020; Dillon et al., 2015; Jones et al., 2014; Pellegrini & Tasciotti, 2014; Sibhatu et al., 2015). Intensifying agricultural production is recognized as a global strategy to address food insecurity.

Given that smallholder farmers typically consume what they produce, diversifying their production and livestock species, alongside increasing agricultural productivity, is seen as a promising approach to combat hunger and undernutrition (Burlingame et al., 2012; Gödecke et al., 2018; Hunter et al., 2013; Jones, 2017b; Khoury et al., 2014; Pingali, 2012). Studies have reported a positive association between on-farm production diversity, dietary diversity, and nutrition (Remans *et al.*, 2011; Sibhatu, Krishna, and Qaim, 2015; Jones, 2017). However, the relationship varies across different regions. For instance, Sibhatu, Krishna, and Qaim (2015) found a positive association between dietary diversity and on-farm production diversity in Malawi and Indonesia, while the exact correlation was not observed in Kenya and Ethiopia. Sibhatu and Qaim (2018) suggested that the impact of production diversity on diet quality is minimal and not universally applicable. In fact, they found adverse effects on dietary diversity when there is already high production diversity, possibly due to income losses resulting from producing numerous species on a small scale instead of specializing.

Other factors, such as household income and infrastructure for market access, also play crucial roles in shaping diet diversity. Commercializing crops and livestock can improve food security by increasing household incomes, allowing for greater market access to diverse foods and essential non-food items. One factor that plays a significant role in market access is the state of infrastructure. Due to poor infrastructure, households often rely on on-farm production diversity as their main source of diversified food (Adjimoti & Kwadzo, 2018) and are less likely to be involved in commercialization. With the development of infrastructure, households gain the ability to access a wider variety of food through the market. Bellon, Ntandou-bouzitou, and Caracciolo (2016) examined the interaction among on-farm crops, markets, and dietary diversity, illustrating it as an interactive triangle. Using an interactive simultaneous equations system that accounts for potential endogeneity between market and on-farm diversity and analyzing data from Benin, they estimated the linkages among crop diversity, market access, and dietary diversity and found that both on-farm diversity and market access positively contribute to the dietary diversity for mothers. They identified on-farm diversity and market access as complementary and recommended promoting both strategies to improve food and nutritional security, although they did not compare which is more effective. Koppmair et al. (2017) demonstrated that comparison through a study in Malawi, although both on-farm diversity and market access positively impact diet diversity, market access has a relatively greater impact on dietary diversity. They recommend promoting market access as a more effective way to improve diets. However, commercialization might also pose risks if it reduces diversity in favor of high-value cash crops or livestock, adversely impacting household food consumption and nutrition (Cazzuffi et al., 2020; Wiggins et al., 2011).

Although literature often focuses on on-farm crop diversity in explaining food security, livestock plays a crucial role in rural livelihoods in Sahelian countries as an essential asset for income food security and as a safety net during periods of drought and economic instability (De Haan et al., 2016). Livestock farming is complementary to crop farming and is an integral part of smallholder farming systems in Sub-Saharan Africa, including the Sahel region (Herrero et al., 2008; Rufino et al., 2009; Thornton & Herrero, 2015). A substantial proportion of rural farm households- approximately two-thirds- are engaged in livestock production (Herrero et al., 2013). Livestock significantly improves nutritional outcomes, reduces poverty, and enhances food security through various mechanisms (J. Smith et al., 2013; Steinfeld et al., 2006; Turner et al., 2014).

In West Africa, particularly in the Sahel, livestock production is a source of income and a key strategy for managing risk and coping with climatic variability (Moll, 2005; Turner, 2009). For example, Molina-Flores et al. (2020) emphasize that livestock helps diversify risks during potential crop failures, providing food and manure for crop production. Their study in Mali demonstrates that livestock rearing supports food security and income generation, especially during economic and environmental stress. Similarly, Moritz (2012) highlights how pastoralists in the Sahel adapt to changing environmental conditions by maintaining diverse herds, which are critical for sustaining livelihoods during dry seasons or droughts.

Murendo et al. (2019) examined the role of crop and livestock diversification on household nutrition in Zimbabwe, finding that crop and livestock diversity positively impact dietary diversity and food consumption. They also showed that market access further enhances dietary diversity by providing households with income that can be used to purchase a variety of food items. While their study is based in Zimbabwe, the findings are relevant to the Sahel region, where market access is often limited, and diversification strategies are crucial for food security.

Furthermore, Hänke & Barkmann (2017) studied smallholder farmers in Southwestern Madagascar, reiterating that livestock acts as insurance for farming households during shocks such as crop failures. This finding aligns with the experiences of smallholder farmers in the Sahel, where livestock provides a crucial safety net during periods of climatic stress (Owen et al., 2005).

This study explores the association between crop and livestock's on-farm production diversity and commercialization, and their contribution to food security in rural farm households in Mali. It is essential to know the factors that contribute more to food security in farm households to make strategic public policies to ensure food security. Smallholder farms in Sub-Saharan Africa are integrated with crop and livestock production. However, most studies did not include livestock in the on-farm diversity(Douyon et al., 2022; N'Danikou et al., 2017). To our knowledge, one study by Murendo *et al.* (2019) tested the causal link between crop and livestock diversification and household diet diversity in Zimbabwe, finding positive effects on nutrition and a positive association with market access and dietary diversity. However, this study has some limitations. The study was conducted only in two districts of Zimbabwe which limits the generalizability of the findings, they use dietary diversity as a proxy to food security and nutrition which may not directly measure that, they touches on the importance of market participation but measure the market access through the distance to the market which does not fully explore the complexities of market participation, and did not consider whether households commercialize their product or not.

To address these gaps, our study examines crop and livestock on-farm diversity and commercialization to determine their relative contributions to food security. We utilize the food insecurity experience scale (FIES) to comprehensively assess food security, capturing various dimensions such as food quantity, quality, variety, and sufficiency. It provides a more holistic understanding of food security beyond traditional indicators such as dietary diversity and food consumption score.

We employ a conditional mixed process (CMP) framework, a simultaneous equation system, to analyze the interrelatedness of on-farm diversity and commercialization with food insecurity. This framework allows us to explore the complex dynamics between production diversity, commercialization, and food security outcomes. This study contributes to the existing literature in three ways. First, an important contribution of our study is that we employ a simultaneous equation system through a conditional mixed process with instrumental variables that resolve the endogeneity due to simultaneity. Second, we consider the role of both crops and livestock in households' food security, whereas many other studies solely focus on crops (Jones et al., 2014; Pellegrini & Tasciotti, 2014; Sibhatu et al., 2015) or livestock (Hoddinott et al., 2015; Leroy & Frongillo, 2007). By examining both crop and livestock diversification and considering the role of commercialization, our study aims to provide valuable insights into the factors that contribute more significantly to food security in farm households in Mali. Finally, we utilize a comprehensive assessment of food security, FIES, that captures both quantity and quality of food consumption. Using the FIES and the CMP framework enhances our understanding of food security by capturing a broader range of dimensions and accounting for the interplay between on-farm diversity and commercialization in addressing food insecurity.

**3.2 Conceptual Framework**

Food security serves as a foundational element for sustainable human capital development encompassing key areas such as health, nutrition, and education while fostering resilience to shocks and crises and long-term social cohesion and economic prosperity (FAO, 2006; World Bank, 2007). Household food security relies on the availability, accessibility, utilization, and stability of food (FAO, 2008). To ensure the well-being and productivity of its members, the household seeks to ensure food security by utilizing its resources, such as productive land and human capital, to secure a healthy and dignified life (L. C. Smith & Haddad, 2000).

Our conceptual framework builds on a triangular approach to analyze the relationship between on-farm production diversity, commercialization, and household food security. Figure 3.1 illustrates two major mechanisms that link on-farm diversity and commercialization with food security- access to diversified food and household income. Empirical evidence supports the connection between crop or livestock diversification and food security. Diversified food consumption is essential for meeting a household’s food security and nutritional requirements.

On-farm diversity directly influences food security by offering various food sources, ensuring dietary variety, and reducing vulnerability to crop failure or market fluctuations (Pretty, 2018). A diverse range of crops and livestock products ensures household access to various foods that provide a comprehensive range of nutrients, reducing malnutrition and improving overall health. Food insecurity tends to increase during shocks such as crop failures, drought, and climate disruptions to food production. However, diversity in food production can mitigate these risks by spreading them across crops and livestock, reducing the impact of pests and other climate shocks, and ultimately minimizing food insecurity (Alinovi, Mane, and Romano, 2010).

Additionally, crop rotation and intercropping practices can improve soil fertility, enhancing long-term agricultural productivity and food security (Tilman et al., 2002). Diverse farming supports natural predators, reducing the use of chemical pest control and promoting ecological balance. It also optimizes water use through complementary water requirements of different crops, improves soil nitrogen, and prevents soil erosion and degradation. These advantages of diverse farming contribute to the long-term sustainability of the land, thereby enhancing food security

(Bommarco, Kleijn, and Potts, 2013). However, producing a diverse array of crops or raising different livestock types may come with the cost of losing economies of scale that can be achieved through specialization (Timmer, 2009).

Household income is another important pathway. Income can be generated through the sale of crops, livestock, and livestock products or from non-farm income. Sales may occur as a part of planned commercialization or distress sales during shocks. Commercialization increases household income, enabling households to purchase food and non-food items of their preference. It also opens access to purchasing diverse foods from the market. Selling farm products in the market increases household income, providing the means to buy food during periods of low on-farm production or crop failure (Ochieng et al., 2020). Increased income through commercialization also supports reinvestment in the farm, leading to higher agricultural productivity through the adoption of modern technologies and practices (Pingali, 2012). This reinvestment can increase productivity by enhancing the adoption rates of improved seed, fertilizer, and other inputs. Distress sales of livestock during economic or climate shocks work as insurance to keep household consumption smooth, and it helps households overcome cash constraints during shocks and crises.

Moreover, commercialization helps develop a better supply chain, ensuring food availability during the lean season.  A well-functioning market can stabilize food prices, enforce quality and safety standards, and ensure that safe and nutritious food is available at affordable prices (Lentz & Barrett, 2013). Commercial farming can also create employment opportunities on and off the farm, improving infrastructure and rural development. This process further escalates food security (Reardon & Timmer, 2007).

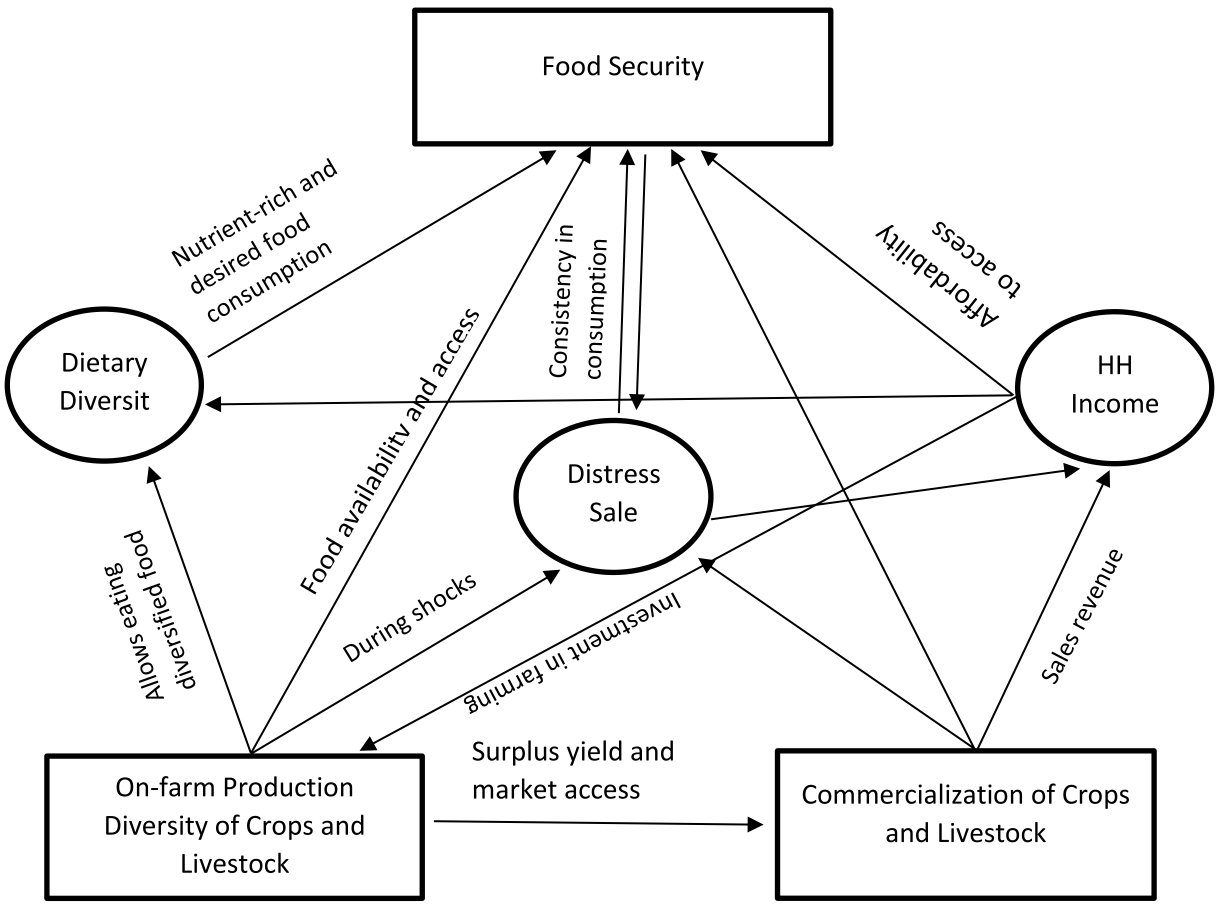
Households that engage in diversified farming and commercialization may have better access to food, either through self-production or market purchases. The household's decision-making process optimizes on-farm production diversity and market participation to ensure food security. The choice between on-farm diversity and purchasing diversified food from the market depends on several factors, including farm and market characteristics. The decision price of crops is endogenous, influenced by transaction costs, market accessibility, household composition, and available resources. Ultimately, food security is determined by the household's consumption of diversified food obtained through on-farm production, market purchases, or donations. The household strives to achieve food security by considering its composition, farm and market characteristics, preferences, and constraints related to production technology, market access, and income levels. The relative importance of diverse farming and commercialization of crops and livestock in contributing to food security may vary depending on the context, particularly in rural farming households in developing countries (Jones & Ejeta, 2016).

Our conceptual framework captures the intricate relationship between on-farm production, commercialization, and household food security within a triangular model. We measure crop diversity by indices such as crop species counts and the Herfindahl index, which measures crop concentration. Livestock diversity is assessed by counting the number of livestock species within a household. We define crop and livestock commercialization by the revenue earned from selling crops and livestock products during the last three months. Crop commercialization includes revenue earned from the sale of crops during the last three months of the survey, while livestock commercialization includes revenue from the sale of livestock or livestock products, such as meat, milk, and eggs, during the same period. Food security is measured by the Food Insecurity

Experience Scale (FIES) ( Ballard, 2013), which combines eight binary questions (yes/no) on the quantity and quality of food accessed by the household during the last months of the survey.

