Three Essays in Economics

by

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Certificate of original authorship

I, Ali Vergili, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Business School at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise indicated in the references or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Abstract

This doctoral dissertation comprises three essays, two in development economics and one in empirical auctions, all interconnected by the theme of individual decision-making.

Chapter 2 delves into the impact of Nigeria's 2003 Child Rights Act (CRA), designed to prohibit marriages below the age of 18 at the federal level. However, conflicts within the Nigerian constitution and partial adoption by states with Islamic legal systems have hindered its full implementation. Using data from the Demographic and Health Surveys (DHS), the study analyzes the staggered reform implementation, revealing an unexpected outcome: the CRA has led to earlier marriages for girls, especially in Muslim-majority areas. This underscores the importance of considering local cultural and religious norms and highlights treatment heterogeneity, exposing biases in standard methods. The study enhances our understanding of legal reforms addressing child marriage.

Chapter 3 explores the connection between infant mortality expectations and fertility decisions, utilizing unique data from Malawi. Population research has long scrutinized the relationship between child mortality and fertility, emphasizing replacement (fertility response to experienced child mortality) and hoarding (fertility response to expected child mortality) behaviors. Using individual-specific subjective infant mortality expectations drawn from the Malawi Longitudinal Study of Families and Health (MLSFH), we employ instrumental variables to address potential endogeneity issues, including the average of parents' ratings of children's health to account for omitted variable bias such as parental preferences for healthy offspring. In line with the hoarding mechanism, we observe a substantial 14 percentage point reduction in the propensity to have a child within the next two years following a 10 percentage point decrease in infant mortality expectations, compared to a baseline propensity of 43%.

Chapter 4 explores price dynamics in sequential Dutch auctions at the Sydney Fish Market. While theoretical models suggest martingale prices, empirical data often reveals variations. Analyzing a comprehensive dataset spanning 27 years, this study identifies non-monotonic price trends and differences in bidding patterns based on bidders' experience levels. The findings underscore the role of signaling, learning, and bidder heterogeneity in shaping the market environment.

In conclusion, this dissertation offers valuable insights into the consequences of legal reforms, fertility decision-making processes, and the dynamics of auction markets. It contributes to our understanding of these complex economic phenomena and their implications for policy and practice.

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Chapter 1

Introduction

This doctoral dissertation is comprised of three independent essays, two of which fall under the field of development economics, while the third empirically examines auctions. These studies collectively delve into diverse aspects of societal and economic dynamics, addressing critical issues spanning child marriage, fertility behavior, and auctions. They shed light on the interplay between policies, individual expectations, and market mechanisms. While each study offers unique insights into its respective area of investigation, together, they underscore the significance of considering local norms, information dissemination, and participant heterogeneity in shaping outcomes. Whether exploring the implications of policy interventions, identifying the links between mortality expectations and fertility decisions, or understanding the complexities of auction pricing, these studies help us better grasp intricate societal and economic dynamics.

Child marriage remains a pressing global issue, affecting around 640 million girls and women (UNICEF, 2023). Despite its well-documented adverse effects, there is a dearth of empirical evidence on the effectiveness of policies aimed at combating child marriage. Chapter 2 focuses on the impact of the Child Rights Act (CRA) in Nigeria, which prohibits marriages for individuals under 18, using data from the Nigeria Demographic and Health Survey. The staggered adoption of CRA among Nigerian states allows for a robust difference-in-differences (DID) analysis, shedding light on its effects. Child marriage poses significant health risks in Nigeria, with young brides facing STDs, premature pregnancies, and obstetric complications, while their children are exposed to elevated mortality rates and malnutrition (Allen and Adekola, 2017; Simbine, Aluko, and Aluko, 2016). The study's primary aim is to analyze the CRA's impact on marriage age, revealing a surprising backlash effect. Contrary to its intent, the

CRA reduces the average marriage age by 0.65 years and raises the likelihood of child marriages in treated states by 5 percentage points. To comprehend this impact, the study investigates the varied communities in Nigeria, taking into account the religious composition and the predominant religion within DHS-clusters. Clusters represent the smallest local units, defined as groupings of households that took part in the survey according to DHS definitions. The results indicate that the negative impact of the CRA on marriage age is most pronounced in majority Muslim clusters, where child marriage prevails. This backlash is attributed to the desire to signal adherence to traditional norms and avoid Western influences. The reform also negatively affects gender norms, leading women to justify domestic violence more frequently. This study underscores the importance of considering local norms when implementing international legal frameworks and offers valuable insights into policy dynamics and their impact on gender norms.