The interactive triangle of on-farm diversity, commercialization, and food security is illustrated in the following figure.

Figure 3.1: Interactive relationship among on-farm diversity, commercialization, and food security




## 3.3 Methods

### 3.1.1 Data

The data used for this study are the 2017 Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) data conducted by the Planning and Statistics Unit of the Ministry of Agriculture of Mali in collaboration with the LSMS team of the World Bank. This multi-topic household survey focuses on various household characteristics and living conditions, particularly agriculture. Two rounds of data collection were conducted for the same households. The first visit took place during the post-planting period between August and October 2017, and the second visit occurred during the harvest/post-harvest period from November 2017 to February 2018.

The survey is nationally representative, covering all regions and areas except Kidal. A random sample of 1070 standard enumerations (SE) areas (*grappe*) was selected with probability proportional to size using the 2009 Census of Population as the base for the sample and the number of households as a measure of size in each agroecological zone. Nine household farms (Exploitations Agricoles Familiales, or EAF) were randomly selected from a list frame in each SE area. The estimated sample size is 9630 (9 households from each SE times 1070 SE). However, for security reasons, the first visit covered 8711 households, while the second one interviewed 8658 households. Households' number 3, 6, and 9 in each SE were surveyed with the full version of the questionnaire (covered 11 sections), and households' number 1, 2, 4, 5, 7, and 8 were surveyed with the lighter version of the questionnaire (covered nine sections).

The Food Insecurity Experience Scale (FIES) module, developed by the Food and Agricultural Organization (Ballard, 2013), was administered, which includes eight binary (yes/no) questions related to the household's resources to ensure food security for its members in terms of both quantity and quality. The indicator is further discussed in section 3.3.3. Our final sample includes 5962 households. In approximately 81% of cases, the household head served as the respondent, with other senior members occasionally responding in the head's absence.

Furthermore, rainfall and temperature directly influence crop yields and livestock productivity, and variations in these factors can lead to differences in agricultural output, affecting the diversity of crops and livestock, commercialization, and food security. For instance, excessive rainfall or prolonged droughts can limit the range of crops grown, reducing on-farm diversity (Lobell et al., 2011). We extracted rainfall and temperature data at the cluster level from the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resource - POWER. Annual time series data from 1981 to 2017 were transformed into mean temperature and annual rainfall coefficient of variation over the given period. A long-time interval, such as the period from 1981 to 2017, captures the long-term climatic trends and variability that might influence agricultural practices and food security. This approach allows the analysis to account for both short-term fluctuations and long-term shifts in climate patterns, which are critical for understanding the sustainability of food security and agricultural practices (Deressa & Hassan, 2009).

### 3.1.2 Empirical strategy

We adopt a simultaneous equation framework to examine the empirical relationships between on-farm crop and livestock diversity, crop and livestock commercialization, and household food insecurity. In this framework, crop diversity is an outcome of smallholders' crop and land allocation choices, while livestock diversity measures the variety of livestock species households own.

We employ a five-structural system of equations to analyze the interrelatedness among crop or livestock diversity, commercialization of crop or livestock, and food insecurity:

$$\begin{cases} D_{cji} = \alpha_{0c} + \alpha_{1c}\boldsymbol{X_1} + \alpha_{2c}\boldsymbol{X_2} + \alpha_{3c}\boldsymbol{X_3} + \alpha_{4c}\boldsymbol{X_4} + \alpha_{5c}\boldsymbol{X_5} + D_{cji}^{i-1} + \varepsilon_{cji} & (1) \\ D_{lji} = \alpha_{0l} + \alpha_{1l}\boldsymbol{X_1} + \alpha_{2l}\boldsymbol{X_2} + \alpha_{3l}\boldsymbol{X_3} + \alpha_{4l}\boldsymbol{X_4} + \alpha_{5l}\boldsymbol{X_5} + D_{lji}^{i-1} + \varepsilon_{lji} & (2) \\ C_{cji} = \beta_{c} + \beta_{1c}\boldsymbol{X_1} + \beta_{2c}X_2 + \beta_{3c}\boldsymbol{X_3} + \beta_{4c}\boldsymbol{X_4} + \beta_{5c}\boldsymbol{X_5} + +C_{cji}^{i-1} + \mu_{cji} & (3) \\ C_{lji} = \beta_{0l} + \beta_{1l}\boldsymbol{X_1} + \beta_{2l}\boldsymbol{X_2} + \beta_{3l}\boldsymbol{X_3} + \beta_{4l}\boldsymbol{X_4} + \beta_{5l}\boldsymbol{X_5} + +C_{lji}^{i-1} + \mu_{lji} & (4) \\ FIES_{ji} = \delta_0 + \delta_1 D_{cji} + \delta_2 D_{lji} + \delta_3 C_{cji} + \delta_4 C_{lji} + \delta_5\boldsymbol{X_1} + \delta_6\boldsymbol{X_2} + \delta_7\boldsymbol{X_3} + \delta_8\boldsymbol{X_4} + \delta_9\boldsymbol{X_5} + \nu_{ji} & (5) \end{cases}$$

In the first four equations, outcome variables $D_{cji}$, $D_{lji}$, $C_{cji}$, and $C_{lji}$ represent on-farm crop diversity, livestock diversity, commercialization of crops, and livestock commercialization, respectively; subscript c and l stands for crops and livestock, i stands for individual households, where j implies survey rounds- j=1 means first round and j=2 means second round of the survey. $D_{cji}^{i-1}$ is the village level average crop diversity of other households in the village. Similarly, $D_{lji}^{i-1}, C_{cji}^{i-1}, and\ C_{lji}^{i-1}$ are the village-level average value for diversity and commercialization variables for the other households in the village. These village-level averages will capture the neighboring effect on individual households' diversity and commercialization behaviors, as studies showed that the behavior of agricultural farms is influenced by the behavior of the neighboring farms (Conley & Udry, 2010; Van Dusen & Taylor, 2005). Exogenous variables are agro-ecological characteristics or long-term weather at the village scale ($X_1$), arid or semiarid zone indicator ($X_2$), market characteristics ($X_3$), and household characteristics ($X_4$), and farm physical or plot characteristics ($X_5$). $\varepsilon_{cji}, \varepsilon_{lji,} \mu_{cji}, and\ \mu_{lji}$ are the error terms in the four equations, respectively. The fifth equation describes the food insecurity experience scale (FIES) as a function of on-farm crop diversity, livestock diversity, crop commercialization, livestock commercialization, agro-ecological characteristics, or long-term weather at the village scale ($X_1$), arid or semiarid zone indicator ($X_2$), market characteristics ($X_3$), and household characteristics ($X_4$), and farm physical or plot characteristics ($X_5$). The error term in this equation is $\nu_{ji}$. Table 3.1 has detailed definitions and summary statistics of the explanatory variables.

The key parameters of interest in this model are $\delta_1$, $\delta_2, \delta_3, and\ \delta_4$, measuring the effect of on-farm crop diversity, livestock diversity, crop commercialization, and livestock commercialization on food insecurity, respectively.

The outcome variables used in this study exhibit different forms, such as left-censored (crops count, livestock count), fractional (Herfindahl index), and continuous (revenue earning from sales). A potential endogeneity issue arises in the fifth equation where the Food Insecurity Experience Scale ($FIES_{ji}$) is regressed on $D_{cji},\ D_{lji}, C_{cji}, and\ C_{lji}$. Since these variables are endogenous- determined by their respective equations they are correlated with their error terms $\varepsilon_{cji}\ \ , \varepsilon_{lji}\ \ , \mu_{cji}, and\ \mu_{lji}$. When $D_{cji},\ D_{lji}, C_{cji}, and\ C_{lji}$ are included as predictors in the fifth equation, the error term $\nu_{ji}$ in the fifth equation is likely to be correlated with these predictors, leading to simultaneity bias.

We measured food insecurity for the last month of the survey, while revenue from the sale of crops and livestock was assessed over the last three months. This timing discrepancy introduces uncertainty about whether a household sold its products early or late within the three months, potentially introducing simultaneity issues between food security and commercialization. If the commercialization overlaps with the food security recall month (the last month of the survey), then there is a possibility of reverse causality, where food insecurity drives commercialization. In such a case, the food insecurity index may act as a determinant of commercialization. However, we cannot include food security in the commercialization equations due to a lack of appropriate instruments. There may also be unobserved factors not included in the model that influence both diversity and commercialization variables.

Additionally, production diversity itself may drive commercialization. Moreover, measurement errors in the outcome variables or reverse causality between food security and other outcome variables used as explanatory variables in the fifth equation could also contribute to endogeneity. We employ a Conditional Mixed Process (CMP) with Instrumental Variables (IVs) to address these potential endogeneity issues.

The village-level average diversity or commercialization of other neighboring households serves as instrumental variables (IVs). As discussed, the diversification or commercialization behavior of neighboring households can influence an individual household's decision regarding crop or livestock diversity and commercialization, but not their food security. Food security is a state rather than a behavior, and it does not directly impact the food security of other households.

Given the mixed nature of dependent and independent variables and the potential for endogeneity, we employ Roodman's (2011) conditional mixed process (CMP) to estimate the model. CMP offers the advantage of accommodating both linear and nonlinear models within the same structural system of equations (Roodman, 2011). As a recursive model, CMP allows for modeling systems of equations that are potentially endogenous. This capability is crucial when dependent variables in one equation also serve as explanatory variables in another, a common source of endogeneity. By specifying a recursive system, CMP recognizes that certain variables, such as food insecurity, are influenced by others, like on-farm crop and livestock production and commercialization, but not vice versa. It helps capture the appropriate causal direction (Jeffrey M Wooldridge, 2010).

CMP allows for the correlation of the error terms across the five equations, addressing potential endogeneity issues that arise from on-farm diversity and commercialization (Roodman, 2011). It is particularly important for dealing with unobserved heterogeneity, which may cause endogeneity (Greene, 2003). Endogeneity can be detected through the correlation coefficients of the error terms. If the error terms are correlated, it suggests that unobserved factors simultaneously affect multiple equations. By estimating these correlations, CMP can provide insights into the presence of endogeneity. Significant correlation coefficients indicate that the errors are not independent, pointing to endogeneity. Positive coefficients suggest that unobserved factors positively affect the errors in both equations, while negative coefficients indicate an opposite effect (Roodman, 2011).

Unlike two-stage least squares (2SLS) estimation, which is limited to linear models, CMP can handle more complex relationships and variable types and simultaneously estimates all equations in the system (Cameron & Trivedi, 2005). This joint estimation approach is crucial for addressing endogeneity, as it accounts for the simultaneity and interdependence of the equations. By examining error term correlations, CMP offers a direct method for detecting endogeneity, while 2SLS primarily relies on using instrumental variables to address it (Jeffrey M Wooldridge, 2010). CMP is a better approach in the case of nonlinear models and systems where the dependent variables are of mixture types, such as one outcome variable being binary and another being continuous. It makes CMP more versatile than 3SLS, which is limited to linear systems.

CMP allows estimate models with endogenous regressors using instrumental variables (IV) just like other IV estimation techniques. We can use instrumental variables in the CMP framework to account for the endogeneity where one or more equations contain endogenous regressors.

In our system of five equations, which considers the potential correlation of the error terms across all the equations, we include four endogenous variables in the food security equation. Potential endogeneity arises because these variables might be correlated with the error term in that equation. The village-level averages of diversity and commercialization variables serve as IVs. These IVs are correlated with the endogenous variables of diversity and commercialization in the first four equations but are assumed to be uncorrelated with the error term in the fifth equation, where FIES is the dependent variable. By incorporating IVs, CMP controls for the potential endogeneity of $D_{cji},\ D_{lji}, C_{cji}, and\ C_{lji}$ in the fifth equation. The IVs replace the endogenous regressors with their predicted values, free from the endogeneity bias. CMP uses maximum likelihood estimation to jointly estimate all five equations, considering the entire system's structure. The joint estimation in CMP further refines these estimates using information from the entire system, making the estimates consistent and efficient.

We include long-term village-level weather variables, household and market characteristics, and plot physical characteristics to account for possible influences on on-farm diversity, commercialization, and food security. Following Dillon, McGee, and Oseni (2015), who assert that local climate variables correlate with production variables, we construct weather variables considering long-term conditions, including average temperature and coefficient of variation in rainfall from 1981 to 2017.

### 3.1.3 Outcome Variables

***Food Insecurity Experience Scale (FIES):*** Food insecurity at the household level is commonly measured using experience-based scales, which provide valuable insights into the extent and severity of food insecurity. There are four widely used scales: the Food Insecurity Experience Scale (FIES), the Household Hunger Scale (HHS), the Household Food Insecurity Access Scale (HFIAS), and the Latin America and Caribbean Food Security Scale (ELCSA) (T. Ballard et al., 2011; Cafiero et al., 2018; Coates et al., 2007). These scales assess food insecurity resulting from resource constraints and can be categorized into two levels: reducing dietary quality and variety due to experiencing hardship and reduced food intake and skipping meals at the individual or household level, indicating high food insecurity (Ballard et al., 2011; Jones et al., 2013).

In this study, we used the FIES food security scale to estimate the prevalence of food insecurity at the household level. The FIES is a reliable, theoretically well-grounded, and accurate experience-based measure of food security developed by the Food and Agriculture Organization

(FAO) Statistics Division in 2013 (Ballard, Kepple, and Cafiero, 2013). The FIES has been widely utilized in various studies to assess food insecurity at the household level. For instance, Smith et al. (2017) applied the FIES to evaluate food security across multiple regions in sub-Saharan Africa, while Vilar-Compte et al. (2021) used it to examine urban food insecurity in Mexico. Similarly, Jones (2017a) employed the FIES to analyze food insecurity trends in the context of global health. FIES consists of eight questions, with a one-month or 12-month recall period, depending on the research priorities. These questions capture different levels of self-reported food insufficiency and insecurity due to resource constraints, with binary responses of yes/no[3]. Here are the eight questions included in the FIES:

1. Worry: In the last month, was there a time when you were worried you would not have enough food to eat because of a lack of money or other resources?
2. Variety of Food: In the last month, were you unable to eat healthy and nutritious meals because of a lack of money or other resources?
3. Balance of Food Choices: In the last month, did you lack enough money to buy the kinds of foods you should be eating?
4. Skipping Meals: In the last month, did you or other household members ever cut the size of your meals or skip meals because there wasn't enough food?
5. Eat Less: In the last month, did you or other household members ever eat less than you felt you should because there wasn't enough food?
6. Running Out of Food: In the last month, did you run out of food because of a lack of money or other resources?

[3] https://www.fao.org/in-action/voices-of-the-hungry/fies/en/

7. Hungry: In the last month, were you or other household members ever hungry but didn't eat because there wasn't enough food?
8. Eat Less Than You Should: In the last month, did you or other household members go without eating for a whole day because there wasn't enough food?

For this study, we use household-level responses based on a one-month recall of experiencing hardships. FIES is constructed based on the responses to these eight questions, providing a range of scores between 0 and 8. A score of 0 indicates no food insecurity (with all responses being 'no'), while a score of 8 indicates severe food insecurity (with all responses being 'yes'). That means the higher the value of the FIES index, the lower the state of food security. Although measuring the multiple dimensions of food insecurity on a single scale can be challenging, the FIES offers a standardized and condensed approach to capturing important aspects of household food security experiences.

The other variables of interest are the indices for on-farm diversity and commercialization of crops and livestock. We measure on-farm diversity by crop count, livestock count, and Herfindahl index. We measure crops and livestock commercialization using the revenue earned from crops and livestock sales during the last three months of the survey.

***Crops count***: Crops count quantifies the number of crops grown by a farm household. It is commonly employed as a straightforward measure of crop diversity. For example, Di Falco et al. (2010) use crop count to assess the impact of climate variability on farm household resilience in Ethiopia, while Morris et al. (2007) apply it to evaluate agricultural diversity and productivity in smallholder farms across Kenya. A higher crop count suggests a diversifying farming system.

***Herfindahl index***: We also use a Herfindahl index to measure on-farm crop diversity. Herfindahl index quantifies the concentration of crops by measuring the distribution of cultivated land area among different types of crops. We calculated it by taking the sum of squared crop area shares. $H = \sum_{i=0}^{n} \mathrm{s}_{\mathrm{i}}^{2}$, where H is the Herfindahl index, $s_i$ is the proportion of land area devoted to crop i, and n is the number of different crops. The Herfindahl index ranges from 0 to 1, with higher values indicating great concentration or lower crop diversity and lower values of the Herfindahl index indicating greater evenness or higher crop diversity.

Several studies have utilized the Herfindahl index as a measure of crop diversity due to its ability to capture the concentration of crop production. For instance, Theriault and Smale (2021) uses the Herfindahl index to examine the unintended consequences of agricultural policies on crop diversity. Similarly, Di Falco and Chavas (2009) used the Herfindahl index to measure crop diversity and its impact on farm productivity in Ethiopia. Joshi et al. (2004) applied it to assess crop diversification's effect on household food security in Nepal. The Herfindahl index serves as a good complement to crop count because, while crop count quantifies the number of crops, the Herfindahl index captures the evenness or concentration in land distribution across these crops, providing a more nuanced understanding of crop diversity.

***Revenue earned from crop sales***: Crop commercialization refers to farmers selling their produce instead of consuming it for household consumption, retaining it for seed, or donating it to friends and neighbors. We consider the revenue earned from the crop sales over the last three months as an indicator of crop commercialization. Higher revenue from crop sales allows households to buy various foods or other goods and services they need from the market and indicates greater involvement in commercial agricultural activities, where farmers sell a significant portion of their produce to the market. Conversely, lower revenue from crop sales indicates that farmers do not have enough surplus production to sell or face constraints in accessing the market. Sibhatu et al. (2015) also apply produce sold to the market as a proxy for market participation.

***Livestock count***: Similar to the crop count, we use a household's livestock count as an index for livestock diversity in a farming household. This index counts the number of different types of livestock in a farming household. Sibhatu et al. (2015) used livestock species counts along with crop count as an indicator of household production diversity, and Herrero et al. (2010) highlighted the importance of livestock diversity in mixed crop-livestock systems.

***Revenue earned from livestock sales***: This variable captures the extent of a household's participation in commercial livestock production by measuring the total monetary value generated from livestock sales over the last three months. Livestock commercialization is assessed by considering the revenue from the sale of live animals and livestock products such as meat, milk, and eggs. Higher revenue values indicate a greater degree of commercialization within the household. This approach is consistent with previous studies that have used revenue from livestock sales as an indicator of commercialization, such as Belay et al. (2021) and Barrett et al. (2001).

## 3.4 Results

### 3.1.4 Crop Commercialization and Summary Statistics

The mean value of the food insecurity index, FIES, is 0.76 during the first visit and 0.20 during the second visit, with the index ranging from 0 to 8. It suggests that households experienced greater food insecurity during the first visit compared to the second, which is expected given that the second visit occurred after the harvest. Notably, 31% of households reported worrying about having enough food during the first visit, compared to 27% during the second. Across all eight food security questions, households were less food insecure in the second period. Remarkably, no household went an entire day without eating during the second visit, while 6% reported doing so during the first visit.

The surveyed households are located an average of 13 kilometers from the nearest paved road, 40 kilometers from the nearest population center, and 68 kilometers from the district center. These distances highlight the significant infrastructural challenges that households face in accessing markets and essential services. Over the last 12 months, the average nonfarm income was approximately 7,000 CFA Francs, indicating limited diversification of income sources beyond agriculture. Literacy levels among adults are relatively low, with only 21% being literate. Additionally, the ratio of plots managed by women compared to men is 0.23, reflecting a notable gender disparity in land management responsibilities. These factors collectively suggest barriers to economic opportunities and access to resources for the surveyed households.

Regarding crop usage, households reported various major purposes, including household consumption, donations to neighbors and relatives, seed stocking, input reimbursement, domestic animal feeding, future storage, selling, and some degradation in the selling process from the field to the market. Appendix Table A 3.1 shows that only 27% of households engaged in selling their crops. Most of the sales occurred in the local market, and other points of sales were neighbors, cooperatives, private operators, and others. Approximately 89% of households donated a portion of their crops to neighbors and relatives, which indicates two things- a good social network or difficulty in commercialization. Regarding storing crops, 30% of households managed to store some of their produce, and in most cases, the main purpose of storage is future consumption. These statistics highlight that households face challenges in storing or selling their crops.

Moreover, only 1.4% of households planned to sell their crops in the future (Appendix Table A 3.1). The major reason households reported not selling their crops was insufficient production (78%). The other reasons respondents mentioned regarding low sales were poor road conditions, low prices, long distances from roads and markets, high transportation costs, and wastage during transportation. Appendix Table A 3.1 presents the household-level summary of crop uses and commercialization.

### 3.1.5 Regression Results

As a starting point, we tested the correlation coefficients of the error terms to determine if there is endogeneity. We found small positive correlation coefficients among the residuals, which indicates that endogeneity exists or that the data leads us to reject the hypothesis of exogeneity. Results are reported in Appendix Table A 3.2. This evidence of endogeneity bolsters our decision to apply a simultaneous equation model, the conditional mixed process with instrumental variables.

Tables 3.2 and 3.3 illustrate the impact of crop and livestock diversity and commercialization on food insecurity, using different indices to measure diversity and commercialization. These tables display the results from maximum likelihood regression models, utilizing various combinations of diversity and commercialization variables of interest. Crop diversity variables include crop count and the Herfindahl index, and livestock diversity variable encompasses on-farm livestock production, such as the count of livestock types. The commercialization indicators include the crop and livestock sales revenue during the last three months.

***Impact of Crop and Livestock Diversity***

Table 3.2 presents the results from the simultaneous equations model analyzing crop count, crop commercialization, livestock counts, livestock commercialization, and food security across two household surveys. Column 6 displays the findings for the first survey period, while column 7 provides for the second survey period. The negative coefficients of the crop count variable suggest that an increase in on-farm crop diversity positively affects food security, consistent with previous literature. For example, Koppmair et al. (2017) found that on-farm production diversity in Malawi positively influences dietary diversity. Similarly, Sibhatu et al. (2015) demonstrated that a diversified farming system is crucial for food security in developing countries. However, no significant impact was observed in the second survey data, which could be attributed to seasonal variations affecting food availability and security as the second survey occurred after the harvest.

Table 3.3 utilizes the Herfindahl index to measure crop diversity. The higher value of the Herfindahl index indicates a higher concentration of few crops, which means lower on-farm diversity. The statistically significant positive coefficients of the Herfindahl index imply that concentrating crop production on a few crops increases food insecurity. In other words, a lack of diversity in crop production is associated with higher food insecurity. It aligns with findings from other studies, such as that by Pellegrini and Tasciotti (2014), who noted that reduced crop diversity leads to poorer dietary outcomes. The coefficient for livestock type counts also indicates similar results, reinforcing the importance of diversity in mitigating food insecurity. The consistent findings in both tables underscore the critical role of on-farm crop diversity in enhancing food security in farm households, regardless of the diversity indices used.

***Impact of Crop and Livestock Commercialization***

In contrast to the impact of crop and livestock diversity on food security, crop commercialization did not significantly affect food security during the first survey period, which aligns with expectations since sales were low during planting season. However, during the second survey period, just after the harvest, we still did not find any coefficient significantly affecting the food insecurity index (FIES). This finding is consistent with studies like that of Jones et al. (2014), which found that the timing of commercialization efforts is crucial for their impact on food security. The lower food insecurity observed just after the harvest can be explained by the relatively higher food access during this period. Additionally, a small portion of households (27%) that sold their crops, with only 1.4% of households indicating an intention to sell crops in the future, suggests that most farm households in Mali do not have enough surplus production to sell or have limited market access.

Given the limited commercialization of crops, the study uses livestock commercialization as an additional measure of market participation. However, even livestock commercialization shows a slight positive association with food insecurity, though the impact is negligible. This result might be due to distress sales, where households sell livestock during financial difficulties rather than as a planned or strategic sale. This finding aligns with the observations of Murendo et al. (2019), who found that livestock sales often reflect immediate needs rather than market opportunities. Overall, the results highlight the importance of on-farm production diversity for enhancing food security in farm households, while commercialization of crops and livestock may not significantly impact food security.

### 3.5 Conclusion and Policy Implications

This study investigates the relative importance of on-farm production diversity and commercialization of crops and livestock in ensuring food security in farm households in Mali. The analysis, based on data from the 2017 LSMS-ISA survey, reveals that most farm households in Mali engage in limited commercialization, potentially due to insufficient production to meet their family's needs and/or high transaction costs in accessing the market. A key contribution of this study is the simultaneous consideration of production diversity and commercialization of both crops and livestock within a single framework to assess their relative impact on household food security. Using a simultaneous equation model with instrumental variables, we explore the linkages among production diversity, commercialization, and food insecurity, utilizing the Food

Insecurity Experience Scale (FIES) as a comprehensive food security. The findings indicate that on-farm crop production diversity has a statistically significant positive impact on food security. In contrast, the relationship between livestock diversity, and crop or livestock commercialization with food security is less pronounced than anticipated.

The study reveals a marginally positive association between livestock commercialization and food insecurity, suggesting that livestock sales may often be distress-driven rather than a strategic decision. It is particularly important to mention that only a small proportion of households sell agricultural products, with even fewer indicating an intention to sell in the future. These findings underscore the importance of promoting on-farm production diversity as a more effective policy tool to enhance food security in rural Mali.

The results highlight the significance of on-farm crop diversity in promoting food security. Given the results, policymakers should focus on strategies encouraging or facilitating on-farm crop diversity. It could include promoting diverse cropping systems and mixed farming practices that integrate livestock. Such approaches are likely to be more effective in improving food security than those centered on commercialization, especially in contexts where market access is limited or production surpluses are insufficient. Moreover, understanding the dynamics of distress sales is critical. Policies that provide safety nets, such as access to credit or insurance schemes, may help prevent households from needing distress sales during crises, thereby protecting their long-term food security.

While this study provides valuable insights, it has several limitations. First, the cross-sectional nature of the data limits the ability to infer causality. Longitudinal studies could provide a clearer picture of how production diversity and commercialization impact food security over time. Second, the analysis relies on self-reported measures of food insecurity, which may be subject to recall bias or social desirability bias. Future research could benefit from incorporating objective measures of food security or triangulating self-reported data with other sources. Third, we have commercialization data for the last three months of the survey, while food security is for one month of recall. It is unclear from the data whether households commercialize earlier or later in that three-month period. Future studies can design a similar timing for the different variables beforehand to avoid this issue.

Additionally, the study primarily focuses on the effects of production diversity and commercialization within a specific period and geographic context. Future research could explore the role of these factors in different regions or under varying climatic conditions. Finally, there is a need for more detailed investigations into the reasons behind distress sales of livestock and the development of interventions to mitigate these occurrences.

## TABLES AND FIGURES OF CHAPTER THREE

Table 3.1: Definitions of key variables and summary statistics

| Variable | Definition | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| **Outcome Variables for the first visit (post-planting season)** | | | | | | |
| Crops count | Types of crops produced | 5,962 | 2.51 | 1.41 | 1 | 8 |
| Herfindahl | Herfindahl index for crops | 5,962 | 0.64 | 0.27 | 0.017 | 1 |
| Livestock count | Total count of livestock types | 5,962 | 5.11 | 2.74 | 0 | 14 |
| Crop Revenue | Total amount (CFA Franc) earned from crop sale during last three months | 5,962 | 149 | 541 | 0 | 6920 |
| Livestock Revenue | Total amount (CFA Franc) earned from livestock during last three months | 5,962 | 104 | 638 | 0 | 19284 |
| FIES1 | Index for food insecurity during last month of first visit | 5,962 | 0.76 | 1.78 | 0 | 8 |
| **Outcome Variables for the second visit (post-harvest season)** | | | | | | |
| Crops count | Types of crops produced | 5,962 | 2.54 | 1.45 | 1 | 9 |
| Herfindahl | Herfindahl index for crops | 5,962 | 0.64 | 0.27 | 0.002 | 1 |
| Livestock count | Total count of livestock types | 5,962 | 5.28 | 2.79 | 0 | 18 |
| Crop Revenue | Total amount (CFA Franc) earned from crop sale during last three months | 5,962 | 30 | 235 | 0 | 4542 |
| Livestock Revenue | Total amount (CFA Franc) earned from livestock during last three months | 5,962 | 16 | 133 | 0 | 3820 |
| FIES2 | Index for food insecurity during last month of 2nd visit | 5,962 | 0.20 | 0.86 | 0 | 7 |
| **Details Description of food insecurity in period 1 (food insecurity in the last 30 days)** | | | | | | |
| Were worried about having enough food to eat | | 5,962 | 0.31 | 0.46 | 0 | 1 |
| Were unable to eat healthy and nutritious meals | | 5,962 | 0.22 | 0.41 | 0 | 1 |
| Ate only few kinds of foods due to lack of resources | | 5,962 | 0.28 | 0.45 | 0 | 1 |
| Skipped meals due to lack of resources | | 5,962 | 0.13 | 0.34 | 0 | 1 |
| Ate less than desired due to lack of resources | | 5,962 | 0.19 | 0.39 | 0 | 1 |
| Ran out of food due to lack of resources | | 5,962 | 0.12 | 0.33 | 0 | 1 |
| Remained hungry without eating for lack of resources | | 5,962 | 0.10 | 0.30 | 0 | 1 |
| Went a whole day without eating for lack of food | | 5,962 | 0.06 | 0.23 | 0 | 1 |
| **Details Description of food insecurity in period 2 (food insecurity in the last 30 days)** | | | | | | |
| Were worried about having enough food to eat | | 5,962 | 0.27 | 0.44 | 0 | 1 |
| Were unable to eat healthy and nutritious meals | | 5,962 | 0.19 | 0.39 | 0 | 1 |
| Ate only few kinds of foods due to lack of resources | | 5,962 | 0.27 | 0.44 | 0 | 1 |
| Skipped meals due to lack of resources | | 5,962 | 0.09 | 0.28 | 0 | 1 |
| Ate less than desired due to lack of resources | | 5,962 | 0.16 | 0.37 | 0 | 1 |
| Ran out of food due to lack of resources | | 5,962 | 0.09 | 0.29 | 0 | 1 |
| Remained hungry without eating for lack of resources | | 5,962 | 0.06 | 0.23 | 0 | 1 |
| Went a whole day without eating for lack of food | | 5,962 | 0 | 0 | 0 | 0 |