Population research has long sought to understand the intricate relationship between child mortality and fertility. Chapter 3 investigates this relationship by examining the causal impact of infant mortality expectations on subsequent fertility in rural Malawi, leveraging unique expectations data from the Malawi Longitudinal Study of Families and Health (MLSFH).

The data reveals substantial heterogeneity in child mortality expectations, largely unexplained by respondent characteristics. To address potential endogeneity concerns, the study employs an instrumental variable approach, using a spatially-weighted average of children's health status in neighboring households as the instrument. The main finding indicates that a 10 percentage point decrease in infant mortality expectations leads to a significant 14 percentage point reduction in the likelihood of having an additional child in the next two years. This effect is more pronounced for older respondents. Excluding respondents who experienced child loss highlights the presence of excess fertility driven by an insurance mechanism against child mortality.

These results suggest that parents consider their infant mortality expectations when making fertility decisions, supporting the hoarding hypothesis in population research. The findings also imply the potential impact of information provision on fertility decisions, offering policy implications for improving the accuracy of parents' expectations through targeted interventions.

Chapter 4 explores the dynamics of auction markets, specifically focusing on seafood auctions like the Sydney Fish Market (SFM). It recognizes that markets are complex systems shaped by participant interactions and heterogeneity, challenging traditional price-setting assumptions. By analyzing extensive

SFM data spanning 27 years, the study unveils how bidder heterogeneity and interactions influence market outcomes.

Examining bidding behavior, information utilization, and the role of bidder expertise, the study finds that prices follow a non-monotonic trend. More experienced bidders tend to pay less, and information signals from initial bids impact subsequent bidding. This research challenges previous auction theories and underscores the significance of information transmission in auction dynamics.

Furthermore, the study highlights the importance of homogeneity within auction lots, enabling a comparison of prices across rounds and bidder experience levels. It departs from traditional martingale patterns and reveals non-monotonic price dispersion in sequential auctions, offering valuable insights into bidder behavior.

In summary, these studies contribute to our understanding of child marriage, fertility behavior, and auction market mechanisms, offering important insights for policy and economic research.

Chapter 2

Failure of International Laws in Local Contexts: The Case of the Child Rights Act in Nigeria

Child marriage remains a widespread issue globally, with approximately 640 million girls and women having experienced underage marriage (UNICEF, 2023). Extensive research highlights the negative consequences of child marriage, including reduced educational opportunities and early childbirth, affecting both women and their children (Ambrus, Field, and Torero, 2010; Chari et al., 2017). In response to these challenges, many countries have enacted age-of-consent laws to combat child marriage, and various UN initiatives target developing countries to protect girls from this practice. Despite numerous policies addressing child marriage, there is a lack of empirical evidence examining their effectiveness.[1] Understanding how these policies impact child marriages, is crucial for designing effective strategies to persistently reduce and eliminate this harmful practice.

The objective of this study is to analyze the impact of the Child Rights Act (CRA), which prohibits marriages for individuals under the age of 18, on marriage age outcomes among Nigerian women using data from the Nigeria Demographic and Health Survey. The adoption of CRA exhibited state-level

[1] McGavock (2021) finds that Ethiopia's minimum age for marriage law led to girls marrying later, resulting in delayed fertility and reduced home births. Bellés-Obrero and Lombardi (2023) shows that raising the minimum marriage age to 18 in Mexico led to fewer registered child marriages but an increase in informal unions. This suggests that age-of-marriage reforms alone may not fully prevent early unions and their negative consequences, emphasizing the importance of considering social norms and informal unions as alternatives.

variation, with the Federal Capital Territory implementing it in 2003, while 11 states had not yet adopted it until the final period in the dataset, which is 2018 (see Figure 2.3 for the adoption years by states). By leveraging the staggered adoption of CRA among states, I employ Callaway and Sant'Anna (2021) difference-in-differences (DID) methodology , incorporating multiple time periods and variations in treatment timing, to investigate this research question.

Child marriage, prevalent in both developing and low-income countries, poses extensive health risks for young girls (WHO, 2023). In Nigeria, where child marriage is a concerning issue, it contributes significantly to severe health challenges. Young brides are subjected to sexually transmitted diseases (STDs), premature pregnancies, and obstetric fistulas, often resulting in maternal and infant mortality (Allen and Adekola, 2017). A study conducted in Bauchi State, Nigeria, found that a considerable proportion of child brides admitted to contracting STDs multiple times, with ensuing complications like prolonged labor and vesicovaginal fistulas (Allen and Adekola, 2017). Furthermore, child marriage heightens the vulnerability of young brides to HIV transmission and various childbirth-related issues (Nour, 2006). Children born to child brides also face considerable health risks, including elevated mortality rates, malnutrition, and low birth weight, which emphasize the imperative of delaying marriage to mitigate these adverse outcomes (Simbine, Aluko, and Aluko, 2016; Nour, 2006). For instance, research conducted by Adedokun, Adeyemi, and Dauda (2016) revealed that respondents initiated childbearing between the ages of 14 and 18, with a staggering 71% of them experiencing at least one significant pregnancy or birth-related health complication. These complications encompassed issues such as excessive bleeding during labor (19.0%), obstructed and/or prolonged labor (49.0%), frequent miscarriages (12.0%), and extended post-childbirth sickness (20%). These findings underscore the urgency of addressing child marriage comprehensively to mitigate its severe and far-reaching health consequences.

This study addresses several important questions to comprehensively explore the implications of the Child Rights Act (CRA) implementation in Nigeria. Initially, I examine the aggregated average treatment effect of minimum age requirement laws on marriage age. Furthermore, following the group-level aggregation method in Callaway and Sant'Anna (2021), I investigate whether women exposed to the CRA in different states at different times exhibit divergent average treatment effects. This analysis underscores the significance of accounting for heterogeneity and preexisting local norms when introducing international legal frameworks. Subsequently, I explore the dynamic treatment effects by assessing how the effect of the CRA varies with the duration of exposure. The results addressing the primary question of this study reveal a notable backlash effect stemming from the reform. Contrary to its intended purpose, the Child Rights Act (CRA) exhibits a negative treatment effect on marriage age, with an average reduction of 0.65 years. To put this into context, the five-year pre-reform average marriage age was 17.8 years. Additionally, the reform significantly raises the likelihood of child marriages in treated states by 5 percentage points, compared to the pre-reform average of 44%. Additionally, my findings illustrate worsening trends in child marriage over the years, pointing towards dynamic treatment effects. The event study plots demonstrate that the reform's negative impact intensifies over the years. Furthermore, the group-level aggregation of treatment effects unveils heterogeneous outcomes with opposing signs among treatment cohorts of states. These observations highlight limitations of conventional difference-in-differences methods that assume homogeneous and static treatment effects.

Next, I further investigate the backlash effect within Nigeria's diverse communities, aiming to identify the driving factors, particularly focusing on religion and the majority religion of a cluster. Here, clusters are defined as the smallest subdivisions of local government areas. Nigeria's rich diversity of ethnicities and religions, sometimes leading to inter-religious tensions, offers a unique opportunity to study the impact of a new law in a highly heterogeneous environment with varying local norms. Figure A1.1 illustrates the disparity in marriage age trends between Muslims and non-Muslims, highlighting a significantly higher prevalence of child marriage among Muslim respondents. I analyze the data separately based on the majority religion in their residing cluster. The results indicate a positive treatment effect on marriage age in majority non-Muslim clusters, while it is negative for majority Muslim clusters. Both of these effects are precise, suggesting that the main effect is primarily driven by respondents in majority Muslim clusters, where child marriage has been more prevalent. I further examine the entire Muslim population, revealing that Muslims residing in majority-Muslim clusters exhibit the most adverse reaction to the reform. These findings emphasize the importance of considering preexisting local norms when introducing international legal frameworks.

The findings presented above shed light on the mechanisms underlying the observed backlash in marriage age trends. This backlash effect is predominantly experienced by Muslim respondents who share beliefs with the majority in their social environment. This finding is consistent with a phenomenon known as 'signaling' behavior, where the CRA encourages respondents to signal they follow traditional norms rather than succumb to 'Westernizing efforts'. Non-compliance with the reform can serve as an indicator of conservatism and having a 'pure' daughter, which is highly desirable in certain marriage markets. To support the argument for expressing more conservative beliefs, I examine another aspect of negative norm shifts by investigating changes in gender norms triggered by the reform. Specifically, I demonstrate that the reform also adversely affects gender norms, as it leads women to justify domestic violence to a greater extent. These insights contribute to a deeper understanding of the CRA's effectiveness in shaping marriage age outcomes and provide valuable insights into the dynamics of policy implementation and their broader implications for gender norms in Nigeria.