Table continued to the next page

Table 3.1 (cont'd)

| Variable | Definition | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| **Agro-ecological Characteristics (overall for both survey period)** | | | | | | |
| Mean temp | Mean temperature of wettest quarter (Celsius) | 5,962 | 27.17 | 14.22 | 24.9 | 32.0 |
| Precipitation | Precipitation of wettest quarter (mm) | 5,962 | 511.97 | 170.30 | 134 | 898 |
| Avg NDVI | Average NDVI (vegetation index) value in the primary growing season | 5,962 | .27 | .06 | .11 | .41 |
| **Market Characteristics (overall for both survey period)** | | | | | | |
| Distance to Population Center | Distance to population center (km) | 5,962 | 62.31 | 40.14 | 0 | 20 |
| Distance to nearest border | Distance to nearest district border (km) | 5,962 | 128.57 | 64.97 | 4 | 27 |
| Distance to road | Distance to the road (km) | 5,962 | 13.04 | 11.95 | 0 | 63 |
| Distance to district | Distance to district center (km) | 5,962 | 117.99 | 68.39 | 0 | 321 |
| **Household Characteristics (overall for both survey period)** | | | | | | |
| Non-farm income | Off-farm income over the last 12 months (in thousand CFA) | 5,962 | 7057.6 | 107506.8 | 0 | 5700000 |
| Adult lit ratio | Adult literature ratio | 5,962 | .21 | .27 | 0 | 1 |
| Total area | Total land (ha) | 5,962 | 6.99 | 7.06 | .23 | 54.14 |
| Total plots | Total number of plots | 5,962 | 3.84 | 2.54 | 1 | 30 |
| **Plot Characteristics (overall for both survey period)** | | | | | | |
| Plot near house | Share of plots area near home | 5,962 | .04 | .142 | 0 | 1 |
| Good soil area share | Share of good soil plots area from respondent's perspective | 5,962 | .27 | .36 | 0 | 1 |
| Non-rainfed area | Share of non-rainfed area | 5,962 | .58 | .33 | 0 | 1 |
| Plot female ratio | Ratio of plots managed by female hh members | 5,962 | .225 | .66 | 0 | 14 |
| Plainland share | Share of plainland area | 5,962 | .489 | .37 | 0 | 1 |

Table 3.2: Simultaneous equation model for five equations (crop diversity index: crops count)

| VARIABLES | Crops count | Livestock counts | Revenue Crop Sale | Revenue Livestock | FIES (1st visit) | FIES ($2^{nd}$ visit) |
|---|---|---|---|---|---|---|
| Crops count | | | | | -0.15* | -0.02 |
| | | | | | (0.09) | (0.03) |
| Livestock counts | | | | | 0.01 | 0.01 |
| | | | | | (0.03) | (0.01) |
| Revenue crop sale (CFA) | | | | | 0.00 | -0.00 |
| | | | | | (0.00) | (0.00) |
| Revenue Livestock (CFA) | | | | | -0.00 | 0.00 |
| | | | | | (0.00) | (0.00) |
| Distance to nearest population center (km) | -0.00** | 0.00 | -0.30** | -0.13 | -0.00 | -0.00** |
| | (0.00) | (0.00) | (0.12) | (0.14) | (0.00) | (0.00) |
| Distance from nearest border crossing (km) | 0.00 | 0.00 | -0.08 | -0.11 | -0.00 | -0.00** |
| | (0.00) | (0.00) | (0.07) | (0.09) | (0.00) | (0.00) |
| Distance from the road (km) | -0.00** | -0.00* | 0.40 | 0.17 | 0.00 | 0.00** |
| | (0.00) | (0.00) | (0.37) | (0.45) | (0.00) | (0.00) |
| Distance from the district headquarter (km) | 0.00** | 0.00 | -0.00 | -0.11 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.07) | (0.09) | (0.00) | (0.00) |
| Non-farm income (CFA Franc) | -0.00*** | -0.00 | 0.00 | 0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Adult literacy ratio | -0.01 | 0.08 | 3.19 | -0.36 | -0.07 | 0.00 |
| | (0.04) | (0.11) | (15.89) | (19.10) | (0.15) | (0.05) |
| Total land (ha) | 0.01*** | 0.06*** | 3.90*** | 0.62 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.74) | (0.89) | (0.01) | (0.00) |
| Mean temperature of wettest quarter (degree C*10) | 0.01*** | -0.00 | -0.11 | 0.13 | 0.01 | 0.01*** |
| | (0.00) | (0.01) | (0.78) | (0.94) | (0.01) | (0.00) |
| Precipitation in wettest quarter (mm) | 0.00*** | -0.00 | 0.13** | 0.10 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.07) | (0.08) | (0.00) | (0.00) |
| Long time average NDVI | 0.79** | -0.79 | 129.58 | -142.10 | 0.68 | -0.01 |
| | (0.35) | (1.04) | (149.99) | (180.19) | (1.46) | (0.44) |
| Arid zone | 0.44*** | 0.49* | 136.48*** | 38.05 | 1.01*** | -0.03 |
| | (0.08) | (0.25) | (36.78) | (43.62) | (0.37) | (0.11) |
| Semi-arid zone | 0.25*** | -0.16 | 61.69*** | 15.23 | 0.13 | 0.02 |
| | (0.05) | (0.16) | (23.21) | (27.64) | (0.23) | (0.07) |
| Total number of plots | 0.25*** | 0.09*** | 4.74** | 5.47** | 0.03 | 0.01 |
| | (0.01) | (0.01) | (2.15) | (2.56) | (0.04) | (0.01) |
| Share of plots near house | -0.15** | -0.48** | 114.91*** | 147.04*** | -0.24 | 0.81*** |
| | (0.07) | (0.21) | (29.54) | (35.49) | (0.20) | (0.11) |

Table continued to the next page

Table 3.2 (cont'd)

| VARIABLES | Crops count | Livestock counts | Revenue Crop Sale | Revenue Livestock | FIES (1st visit) | FIES ($2^{nd}$ visit) |
|---|---|---|---|---|---|---|
| Share of plots with good soil from respondent's perspective | -0.02 | 0.21** | 25.81** | 40.15*** | -0.19* | 0.03 |
| | (0.03) | (0.08) | (11.81) | (14.16) | (0.11) | (0.04) |
| Share of plots non-rainfed | 0.08** | 0.49*** | 2.30 | 6.88 | -0.00 | -0.04 |
| | (0.04) | (0.11) | (15.61) | (18.77) | (0.16) | (0.05) |
| Share of plots manage by women adults | -0.14*** | 0.05 | 2.84 | 13.32 | -0.04 | 0.03 |
| | (0.02) | (0.05) | (7.03) | (8.45) | (0.07) | (0.02) |
| Share of plainland plots | -0.06** | 0.10 | -0.58 | -2.14 | -0.22* | -0.00 |
| | (0.03) | (0.08) | (12.00) | (14.43) | (0.12) | (0.04) |
| Village average of crops count | 0.55*** | | | | | |
| | (0.01) | | | | | |
| Village average of livestock species count | | 0.76*** | | | | |
| | | (0.01) | | | | |
| Village average of crop revenue | | | 0.40*** | | | |
| | | | (0.03) | | | |
| Village average of livestock revenue | | | | 0.08** | | |
| | | | | (0.03) | | |
| Constant | -2.46*** | 1.64 | -145.04 | -49.87 | -1.97 | -1.50** |
| | (0.54) | (1.68) | (232.54) | (279.49) | (2.35) | (0.72) |
| N | 5962 | 5962 | 5962 | 5962 | 5962 | 5962 |
| Wald Chi2 | 23451 | 23451 | 23451 | 23451 | 23451 | 23383 |
| p-value | 0 | 0 | 0 | 0 | 0 | 0 |

Source: Authors' calculation. Maximum likelihood estimation. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.3: Simultaneous equation model for five equations (crop diversity: Herfindahl Index)

| VARIABLES | Herfindahl Index | Livestock counts | Revenue Crop Sale | Revenue Livestock | FIES (1st visit) | FIES ($2^{nd}$ visit) |
|---|---|---|---|---|---|---|
| Herfindahl Index | | | | | 0.82** | 0.02 |
| | | | | | (0.39) | (0.12) |
| Livestock counts | | | | | 0.00 | 0.00 |
| | | | | | (0.03) | (0.01) |
| Revenue crop sale (CFA) | | | | | 0.00 | -0.00 |
| | | | | | (0.00) | (0.00) |
| Revenue Livestock (CFA) | | | | | -0.00 | 0.00 |
| | | | | | (0.00) | (0.00) |
| Distance to nearest population center (km) | 0.00 | 0.00 | -0.30** | -0.13 | -0.00 | -0.00** |
| | (0.00) | (0.00) | (0.12) | (0.14) | (0.00) | (0.00) |
| Distance from nearest border crossing (km) | -0.00 | 0.00 | -0.08 | -0.11 | -0.00 | -0.00** |
| | (0.00) | (0.00) | (0.07) | (0.09) | (0.00) | (0.00) |
| Distance from the road (km) | 0.00** | -0.00* | 0.40 | 0.17 | 0.00 | 0.00** |
| | (0.00) | (0.00) | (0.37) | (0.45) | (0.00) | (0.00) |
| Distance from the district headquarter (km) | -0.00 | 0.00 | -0.00 | -0.11 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.07) | (0.09) | (0.00) | (0.00) |
| Non-farm income (CFA Franc) | 0.00 | -0.00 | 0.00 | 0.00 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Adult literacy ratio | 0.01 | 0.08 | 3.20 | -0.36 | -0.10 | 0.00 |
| | (0.01) | (0.11) | (15.89) | (19.10) | (0.15) | (0.05) |
| Total land (ha) | -0.00*** | 0.06*** | 3.90*** | 0.62 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.74) | (0.89) | (0.01) | (0.00) |
| Mean temperature of wettest quarter (degree C*10) | -0.00*** | -0.00 | -0.11 | 0.13 | 0.01* | 0.01*** |
| | (0.00) | (0.01) | (0.78) | (0.94) | (0.01) | (0.00) |
| Precipitation in wettest quarter (mm) | -0.00*** | -0.00 | 0.13** | 0.10 | -0.00 | -0.00 |
| | (0.00) | (0.00) | (0.07) | (0.08) | (0.00) | (0.00) |
| Long time average NDVI | -0.16** | -0.79 | 129.49 | -142.10 | 0.75 | -0.05 |
| | (0.08) | (1.04) | (149.99) | (180.19) | (1.45) | (0.44) |
| Arid zone | -0.04** | 0.49* | 136.36*** | 38.05 | 0.97*** | -0.04 |
| | (0.02) | (0.25) | (36.78) | (43.62) | (0.36) | (0.11) |
| Semi-arid zone | -0.02 | -0.16 | 61.62*** | 15.23 | 0.11 | 0.01 |
| | (0.01) | (0.16) | (23.21) | (27.64) | (0.23) | (0.07) |
| Total number of plots | -0.03*** | 0.09*** | 4.73** | 5.47** | 0.01 | 0.00 |
| | (0.00) | (0.01) | (2.15) | (2.56) | (0.03) | (0.01) |
| Share of plots near house | 0.03** | -0.48** | 114.92*** | 147.04*** | -0.25 | 0.81*** |
| | (0.02) | (0.21) | (29.54) | (35.49) | (0.20) | (0.11) |

Table continued to the next page

Table 3.3 (cont'd)

| VARIABLES | Herfindahl Index | Livestock counts | Revenue Crop Sale | Revenue Livestock | FIES (1st visit) | FIES ($2^{nd}$ visit) |
|---|---|---|---|---|---|---|
| Share of plots with good soil from respondent's perspective | 0.01 | 0.21** | 25.80** | 40.14*** | -0.21* | 0.03 |
| | (0.01) | (0.08) | (11.81) | (14.16) | (0.11) | (0.04) |
| Share of plots non-rainfed | -0.04*** | 0.49*** | 2.31 | 6.88 | 0.04 | -0.05 |
| | (0.01) | (0.11) | (15.61) | (18.77) | (0.16) | (0.05) |
| Share of plots manage by women adults | 0.00 | 0.05 | 2.84 | 13.32 | -0.02 | 0.04 |
| | (0.00) | (0.05) | (7.03) | (8.45) | (0.07) | (0.02) |
| Share of plainland plots | 0.00 | 0.10 | -0.58 | -2.14 | -0.22* | -0.00 |
| | (0.01) | (0.08) | (12.00) | (14.43) | (0.12) | (0.04) |
| Village average of Herfindahl Index | 0.66*** | | | | | |
| | (0.02) | | | | | |
| Village average of livestock species count | | 0.76*** | | | | |
| | | (0.01) | | | | |
| Village average of crop revenue | | | 0.41*** | | | |
| | | | (0.03) | | | |
| Village average of livestock revenue | | | | 0.08** | | |
| | | | | (0.03) | | |
| Constant | 0.92*** | 1.64 | -145.00 | -49.85 | -3.65 | -1.46* |
| | (0.14) | (1.68) | (232.54) | (279.49) | (2.59) | (0.79) |
| N | 5962 | 5962 | 5962 | 5962 | 5962 | 5,962 |
| Wald Chi2 | 14147 | 14147 | 14147 | 14147 | 14147 | 14078 |
| p-value | 0 | 0 | 0 | 0 | 0 | 0 |

Source: Authors' calculation. Maximum likelihood estimation. *** p<0.01, ** p<0.05, * p<0.1.

BIBLIOGRAPHY


Acquisti, A., & Fong, C. (2020). An experiment in hiring discrimination via online social networks. *Management Science*, *66*(3), 1005–1024.

Adjimoti, G. O., & Kwadzo, G. T.-M. (2018). Crop diversification and household food security status: evidence from rural Benin. *Agriculture & Food Security*, *7*(1), 1–12.

Adjimoti, G. O., Kwadzo, G. T., Sarpong, D. B., & Onumah, E. E. (2017). Input policies and crop diversification: Evidence from the Collines Region in Benin. *African Development Review*, *29*(3), 512–523.

AFAP. (2020). *Africa Fertilizer Map 2020*. https://www.afap-partnership.org/africa-fertilizer-map-2020/

Ahmed, S., & Maitra, P. (2010). Gender wage discrimination in rural and urban labour markets of Bangladesh. *Oxford Development Studies, 38*(1), 83–112.

Ahmed, S., & Maitra, P. (2015). A distributional analysis of the gender wage gap in Bangladesh. *The Journal of Development Studies*, *51*(11), 1444–1458.

Akbaba, Y. (2023). Religious Discrimination against Minorities: Theories and Findings. *Social Sciences*, *12*(9), 522.

Alesina, A. F., Lotti, F., & Mistrulli, P. E. (2013). Do women pay more for credit? Evidence from Italy. *Journal of the European Economic Association*, *11*(suppl_1), 45–66.

Ali, I., Anwar, M., & Sharmin, T. (2021). Job Opportunities and Obstacles of Madrasah Graduates in Bangladesh. *International Fellowship Journal of Interdisciplinary Research*, *1*(1), 36–47.

Alinovi, L., Mane, E., & Romano, D. (2010). Measuring household resilience to food insecurity: Application to Palestinian households. *Agricultural Survey Methods*, 341–368.

Altonji, J. G., & Blank, R. M. (1999). Race and gender in the labor market. *Handbook of Labor Economics*, *3*, 3143–3259.

Anderzén, J., Guzmán, A., Luna-gonzález, D. V, Merrill, S. C., Caswell, M., Méndez, V. E., Hernández, R., Mier, M., & Cacho, G. (2020). Effects of on-farm diversification strategies on smallholder coffee farmer food security and income sufficiency in Chiapas , Mexico. *Journal of Rural Studies*, *77*(September 2019), 33–46.

Ariga, J., Mabaya, E., Waithaka, M., & Wanzala-Mlobela, M. (2019). Can improved agricultural technologies spur a green revolution in Africa? A multicountry analysis of seed and fertilizer delivery systems. *Agricultural Economics*, *50*, 63–74.

Arrow, K. J. (1973). The theory of discrimination. In *Discrimination in labor markets* (pp. 1–33). Princeton University Press.

Asadullah, M. N., & Chaudhury, N. (2013). Peaceful Coexistence? The Role of Religious Schools and Madrassahs in Bangladesh. In *Education in East Asia* (pp. 107–134). Springer.

Asfaw, S., Pallante, G., & Palma, A. (2018). Diversification strategies and adaptation deficit: Evidence from rural communities in Niger. *World Development*, *101*, 219–234.

Ballard, T., Coates, J., Swindale, A., & Deitchler, M. (2011). Household Hunger Scale (HHS): Indicator Definition and Measurement Guide Food and Nutrition Technical Assistance III Project (FANTA). *Washington, DC: FANTA*.

Ballard, T. J., Kepple, A. W., & Cafiero, C. (2013). *The food insecurity experience scale*.

Banerjee, A., Bertrand, M., Datta, S., & Mullainathan, S. (2009). Labor market discrimination in Delhi: Evidence from a field experiment. *Journal of Comparative Economics*, *37*(1), 14–27.

Bank, W. (2007). *World development report 2008: Agriculture for development*. The World Bank.

Bardhan, P., & Udry, C. (1999). *Development microeconomics*. OUP Oxford.

Barrett, C. B. (2010). Measuring food insecurity. *Science*, *327*(5967), 825–828.

Barrett, C. B., Reardon, T., & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food Policy*, *26*(4), 315–331.

Bayraklı, E., & Hafez, F. (2019). *Islamophobia in Muslim majority societies*. Routledge Abingdon-on-Thames.

Becker, G. S. (1971). *The economics of discrimination*. University of Chicago press.

Belay, G. H., Mengstu, K. A., Mehammedberhan Kahsay, H., Hosseininia, G., Işık Özgüven, A., Viira, A.-H., & Azadi, H. (2021). Determinants of smallholder commercialization of livestock: A case study from Tigray, Ethiopia. *Cogent Food & Agriculture*, *7*(1), 1921950.

Bellon, M. R., Kotu, B. H., Azzarri, C., & Caracciolo, F. (2020). To diversify or not to diversify, that is the question. Pursuing agricultural development for smallholder farmers in marginal areas of Ghana. *World Development*, *125*, 104682.

Bellon, M. R., Ntandou-bouzitou, G. D., & Caracciolo, F. (2016). *On-Farm Diversity and Market Participation Are Positively Associated with Dietary Diversity of Rural Mothers in Southern Benin , West Africa*. 1–20.

Benin, S., Smale, M., Pender, J., Gebremedhin, B., & Ehui, S. (2004). The economic determinants of cereal crop diversity on farms in the Ethiopian highlands. *Agricultural Economics*, *31*(2-3), 197–208.

Bertrand, M., & Duflo, E. (2017). Field experiments on discrimination. *Handbook of Economic Field Experiments*, *1*, 309–393.

Bertrand, M., & Mullainathan, S. (2004). Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination. *American Economic Review*, *94*(4), 991–1013.

Bezu, S., Kassie, G. T., Shiferaw, B., & Ricker-Gilbert, J. (2014). Impact of improved maize adoption on welfare of farm households in Malawi: a panel data analysis. *World Development*, *59*, 120–131.

Bidisha, S. H., Faruk, A., & Mahmood, T. (2022). How Are Women Faring in the Bangladeshi Labour Market? Evidence from Labour Force Survey Data. *South Asia Economic Journal*, *23*(2), 201–227.

Blinder, A. S. (1973). Wage discrimination: reduced form and structural estimates. *Journal of Human Resources*, 436–455.

Bommarco, R., Kleijn, D., & Potts, S. G. (2013). Ecological intensification: harnessing ecosystem services for food security. *Trends in Ecology & Evolution*, *28*(4), 230–238.

Bosch, M., Carnero, M. A., & Farré, L. (2009). Discrimination against Immigrants in the Spanish Rental Market. Evidence from Field Experiments. *European Economic Association & Econometric Society*.

Bozzola, M., & Smale, M. (2020). The welfare effects of crop biodiversity as an adaptation to climate shocks in Kenya. *World Development*, *135*, 105065.

Burlingame, B., Charrondiere, U. R., Dernini, S., Stadlmayr, B., & Mondovì, S. (2012). Food biodiversity and sustainable diets: Implications of applications for food production and processing. In *Green technologies in food production and processing* (pp. 643–657). Springer.

Cafiero, C., Viviani, S., & Nord, M. (2018). Food security measurement in a global context: The food insecurity experience scale. *Measurement*, *116*, 146–152.

Cain, G. G. (1986). The economic analysis of labor market discrimination: A survey. *Handbook of Labor Economics*, *1*, 693–785.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: methods and applications*. Cambridge university press.

Cazzuffi, C., McKay, A., & Perge, E. (2020). The impact of agricultural commercialisation on household welfare in rural Vietnam. *Food Policy*, *94*, 101811.

Chibwana, C., Fisher, M., & Shively, G. (2012). Cropland allocation effects of agricultural input subsidies in Malawi. *World Development*, *40*(1), 124–133.

Coates, J., Swindale, A., & Bilinsky, P. (2007). *Household Food Insecurity Access Scale (HFIAS) for measurement of food access: indicator guide: version 3*.

Conley, T. G., & Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *American Economic Review*, *100*(1), 35–69.

Dawe, D. (2007). The practical experience with agricultural trade liberalization in Asia. *Agricultural Trade Liberalization and the Least Developed Countries, Springer*, 175–195.

De Haan, C., Dubern, E., Garancher, B., & Quintero, C. (2016). *Pastoralism development in the Sahel: a road to stability?* World Bank Washington, DC, USA.

De Janvry, A., Fafchamps, M., & Sadoulet, E. (1991). Peasant household behaviour with missing markets: some paradoxes explained. *The Economic Journal*, *101*(409), 1400–1417.

Deressa, T. T., & Hassan, R. M. (2009). Economic impact of climate change on crop production in Ethiopia: evidence from cross-section measures. *Journal of African Economies*, *18*(4), 529–554.

Di Falco, S., Bezabih, M., & Yesuf, M. (2010). Seeds for livelihood: crop biodiversity and food production in Ethiopia. *Ecological Economics*, *69*(8), 1695–1702.

Di Falco, S., & Chavas, J.-P. (2008). Rainfall shocks, resilience, and the effects of crop biodiversity on agroecosystem productivity. *Land Economics*, *84*(1), 83–96.

Dillon, A., McGee, K., & Oseni, G. (2015). Agricultural production, dietary diversity and climate variability. *The Journal of Development Studies*, *51*(8), 976–995.

Douyon, A., Worou, O. N., Diama, A., Badolo, F., Denou, R. K., Touré, S., Sidibé, A., Nebie, B., & Tabo, R. (2022). Impact of crop diversification on household food and nutrition security in southern and central Mali. *Frontiers in Sustainable Food Systems*, *5*, 751349.

Drydakis, N. (2010). Religious affiliation and employment bias in the labor market. *Journal for the Scientific Study of Religion*, *49*(3), 477–493.

Erisman, J. W., Sutton, M. A., Galloway, J., Klimont, Z., & Winiwarter, W. (2008). How a century of ammonia synthesis changed the world. *Nature Geoscience*, *1*(10), 636–639.

FAO. (2019). *Regional Overview of Food Security and Nutrition*.

FAO. (2020). World Food and Agriculture—Statistical Yearbook 2020. *World Food and Agriculture-Statistical Yearbook*.

FAO. (2021). *The state of food security and nutrition in the world 2021*.

Fernández-Reino, M., Di Stasio, V., & Veit, S. (2022). Discrimination Unveiled: A Field Experiment on the Barriers Faced by Muslim Women in Germany, the Netherlands, and Spain. *European Sociological Review*, *1*, 19.

Flabbi, L., Macis, M., Moro, A., & Schivardi, F. (2019). Do female executives make a difference? The impact of female leadership on gender gaps and firm performance. *The Economic*

*Journal*, *129*(622), 2390–2423.

Fortin, N., Lemieux, T., & Firpo, S. (2011). Decomposition methods in economics. In *Handbook of labor economics* (Vol. 4, pp. 1–102). Elsevier.

FSIN and Global Network Against Food Crises. (2024). *GRFC 2024*.

Furman, B., Noorani, A., & Mba, C. (2021). On-Farm Crop Diversity for Advancing Food Security and Nutrition. In *Landraces-Traditional Variety and Natural Breed*. IntechOpen.

Gaddis, S. M. (2015). Discrimination in the credential society: An audit study of race and college selectivity in the labor market. *Social Forces*, *93*(4), 1451–1479.

Gaddis, S. M. (2019). Understanding the "how" and "why" aspects of racial-ethnic discrimination: A multimethod approach to audit studies. *Sociology of Race and Ethnicity*, *5*(4), 443–455.

Gödecke, T., Stein, A. J., & Qaim, M. (2018). The global burden of chronic and hidden hunger: trends and determinants. *Global Food Security*, *17*, 21–29.

Greene, W. H. (2003). *Econometric analysis*. Pearson Education India.

Gro Intelligence. (2016). *The World's Most Expensive Fertilizer Market: Sub-Saharan Africa*. Gro Intelligence, New York.

Haider, H., Smale, M., & Thériault, V. (2018). *Yield response of dryland cereals in Mali to fertilizer: Insights from household survey data*.

Haider, S. H. (2018). *Intensification & Asset Dynamics: Intrahousehold Decision-making in Burkina Faso*. PhD Dissertation. Michigan State University, East Lansing, MI, USA.

Hänke, H., & Barkmann, J. (2017). Insurance function of livestock, Farmers coping capacity with crop failure in southwestern Madagascar. *World Development*, *96*, 264–275.

Hanson, A., & Hawley, Z. (2011). Do landlords discriminate in the rental housing market? Evidence from an internet field experiment in US cities. *Journal of Urban Economics*, *70*(2–3), 99–114.

Heckman, J. J. (1998). Detecting discrimination. *Journal of Economic Perspectives*, *12*(2), 101–116.

Heisey, P. W., & Norton, G. W. (2007). Fertilizers and other farm chemicals. *Handbook of Agricultural Economics*, *3*, 2741–2777.

Herrero, M., Grace, D., Njuki, J., Johnson, N., Enahoro, D., Silvestri, S., & Rufino, M. C. (2013). The roles of livestock in developing countries. *Animal*, *7*(s1), 3–18.

Herrero, M., Thornton, P. K., Kruska, R., & Reid, R. S. (2008). Systems dynamics and the spatial distribution of methane emissions from African domestic ruminants to 2030. *Agriculture, Ecosystems & Environment*, *126*(1–2), 122–137.

Herrero, M., Thornton, P. K., Notenbaert, A. M., Wood, S., Msangi, S., Freeman, H. A., Bossio, D., Dixon, J., Peters, M., & van de Steeg, J. (2010). Smart investments in sustainable food production: revisiting mixed crop-livestock systems. *Science*, *327*(5967), 822–825.

Hoddinott, J., Headey, D., & Dereje, M. (2015). Cows, missing milk markets, and nutrition in rural Ethiopia. *The Journal of Development Studies*, *51*(8), 958–975.

Holzer, H. J. (1996). *What employers want: Job prospects for less-educated workers*. Russell Sage Foundation.

Huang, F. L. (2022). Alternatives to logistic regression models in experimental studies. *The Journal of Experimental Education*, *90*(1), 213–228.

Hunter, D., Fanzo, J., Franzo, J., Borelli, T., & Mattei, F. (2013). *Diversifying Food and Diets: Using Agricultural Biodiversity to Improve Nutrition and Health*.

Isbell, F., Adler, P. R., Eisenhauer, N., Fornara, D., Kimmel, K., Kremen, C., Letourneau, D. K., Liebman, M., Polley, H. W., & Quijas, S. (2017). Benefits of increasing plant diversity in sustainable agroecosystems. *Journal of Ecology*, *105*(4), 871–879.

Jann, B. (2008). The Blinder–Oaxaca decomposition for linear regression models. *The Stata Journal*, *8*(4), 453–479.

Jayne, T. S., Mason, N. M., Burke, W. J., & Ariga, J. (2018). Taking stock of Africa's second-generation agricultural input subsidy programs. *Food Policy*, *75*, 1–14.

Jayne, T. S., Mather, D., & Mghenyi, E. (2010). Principal challenges confronting smallholder agriculture in sub-Saharan Africa. *World Development*, *38*(10), 1384–1398.

Jones, A. D. (2017a). Food insecurity and mental health status: a global analysis of 149 countries. *American Journal of Preventive Medicine*, *53*(2), 264–273.

Jones, A. D. (2017b). *On-Farm Crop Species Richness Is Associated with Household Diet Diversity and Quality in Subsistence- and Market-Oriented Farming Households in Malawi 1 – 3. 4*.

Jones, A. D., & Ejeta, G. (2016). A new global agenda for nutrition and health: the importance of agriculture and food systems. *Bulletin of the World Health Organization*, *94*(3), 228.

Jones, A. D., Ngure, F. M., Pelto, G., & Young, S. L. (2013). What are we assessing when we measure food security? A compendium and review of current metrics. *Advances in Nutrition*, *4*(5), 481–505.

Jones, A. D., Shrinivas, A., & Bezner-Kerr, R. (2014). Farm production diversity is associated with greater household dietary diversity in Malawi: Findings from nationally representative data. *Food Policy*, *46*, 1–12.

Kaminski, J. (2011). Cotton dependence in Burkina Faso: Constraints and opportunities for balanced growth. *Yes Africa Can: Success Stories from a Dynamic Continent*, 107–124.

Karamba, R. W. (2013). *Input subsidies and their effect on cropland allocation, agricultural productivity, and child nutrition: Evidence from Malawi*. American University.

Kazianga, H., & Wahhaj, Z. (2013). Gender, social norms, and household production in Burkina Faso. *Economic Development and Cultural Change*, *61*(3), 539–576.

Khattab, N. (2009). Ethno-religious background as a determinant of educational and occupational attainment in Britain. *Sociology*, *43*(2), 304–322.

Khonje, M. G., Ricker-Gilbert, J., Muyanga, M., & Qaim, M. (2022). Farm-level production diversity and child and adolescent nutrition in rural sub-Saharan Africa: a multicountry, longitudinal study. *The Lancet Planetary Health*, *6*(5), e391–e399.

Khonje, M., Nyondo, C., Mangisoni, J. H., Ricker-Gilbert, J., Burke, W. J., Chadza, W., & Muyanga, M. (2021). *Does Subsidizing Legume Seeds Improve Farm Productivity and Nutrition in Malawi?*

Khoury, C. K., Bjorkman, A. D., Dempewolf, H., Ramirez-Villegas, J., Guarino, L., Jarvis, A., Rieseberg, L. H., & Struik, P. C. (2014). Increasing homogeneity in global food supplies and the implications for food security. *Proceedings of the National Academy of Sciences*, *111*(11), 4001–4006.

Klasen, S. (2019). What explains uneven female labor force participation levels and trends in developing countries? *The World Bank Research Observer*, *34*(2), 161–197.

KOCAMAN, K., & UDDIN, A. H. M. E. (2021). Religious/Islamic Educational Institutions In Bangladesh: Madrases. *Talim: Journal Of Education In Muslim Societies And Communities*.

Koppmair, S., Kassie, M., & Qaim, M. (2017). Farm production, market access and dietary diversity in Malawi. *Public Health Nutrition*, *20*(2), 325–335.

Kozicka, M., Gotor, E., Ocimati, W., de Jager, T., Kikulwe, E., & Groot, J. C. J. (2020). Responding to future regime shifts with agrobiodiversity: A multi-level perspective on small-scale farming in Uganda. *Agricultural Systems*, *183*, 102864.

LaFave, D., Peet, E., & Thomas, D. (2013). *Are rural markets complete? Prices, profits and recursion*. Mimeo. http://web. colby. edu/drlafave/files/2012/08/farmprices_ 15jan13. pdf.

Lahey, J. N., & Beasley, R. A. (2009). Computerizing audit studies. *Journal of Economic Behavior & Organization*, *70*(3), 508–514.

Langyintuo, A. S., Lowenberg-DeBoer, J., Faye, M., Lambert, D., Ibro, G., Moussa, B., Kergna, A., Kushwaha, S., Musa, S., & Ntoukam, G. (2003). Cowpea supply and demand in West and Central Africa. *Field Crops Research*, *82*(2–3), 215–231.

Lentz, E. C., & Barrett, C. B. (2013). The economics and nutritional impacts of food assistance policies and programs. *Food Policy, 42*, 151–163.

Leroy, J. L., & Frongillo, E. A. (2007). Can interventions to promote animal production ameliorate undernutrition? *The Journal of Nutrition*, *137*(10), 2311–2316.

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. *Science, 333*(6042), 616–620.

Maggio, G., & Sitko, N. J. (2021). Diversification is in the detail: Accounting for crop system heterogeneity to inform diversification policies in malawi and zambia. *The Journal of Development Studies*, *57*(2), 264–288.

Maître d'Hôtel, E., & Issoufou, P. (2018). *Quelles actions politiques pour renforcer l'accès des producteurs agricoles à des engrais chimiques à prix réduits au Burkina Faso. Rapport d'analyse de politique. SAPAA (Projet de Suivi et analyse des politiques agricoles et alimentaires).* FAO.

Mason, N. M., Jayne, T. S., & Mofya-Mukuka, R. (2013). Zambia's input subsidy programs. *Agricultural Economics, 44*(6), 613–628.

Mason, N. M., & Smale, M. (2013). Impacts of subsidized hybrid seed on indicators of economic well-being among smallholder maize growers in Zambia. *Agricultural Economics*, *44*(6), 659–670.

Mason, N. M., Wineman, A., Kirimi, L., & Mather, D. (2017). The Effects of Kenya's 'Smarter'Input Subsidy Programme on Smallholder Behaviour and Incomes: Do Different Quasi-Experimental Approaches Lead to the Same Conclusions? *Journal of Agricultural Economics*, *68*(1), 45–69.

Masset, E., Haddad, L., Cornelius, A., & Isaza-Castro, J. (2012). Effectiveness of agricultural interventions that aim to improve nutritional status of children: systematic review. *Bmj*, *344*.

Mbaye, A. A., & Gueye, F. (2018). *Labor Markets and Jobs in West Africa*. African Development Bank Group.

Michler, J. D., & Josephson, A. L. (2017). To specialize or diversify: Agricultural diversity and poverty dynamics in Ethiopia. *World Development*, *89*, 214–226.

Ministère de l'Agriculture des Aménagements Hydro-Agricoles et de la Mécanisation (MAAHAM). (2021). *Mécanismes de distribution des intrants, équipements agricoles et animaux de trait de la campagne agricole 2021-2022. Document. Burkina Faso.*

Ministère de l'Agriculture et de la Sécurité Alimentaire. (2014). *Mécanisme Général de Mise en Œuvre des Opérations Intrants et Equipements Agricoles (Semences, engrais et équipements agricoles)*. Secrétariat Général, Direction Générale des Productions Végétales, Burkina Faso.

Molina-Flores, B., Manzano-Baena, P., & Coulibaly, M. D. (2020). The role of livestock in food security, poverty reduction and wealth creation in West Africa. *Accra: FAO*.

Moll, H. A. J. (2005). Costs and benefits of livestock systems and the role of market and nonmarket relationships. *Agricultural Economics*, *32*(2), 181–193.

Moritz, M. (2012). Pastoral intensification in West Africa: implications for sustainability. *Journal of the Royal Anthropological Institute*, *18*(2), 418–438.

Morris, M. L., Kelly, V., Kopicki, R., & Byerlee, D. (2007). *Fertilizer use in African agriculture: Lessons learned and good practice guidelines*. World Bank Publications.

Mozumdar, L. (2012). Agricultural productivity and food security in the developing world. *Bangladesh Journal of Agricultural Economics*, *35*, 53–69.

Mulwa, C., Marenya, P., & Kassie, M. (2017). Response to climate risks among smallholder farmers in Malawi: A multivariate probit assessment of the role of information, household demographics, and farm characteristics. *Climate Risk Management*, *16*, 208–221.

Murendo, C., Gwara, S., Mazvimavi, K., & Arensen, J. S. (2019). Linking crop and livestock diversification to household nutrition: Evidence from Guruve and Mt Darwin districts, Zimbabwe. *World Development Perspectives*, *14*, 100104.

Murshid, K. A. S., Mahmood, T., & Shashi, N. A. (2019). Employment and Unemployment amongst Educated Youth in Bangladesh. *The Bangladesh Development Studies*, *42*(4), 1–49.

Muzari, W. (2016). Agricultural productivity and food security in sub-Saharan Africa. *International Journal of Science and Research*, *5*(1), 1769–1776.

N'Danikou, S., Vodouhe, R. S., R. Bellon, M., Sidibé, A., & Coulibaly, H. (2017). Foraging is determinant to improve smallholders' food security in rural areas in Mali, West Africa. *Sustainability*, *9*(11), 2074.

National Research Council. (2006). *Lost Crops of Africa: Volume II: Vegetables*. National Academic Press.

Naylor, R. E. L. (2006). Valuing Crop Biodiversity. On-farm Genetic Resources and Economic Change, ed. M. Smale. 336 pp. Wallingford, UK. *The Journal of Agricultural Science*, *144*(3), 281–282.

Neumark, D. (2004). Employers' discriminatory behavior and the estimation of wage discrimination. In *Sex Differences in Labor Markets* (pp. 163–177). Routledge.

Neumark, D. (2012). Detecting discrimination in audit and correspondence studies. *Journal of Human Resources*, *47*(4), 1128–1157.

Neumark, D. (2018). Experimental research on labor market discrimination. *Journal of Economic Literature*, *56*(3), 799–866.

Neumark, D., Bank, R. J., & Van Nort, K. D. (1996). Sex discrimination in restaurant hiring: An audit study. *The Quarterly Journal of Economics*, *111*(3), 915–941.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International Economic Review*, 693–709.

Ochieng, J., Knerr, B., Owuor, G., & Ouma, E. (2020). Food crops commercialization and household livelihoods: Evidence from rural regions in Central Africa. *Agribusiness*, *36*(2), 318–338.

Ogundari, K., & Awokuse, T. (2016). *Assessing the Contribution of agricultural productivity to food security levels in sub-Saharan African countries*.

Owen, E., Kitalyi, A., Jayasuriya, N., & Smith, T. (2005). *Livestock and wealth creation: improving the husbandry of animals kept by resource-poor people in developing countries*. Nottingham University Press.

Pager, D. (2003). The mark of a criminal record. *American Journal of Sociology*, *108*(5), 937–975.

Pager, D. (2007). The use of field experiments for studies of employment discrimination: Contributions, critiques, and directions for the future. *The Annals of the American Academy of Political and Social Science*, *609*(1), 104–133.

Pellegrini, L., & Tasciotti, L. (2014). Crop diversification, dietary diversity and agricultural income: empirical evidence from eight developing countries. *Canadian Journal of Development Studies/Revue Canadienne d'études Du Développement*, *35*(2), 211–227.

Phelps, E. S. (1972). The statistical theory of racism and sexism. *The American Economic Review*, *62*(4), 659–661.

Pierné, G. (2013). Hiring discrimination based on national origin and religious closeness: results from a field experiment in the Paris area. *IZA Journal of Labor Economics*, *2*(1), 1–15.

Pingali, P. L. (2012). Green revolution: impacts, limits, and the path ahead. *Proceedings of the National Academy of Sciences*, *109*(31), 12302–12308.

Pingali, P. L., & Rosegrant, M. W. (1995). Agricultural commercialization and diversification: processes and policies. *Food Policy*, *20*(3), 171–185.

Porgo, M., Kuwornu, J. K. M., Zahonogo, P., Jatoe, J. B. D., & Egyir, I. S. (2017). Credit constraints and labour allocation decisions in rural Burkina Faso. *Agricultural Finance Review*.

Practical, G. (2008). An introduction to the basic concepts of food security. *FAO: Rome, Italy*.

Pretty, J. (2018). Intensification for redesigned and sustainable agricultural systems. *Science*, *362*(6417), eaav0294.

Quillian, L., Pager, D., Hexel, O., & Midtbøen, A. H. (2017). Meta-analysis of field experiments shows no change in racial discrimination in hiring over time. *Proceedings of the National Academy of Sciences*, *114*(41), 10870–10875.

Rahman, M. M. (2015, December 23). The bias against Madrasa students. *The Daily Star*. https://www.thedailystar.net/op-ed/the-bias-against-madrasa-students-191032

Reardon, T., & Barrett, C. B. (2000). Agroindustrialization, globalization, and international development: An overview of issues, patterns, and determinants. *Agricultural Economics*, *23*(3), 195–205.

Reardon, T., Delgado, C., & Matlon, P. (1992). Determinants and effects of income diversification amongst farm households in Burkina Faso. *The Journal of Development Studies*, *28*(2), 264–296.

Reardon, T., & Timmer, C. P. (2007). Transformation of markets for agricultural output in developing countries since 1950: How has thinking changed? *Handbook of Agricultural Economics*, *3*, 2807–2855.

Redlich, S., Martin, E. A., & Steffan-Dewenter, I. (2018). Landscape-level crop diversity benefits biological pest control. *Journal of Applied Ecology*, *55*(5), 2419–2428.

Remans, R., Flynn, D. F. B., Declerck, F., Diru, W., Fanzo, J., Gaynor, K., Lambrecht, I., Mudiope, J., Mutuo, P. K., Nkhoma, P., Siriri, D., Sullivan, C., & Palm, C. A. (2011). *Assessing Nutritional Diversity of Cropping Systems in African Villages*. *6*(6).

Riach, P. A., & Rich, J. (2002). Field experiments of discrimination in the market place. *The Economic Journal*, *112*(483), F480–F518.

Roodman, D. (2011). Fitting fully observed recursive mixed-process models with cmp. *The Stata Journal*, *11*(2), 159–206.

Rufino, M. C., Herrero, M., Van Wijk, M. T., Hemerik, L., De Ridder, N., & Giller, K. E. (2009). Lifetime productivity of dairy cows in smallholder farming systems of the Central highlands of Kenya. *Animal*, *3*(7), 1044–1056.

Saint Ville, A., Po, J. Y. T., Sen, A., Bui, A., & Melgar-Quiñonez, H. (2019). Food security and the Food Insecurity Experience Scale (FIES): ensuring progress by 2030. In *Food Security* (Vol. 11, pp. 483–491). Springer.

Sibhatu, K. T., Krishna, V. V, & Qaim, M. (2015). *Farm production diversity and dietary diversity in developing countries*.

Sibhatu, K. T., & Qaim, M. (2018). Farm production diversity and dietary quality: linkages and measurement issues. *Food Security*, *10*(1), 47–59.

Singh, I., Squire, L., & Strauss, J. (1986). *Agricultural household models: Extensions, applications, and policy*. The World Bank.

Skoet, J., & Stamoulis, K. G. (2006). *The state of food insecurity in the world 2006: Eradicating world hunger-taking stock ten years after the world food summit*. Food & Agriculture Org.

Smale, M., & Thériault, V. (2021). Input subsidy effects on crops grown by smallholder farm women: The example of cowpea in Mali. *Oxford Development Studies*, 1–15.

Smale, M. V. T., & Thériault, V. (2019). A cross-country summary of fertilizer subsidy programs in Sub-Saharan Africa. *Michigan, Michigan State University*.

Smil, V. (2002). Nitrogen and food production: proteins for human diets. *AMBIO: A Journal of the Human Environment*, *31*(2), 126–131.

Smith, J., Sones, K., Grace, D., MacMillan, S., Tarawali, S., & Herrero, M. (2013). Beyond milk, meat, and eggs: Role of livestock in food and nutrition security. *Animal Frontiers*, *3*(1), 6–13.

Smith, L. C., & Haddad, L. J. (2000). *Explaining child malnutrition in developing countries: A cross-country analysis* (Vol. 111). Intl Food Policy Res Inst.

Smith, M. D., Rabbitt, M. P., & Coleman-Jensen, A. (2017). Who are the world's food insecure? New evidence from the Food and Agriculture Organization's food insecurity experience scale. *World Development*, *93*, 402–412.

Steinfeld, H., Gerber, P., Wassenaar, T. D., Castel, V., Rosales, M., Rosales, M., & de Haan, C. (2006). *Livestock's long shadow: environmental issues and options*. Food & Agriculture Org.

Terri J. Ballard, A. W. K. and C. C. (2013). *The food insecurity experience scale: Developing a global standard for monitoring hunger worldwide. Technical Paper*. *October*, 1–58.

Theriault, V., & Serra, R. (2014). Institutional environment and technical efficiency: A stochastic frontier analysis of cotton producers in West Africa. *Journal of Agricultural Economics*, *65*(2), 383–405.

Theriault, V., & Smale, M. (2021). The unintended consequences of the fertilizer subsidy program on crop species diversity in Mali. *Food Policy*, *102*, 102121.

Thomas, D. A., & Ely, R. J. (1996). Making differences matter. *Harvard Business Review*, *74*(5), 79–90.

Thornton, P. K., & Herrero, M. (2015). Adapting to climate change in the mixed crop and livestock farming systems in sub-Saharan Africa. *Nature Climate Change*, *5*(9), 830–836.

Thorsen, D. (2002). 'We Help our Husbands!'Negotiating the household budget in rural Burkina Faso. *Development and Change*, *33*(1), 129–146.

Tilman, D., Cassman, K. G., Matson, P. A., Naylor, R., & Polasky, S. (2002). Agricultural sustainability and intensive production practices. *Nature*, *418*(6898), 671–677.

Timmer, C. P. (2009). *A world without agriculture: The structural transformation in historical perspective*. Aei Press Washington, DC.

Trenerry, B., Franklin, H., & Paradies, Y. (2012). *Preventing race-based discrimination and supporting cultural diversity in the workplace: an evidence review: full report*.

Turner, M. D. (2009). Capital on the move: The changing relation between livestock and labor in Mali, West Africa. *Geoforum*, *40*(5), 746–755.

Turner, M. D., McPeak, J. G., & Ayantunde, A. (2014). The role of livestock mobility in the livelihood strategies of rural peoples in semi-arid West Africa. *Human Ecology*, *42*, 231–247.

Udry, C. (1996). Gender, agricultural production, and the theory of the household. *Journal of Political Economy*, *104*(5), 1010–1046.

UNICEF, & WHO. (2017). *The state of food security and nutrition in the world 2017: Building resilience for peace and food security*.

Valfort, M.-A. (2015). Religious discrimination in access to employment: a reality. *Policy Paper. Paris: Institut Montaigne*.

Van Dusen, M. E., & Taylor, J. E. (2005). Missing markets and crop diversity: evidence from Mexico. *Environment and Development Economics*, *10*(4), 513–531.

Vilar-Compte, M., Burrola-Méndez, S., Lozano-Marrufo, A., Ferré-Eguiluz, I., Flores, D., Gaitán-Rossi, P., Teruel, G., & Pérez-Escamilla, R. (2021). Urban poverty and nutrition challenges associated with accessibility to a healthy diet: a global systematic literature review. *International Journal for Equity in Health*, *20*, 1–19.

Vuolo, M., Uggen, C., & Lageson, S. (2016). Statistical power in experimental audit studies: Cautions and calculations for matched tests with nominal outcomes. *Sociological Methods & Research*, *45*(2), 260–303.

Wallace, M., Wright, B. R. E., & Hyde, A. (2014). Religious affiliation and hiring discrimination in the American South: A field experiment. *Social Currents*, *1*(2), 189–207.

Wanzala-Mlobela, M., Fuentes, P., & Mkumbwa, S. (2013). Practices and policy options for the improved design and implementation of fertilizer subsidy programs in sub-Saharan Africa. *NEPAD Agency Policy Study, A Joint Publication by the NEPAD Planning and Coordinating Agency (NPCA), the United Nations Food and Agriculture Organization, and the International Fertiliser and Development Centre (IFDC)*, *35*(155.254), 0.

Weichselbaumer, D. (2020). Multiple discrimination against female immigrants wearing headscarves. *ILR Review*, *73*(3), 600–627.

Wiebe, K. D. (2003). Linking land quality, agricultural productivity, and food security. *USDA-ERS Agricultural Economic Report*, *823*.

Wiggins, S., Argwings-Kodhek, G., Leavy, J., & Poulton, C. (2011). Small farm commercialisation in Africa: Reviewing the issues. *Future Agricultures Consortium, Research Paper*, *23*.

Wooldridge, J. (2012). Panel data models with heterogeneity and endogeneity. *Institute for Fiscal Studies*.

Wooldridge, J M. (2008). Nonlinear Dynamic Panel Data Models with Unobserved Effects. *Invited Lecture, Canadian Econometrics Study Group, Montreal*.

Wooldridge, Jeffrey M. (2005). Unobserved heterogeneity and estimation of average partial effects. *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, 27–55.

Wooldridge, Jeffrey M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Wooldridge, Jeffrey M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*, *50*(2), 420–445.

World Bank. (2019). *World Development Indicators*.

World Bank. (2020). *World Development Indicators*.

World Food Summit. (1996). *Rome Declaration on World Food Security and World Food Summit Plan of Action*.

Wright, B. R. E., Wallace, M., Bailey, J., & Hyde, A. (2013). Religious affiliation and hiring discrimination in New England: A field experiment. *Research in Social Stratification and Mobility*, *34*, 111–126.

Zaman, N. T., Sohel, M. S., Obaidullah, M., Hossen, M. S., Rahman, M. T., Sifullah, M. K., & Sarker, M. F. H. (2023). Factors shaping Bangladeshi students' migration decision using push–pull theory: a focus group study. *SN Social Sciences*, *4*(1), 4.

Zhang, J., Jin, S., Li, T., & Wang, H. (2021). Gender discrimination in China: Experimental evidence from the job market for college graduates. *Journal of Comparative Economics*, *49*(3), 819–835.

Zulu, P., Kalinda, T., & Tembo, G. (2014). Effects of the maize input subsidy program on groundnuts production in Zambia. *Journal of Agricultural Science*, *6*(7), 253.

APPENDIX FOR CHAPTER ONE

Table A 1.1a: Resume characteristics (balanced test for Experiment #1)

| | General School | Madrasah | Diff | p-value |
|---|---|---|---|---|
| SSC GPA | 5 | 5 | 0 | . |
| HSC GPA | 5 | 5 | 0 | 0.32 |
| BS GPA | 3.35 | 3.40 | -0.06 | 0.30 |
| MS GPA | 3.37 | 3.40 | -0.03 | 0.59 |
| Work Experience (year) | 2.42 | 2.39 | 0.032 | 0.40 |
| Voluntary Experience (%) | 50 | 49 | 0.68 | 0.70 |
| Work at School (%) | 49 | 49 | 0.18 | 0.92 |
| Computer Skill (%) | 100 | 100 | 0 | . |
| Leadership Experience (%) | 50 | 49 | 0.68 | 0.70 |
| Training (%) | 49 | 49 | 0.18 | 0.92 |
| N | 1624 | 1624 | | |

Note: Resume characteristics of two high school groups and differences.

Table A 1.1b: Resume characteristics (balanced test for Experiment #2)

| | General School | Madrasah | Diff | p value |
|---|---|---|---|---|
| **For high resume quality** | | | | |
| SSC GPA | 5 | 5 | 0 | . |
| HSC GPA | 5 | 5 | 0 | . |
| BS GPA | 3.56 | 3.57 | -0.01 | 0 |
| MS GPA | 3.61 | 3.6 | 0.01 | 0 |
| Work Experience (year) | 4.21 | 4.26 | -0.04 | 0.37 |
| Voluntary Experience (%) | 100 | 100 | 0 | . |
| Work at School (%) | 50 | 50 | 0 | 1 |
| Computer Skill (%) | 100 | 100 | 0 | . |
| Leadership Experience (%) | 100 | 100 | 0 | . |
| Training (%) | 50 | 50 | 0 | 1 |
| N | 1258 | 1258 | | |
| **For low resume quality** | | | | |
| SSC GPA | 5 | 5 | 0 | . |
| HSC GPA | 4.95 | 4.95 | 0 | 0.38 |
| BS GPA | 3.33 | 3.24 | 0.09 | 0 |
| MS GPA | 3.34 | 3.35 | -0.01 | 0 |
| Work Experience (year) | 2.66 | 2.63 | 0.02 | 0.69 |
| Voluntary Experience (%) | 0 | 0 | 0 | . |
| Work at School (%) | 0 | 0 | 0 | . |
| Computer Skill (%) | 100 | 100 | 0 | . |
| Leadership Experience (%) | 0 | 0 | 0 | . |
| Training (%) | 7.47 | 0 | 7.47 | 0 |
| N | 1258 | 1258 | | |

Note: Resume characteristics of two high school groups and the difference between high- and low-quality resumes

Table A 1.2a: Job characteristics in Experiment #1

| | Total Sample | NGO | Corporate | Media | IT |
|---|---|---|---|---|---|
| Number of jobs | 406 | 120 | 122 | 70 | 94 |
| Number of resumes | 3248 | 960 | 976 | 560 | 752 |
| Callback rates (%) | 9.36 | 6.88 | 9.63 | 12.50 | 9.84 |
| Job located in capital city: Dhaka (%) | 73 | 39 | 84 | 97 | 85 |
| Entry level job (%) | 32 | 21 | 41 | 24 | 38 |
| Mid-level job (%) | 68 | 79 | 59 | 76 | 62 |
| Average Salary (in BDT) | 33102 | 38078 | 35119 | 32941 | 24250 |
| Experience required (year) | 3 | 3 | 3 | 3 | 2 |
| Master's degree required (%) | 44 | 73 | 52 | 30 | 9 |
| Specific major required (%) | 38 | 40 | 43 | 36 | 31 |
| Specific college preferred (%) | 2 | 3 | 3 | 1 | 1 |
| Minimum GPA required (%) | 2 | 3 | 4 | 0 | 0 |
| Computer skill required (%) | 79 | 93 | 49 | 79 | 100 |
| Gender preference (%) | 0 | 0 | 1 | 0 | 0 |
| Benefits (%) | 56 | 48 | 51 | 66 | 64 |
| Higher client Interaction (%) | 48 | 72 | 56 | 51 | 4 |

Note: overall and industry-wise job characteristics

Table A 1.2b: Job characteristics in Experiment #2

| | Total Sample | Industry | | Job Category | | | |
|---|---|---|---|---|---|---|---|
| | | NGO | Corporate | Admin | Sales | Management | Others |
| Number of jobs | 629 | 314 | 315 | 118 | 149 | 203 | 159 |
| Number of resumes | 5032 | 2512 | 2520 | 944 | 1192 | 1624 | 1272 |
| Callback rates (%) | 10.75 | 9.16 | 12.34 | 9.43 | 11.07 | 10.84 | 11.32 |
| Job located in Dhaka city (%) | 56 | 43 | 69 | 58 | 64 | 45 | 62 |
| Entry level job (%) | 47 | 30 | 64 | 33 | 62 | 31 | 64 |
| Mid-level job (%) | 53 | 70 | 36 | 67 | 38 | 69 | 36 |
| Average Salary (in thousands BDT) | 32 | 39 | 25 | 37 | 23 | 38 | 29 |
| Experience required (year) | 3 | 3 | 2 | 3 | 3 | 3 | 2 |
| Master's degree required (%) | 41 | 68 | 14 | 47 | 17 | 66 | 27 |
| Specific major required (%) | 38 | 39 | 36 | 47 | 41 | 35 | 30 |
| Specific college preferred (%) | 2 | 0 | 4 | 4 | 3 | 0 | 1 |
| Minimum GPA required (%) | 2 | 3 | 2 | 1 | 3 | 4 | 1 |
| Computer skill required (%) | 80 | 100 | 60 | 75 | 55 | 96 | 86 |
| Gender preference (%) | 1 | 0 | 2 | 0 | 1 | 0 | 2 |
| Benefits (%) | 62 | 49 | 76 | 62 | 79 | 50 | 63 |
| Higher client Interaction (%) | 49 | 35 | 63 | 15 | 97 | 33 | 51 |

Note: Overall, industry-wise, and category-wise job characteristics

Figure A 1.1: Diagrammatic representation of the first experimental design

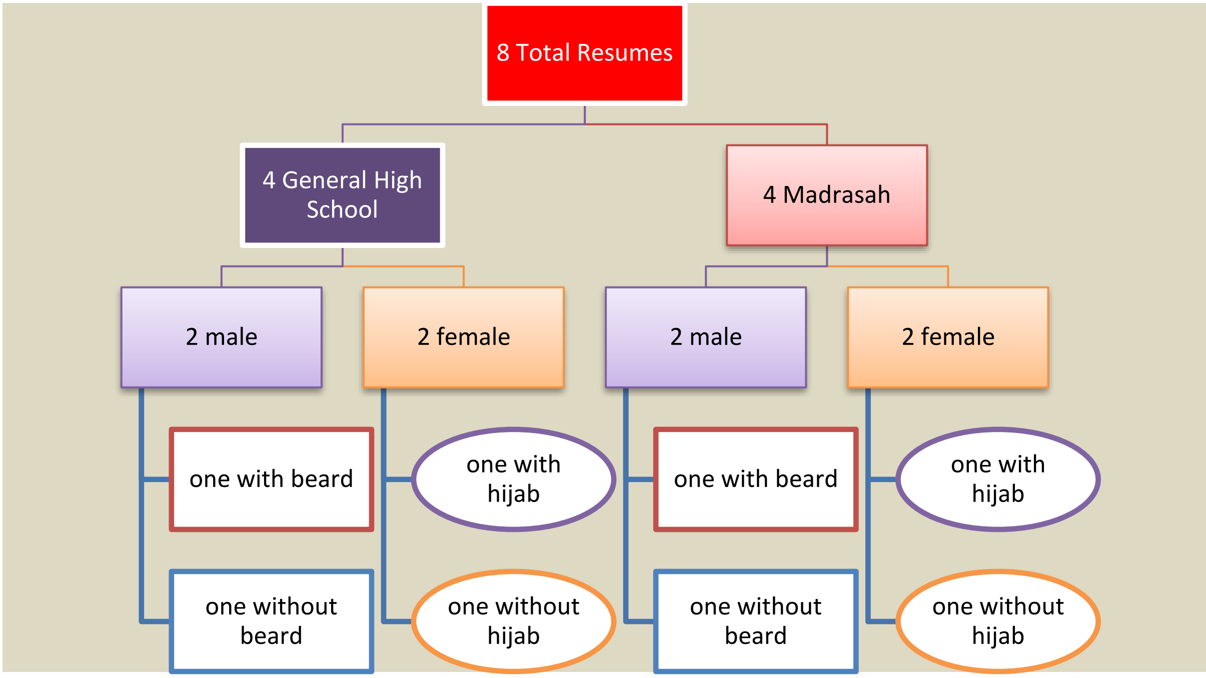
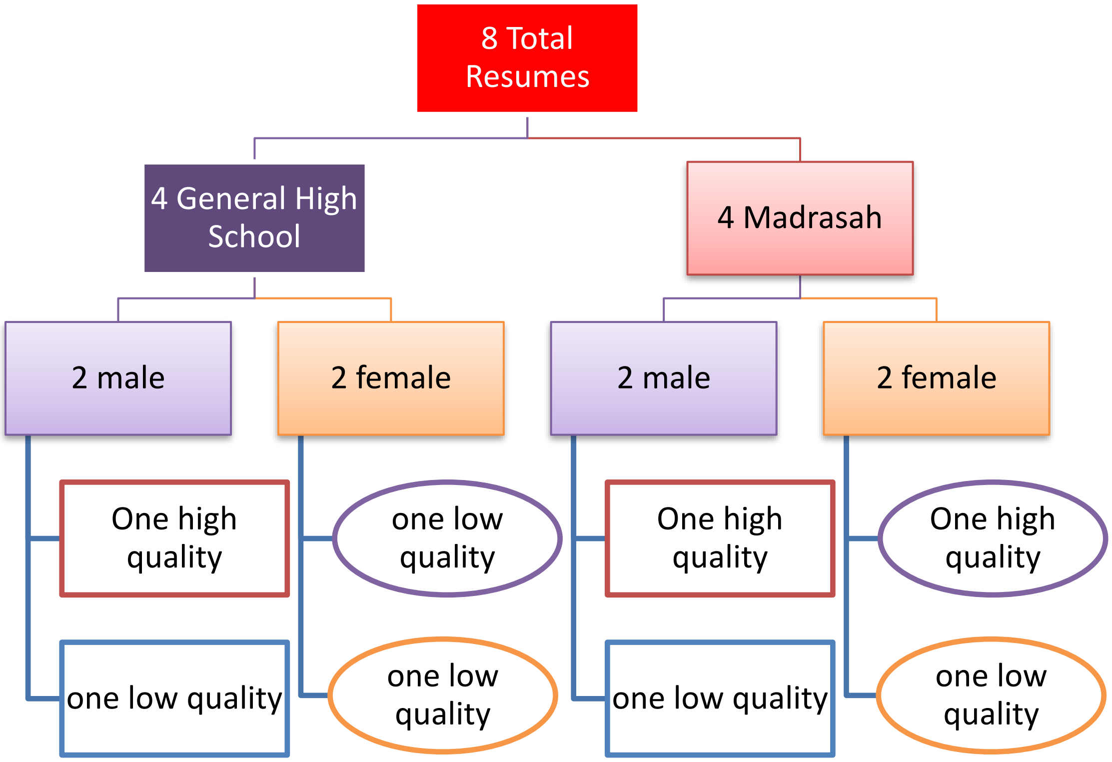


Figure A 1.2: Diagrammatic representation of the second experimental design



CONSENT LETTER TEMPLATE FOR PHOTOGRAPH USE

Consent Letter for Using Headshots for the Research Experiment to Investigate Labor Market Discrimination in Bangladesh Conducted by Michigan State University

I hereby grant Michigan State University the authorization to use my headshot for the research experiment aimed at investigating labor market discrimination in Bangladesh. As part of this study, MSU researchers will be submitting fictitious resumes to various job openings. I fully understand that my headshot will be utilized exclusively for research purposes and relevant internal review processes, with an assurance that it will not be disseminated elsewhere.

I confirm that I am over 18 years old and have willingly provided my headshot/photograph with explicit consent for its use in this experiment. I am optimistic that the outcomes of this research will contribute significantly towards addressing and rectifying labor market discrimination in Bangladesh. It is my pleasure to be involved in this experiment, and I anticipate that the findings will contribute positively to the broader understanding of this critical issue.

I would like to reaffirm that my verbal consent was given in August 2021, and I am formalizing this agreement by signing this written consent letter today.

Signature:

Name:

Date:

## APPENDIX FOR CHAPTER TWO

**CFA Test of Endogeneity**

The CFA tests and addresses the endogeneity issue in the following way:

Let, $y_{it1} = \beta_0 + X_{it}\beta_1 + \beta_2 y_{it2} + u_{it}$ (A)

Where $y_{it2}$ endogenous. $E(y_{it2}u_{it}) \neq 0$, $X_{it}$ vector of exogenous variable and $z_t$ is an exogenous variable that can be used as IV for $y_{it2}$; $E(z_{it}u_{it}) = 0$

Reduced form for $y_{it2}$ is, $y_{it2} = X_{it}\Pi_{21} + z_{it}\Pi_{22} + v_{it}$ (B)

where $z_{it}$ is the instrumental variable. $E(z_{it}v_{it}) = 0$

Linear projection of $u_{it} and\ v_{it}$ is: $u_{it} = v_{it}\rho_1 + e_{it}$ where $E(v_{it}e_{it}) = 0$

Hence, $E(z_{it}e_{it}) = E[z_{it}(u_{it} - v_{it}\rho_1)] = E(z_{it}\, u_{it}) - \rho_1 E(z_{it}v_{it}) = 0$

$$E(y_{it2}e_{it}) = \Pi_{22}E(z_{it}e_{it}) + E(v_{it}e_{it}) = 0$$

Plugging $u_{it}$ in equation (A): $y_{it1} = \beta_0 + X_{it}\beta_1 + \beta_2 y_{it2} + v_{it}\rho_1 + e_{it}$

Now $E(y_{it2}e_{it}) = 0, E(X_{it}e_{it}) = 0, E(v_{it}e_{it}) = 0$; No endogeneity anymore. So, regressing $y_{it1}$ on $y_{it2}, X_{it}, v_{it}$ will produce consistent estimators. Since we $v_{it}$ is not observed, we can obtain $\hat{v}_{it}$ from the reduced form of $y_{it2}$ (equation B), the first stage regression. Then in the 2nd stage, we run the regression $y_{it1}$ on $y_{it2}, X_{it}, \hat{v}_{it}$. By rejecting the null hypothesis of no endogeneity ($H_0$: $\rho_1 = 0$) will ensure the endogeneity of $y_{it2}$.

Table A 2.1: First Stage regressions of binary endogenous variables

| | Fertilizer Subsidy | Seed Subsidy | Interaction |
|---|---|---|---|
| #of HH members received training during last 10 years | 0.05* | 0.04* | 0.03* |
| | (0.03) | (0.02) | (0.02) |
| #of HH member involved with non-crop associations | -0.03** | -0.05*** | -0.05*** |
| | (0.01) | (0.01) | (0.01) |
| Interaction of both IV | -0.00 | -0.01* | -0.00 |
| | (0.00) | (0.00) | (0.01) |
| Percentage of individual plots | 0.00* | 0.00* | 0.00 |
| | (0.00) | (0.00) | (0.00) |
| Plot plainland | -0.00 | 0.02** | 0.02 |
| | (0.01) | (0.01) | (0.01) |
| Plot lowland | -0.00 | -0.02 | -0.00 |
| | (0.02) | (0.02) | (0.04) |
| Plot with tree | -0.04*** | -0.01 | -0.02 |
| | (0.01) | (0.01) | (0.02) |
| Intercrop plot | 0.00 | 0.04** | 0.04* |
| | (0.02) | (0.02) | (0.02) |
| Area total (ha) | 0.04*** | 0.03** | 0.04** |
| | (0.01) | (0.01) | (0.02) |
| Non-farm employment | -0.07* | -0.12** | -0.11* |
| | (0.04) | (0.05) | (0.06) |
| Credit | -0.05 | -0.04 | -0.02 |
| | (0.05) | (0.04) | (0.03) |
| Livestock | 0.00 | 0.00 | 0.02 |
| | (0.02) | (0.02) | (0.03) |
| Higher education | 0.00 | 0.03 | 0.03 |
| | (0.04) | (0.04) | (0.06) |
| Male adult per ha | 0.00 | 0.08 | -0.19 |
| | (0.09) | (0.08) | (0.20) |
| Female adult per ha | 0.08 | 0.03 | 0.23 |
| | (0.08) | (0.06) | (0.19) |
| Child | 0.02 | 0.02 | 0.01 |
| | (0.02) | (0.01) | (0.03) |
| Head female | -0.30** | -0.11 | -0.43** |
| | (0.14) | (0.10) | (0.22) |

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Table A 2.1 (cont'd)

| | Fertilizer Subsidy | Seed Subsidy | Interaction |
|---|---|---|---|
| Manure use per ha | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) |
| Year 2017 | -0.18*** | -0.13** | -0.09 |
| | (0.04) | (0.05) | (0.06) |
| Mean (time-varying variables) | Yes*** | Yes*** | Yes*** |
| Constant | -1.09*** | -1.60*** | -1.53*** |
| | (0.08) | (0.08) | (0.10) |
| N | 8498 | 8498 | 8498 |
| r2_p | 0.18 | 0.12 | 0.20 |
| chi2 | 2591.68 | 1241.65 | 857.38 |
| p | 0.00 | 0.00 | 0.00 |

Source: Authors' calculation. Bootstrap standard errors. *, **, and *** denote statistically significant at 10%, 5%, and 1%.

Table A 2.2: Fixed effect model to estimate the effect of participation in the subsidy programs on outcome variables

| | Area Share to Target Crops | Area Share to Cowpea as Primary Crop | Area Share to Cowpea as Intercrop | Total Crop Counts |
|---|---|---|---|---|
| Fertilizer subsidy | 0.51 | -0.24 | -1.20 | 6.21 |
| | (0.49) | (0.29) | (1.12) | (44.71) |
| Seed subsidy | -0.00 | -0.29 | -0.23 | 46.80 |
| | (2.69) | (1.49) | (1.56) | (228.54) |
| Interaction | -0.58 | 0.44 | 0.58 | 18.15 |
| | (2.16) | (1.21) | (1.55) | (160.90) |
| Percentage of individual plots | -0.00 | 0.00 | 0.00 | -0.01 |
| | (0.00) | (0.00) | (0.00) | (0.07) |
| Plot plainland | -0.00 | 0.00 | 0.00 | 0.05 |
| | (0.00) | (0.00) | (0.00) | (0.32) |
| Plot lowland | 0.00 | 0.00 | 0.01 | 0.10 |
| | (0.00) | (0.00) | (0.02) | (0.31) |
| Plot with tree | -0.00 | 0.00 | -0.00 | 0.16 |
| | (0.01) | (0.00) | (0.01) | (0.54) |
| Intercrop plot | -0.01 | -0.00 | 0.01* | -0.09 |
| | (0.01) | (0.01) | (0.01) | (1.04) |
| Area total | 0.00 | 0.00 | 0.02 | -0.50 |
| | (0.03) | (0.02) | (0.03) | (2.28) |
| Non-farm income | -0.00 | -0.00 | -0.01 | 0.58 |
| | (0.03) | (0.02) | (0.03) | (2.65) |
| Credit | 0.03 | -0.01 | -0.02 | 1.09 |
| | (0.05) | (0.03) | (0.03) | (4.75) |
| Livestock | 0.00 | -0.00 | -0.01 | -0.14 |
| | (0.01) | (0.01) | (0.01) | (0.73) |
| Higher education | 0.00 | 0.00 | 0.01 | 0.04 |
| | (0.01) | (0.00) | (0.01) | (0.56) |
| Male adult per ha | 0.01 | 0.00 | -0.01 | -0.39 |
| | (0.02) | (0.01) | (0.04) | (1.96) |
| Female adult per ha | 0.01 | -0.01 | 0.02 | -0.07 |
| | (0.01) | (0.01) | (0.01) | (0.83) |
| Child | 0.00 | 0.00 | 0.00 | -0.17 |
| | (0.01) | (0.00) | (0.01) | (0.70) |
| Head female | -0.02 | -0.01 | 0.02 | 1.07 |
| | (0.07) | (0.04) | (0.10) | (5.15) |
| Manure use per ha | 0.00 | -0.00 | 0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Year Dummy | 0.03 | 0.01 | -0.01 | 0.99 |
| | (0.05) | (0.03) | (0.04) | (4.85) |

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Table A 2.2 (cont'd)

| | Area Share to Target Crops | Area Share to Cowpea as Primary Crop | Area Share to Cowpea as Intercrop | Total Crop Counts |
|---|---|---|---|---|
| Constant | 0.21*** | 0.05 | 0.61*** | 2.11 |
| | (0.07) | (0.04) | (0.06) | (6.75) |
| N | 8,498 | 8,498 | 5,720 | 8,498 |
| Wald Chi2 | 50434 | 2884 | 35151 | 2587 |
| p-value | 0 | 0 | 0 | 0 |

Source: Authors' calculation. Robust standard errors are in parentheses. *, **, and *** denote statistically significant at 10%, 5%, and 1%.

APPENDIX FOR CHAPTER THREE

Table A 3.1: Descriptive Statistics (Household Level) of crop uses and commercialization in the last three months.

| Variable | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Sold crops | 5,962 | .27 | .44 | 0 | 1 |
| Plan to sell in future | 5,962 | .014 | .12 | 0 | 1 |
| Stored Crops | 5,962 | .30 | .46 | 0 | 1 |
| Crops Donated | 5,962 | .89 | .32 | 0 | 1 |
| Faced difficulty in Selling | 5,962 | .03 | .18 | 0 | 1 |
| Utilization of crop production (in KG) | | | | | |
| Consumption | 5,962 | 39.05 | 102.21 | 0 | 2500 |
| Donation | 5,962 | 22.08 | 60.83 | 0 | 900 |
| Stock For Seed | 5,962 | 21.06 | 60.02 | 0 | 900 |
| Reimburse Input | 5,962 | 6.86 | 59.32 | 0 | 1100 |
| Animal Feed | 5,962 | 3.06 | 33.62 | 0 | 1200 |
| Storage | 5,962 | 65.49 | 166.36 | 0 | 3850 |
| Degraded | 5,962 | .57 | 19.19 | 0 | 1000 |
| Amount Sold | 5,962 | 19.20 | 120.96 | 0 | 3000 |
| Loss Enroute to sale | 5,962 | .21 | .79 | 0 | 8 |
| Plan To Sell | 5,962 | 2.10 | 33.06 | 0 | 1000 |

Table A 3.2: Correlation coefficients of the residuals

| Variables | Residual 1 | Residual 2 | Residual 3 | Residual 4 | Residual 5 |
|---|---|---|---|---|---|
| Residual 1 | 1.000 | | | | |
| Residual 2 | 0.138 | 1.000 | | | |
| Residual 3 | 0.086 | 0.008 | 1.000 | | |
| Residual 4 | 0.048 | 0.020 | 0.216 | 1.000 | |
| Residual 5 | 0.000 | 0.000 | 0.000 | -0.000 | 1.000 |