This study is linked to a body of literature that examines age-of-marriage laws. Notably, McGavock (2021) and Garcia-Hombrados (2022) explore the impact of raising the legal marriage age in Ethiopia, finding that this reform effectively reduces child marriages. Similarly, Bellés-Obrero and Lombardi (2023) investigate a staggered age-of-marriage law in Mexico and observe that while registered child marriages decrease significantly, informal unions increase, highlighting that reform itself is not enough when there are other options of unions. Bharadwaj (2015) analyzes the effects of a minimum age for marriage reform in Mississippi, revealing a substantial decline in the overall marriage rate. Wilson (2022) examines child marriage bans in 17 low- and middle-income countries and observes that elevating the minimum legal age of marriage to 18 leads to an increase in the age at marriage. However, this change does not seem to have resulted in a reduction of child marriage occurrences in rural areas. In the most related work to this study, McGavock (2021) explored the staggered implementation of similar laws in Ethiopia, highlighting treatment effect heterogeneity. She found that the impact of the reform was negligible among women from ethnic groups with strong early marriage norms. Unlike the reforms studied previously, Nigeria's age-of-marriage reform was designed by the UN rather than the country's legislative bodies. This study's primary contribution is its focus on treatment heterogeneity and the need to consider local factors like traditions and religion when assessing reform effects. While McGavock (2021) documented treatment effect heterogeneity and emphasized the importance of accounting for dynamic effects, their methodology, conventional difference-in-differences approach (DiD) may not fully address bias resulting from treatment heterogeneity. By employing the heterogeneity-robust difference-in-differences approach proposed by Callaway and Sant'Anna (2021), I demonstrate that in contexts of weak enforcement and conflicting local traditions, the reform is not only ineffective but can also trigger backlash in areas where child marriage is deeply rooted. Findings obtained through conventional DiD show sign changes in the treatment effect of the primary outcome, emphasizing the need to address bias from dynamic and heterogeneous treatment effects.

This study contributes to broader research examining the determinants of child marriage, particularly the influence of traditions and institutions on marital choices. UNICEF (2018) underscores that cultural, religious, and economic factors often compel early marriages. Notably, recent research explores how natural and economic shocks impact marriage timing (Corno, Hildebrandt, and Voena, 2020; Corno and Voena, 2023; Chowdhury, Mallick, and Chowdhury, 2020), with marriage-related payments playing a role in consumption smoothing. For instance, Baird, McIntosh, and Özler (2011) found that unconditional cash transfers reduce child marriage and teenage childbearing in Malawi. In Bangladesh, Buchmann et al. (2021) examined a program providing conditional transfers to girls delaying marriage until 18; financial incentives reduced early marriages, while empowerment treatments did not.[2] The model in Buchmann et al. (2021) is relevant to this study. Their theoretical findings imply that delayed marriage could signal lower bride quality in an environment favoring conservatism and obedience, potentially resulting in early marriage as a means of signaling desirability. This model implies that policies aimed at reducing child marriage might paradoxically lead to an increase in the marriage age. This is because altering bride type distributions raises the value of signaling by introducing information asymmetry. In this study, I argue that introducing international law without sufficient domestic adaptation can create an asymmetric environment in which individuals may need to signal their type-either by adhering to traditional and religious values, which can seem more favorable to conservative parents, or by adopting 'Westernized' values. This attempt to adopt Western practices, particularly in marriage law, triggers a backlash among Muslims in majority-Muslim areas where child marriage is highly prevalent, possibly due to signaling dynamics and perceived social sanctions for deviating from norms (Bursztyn, Egorov, and Fiorin, 2020; Bursztyn, González, and Yanagizawa-Drott, 2020).

This work relates to literature addressing the consequences of weakly enforced laws, which often arise when legal norms clash with prevailing social ones (Acemoglu and Jackson, 2017). Figure 2.1 illustrates that between 2013 and 2018, despite over half of the states adopting the CRA, nearly 40% of women were still marrying before age 18, indicating enforcement challenges. Wodon et al. (2017) estimates that at least 7.5 million girls were married illegally in 2017 under age-of-marriage laws. A global survey by Collin and Talbot (2023) using DHS and Multiple Indicator Cluster Surveys (MICS) data suggests that outlawing early marriage may not effectively deter the practice, even in regions where early marriage rates seem to be declining. Similarly, studies in Indonesia (Cammack, Young, and Heaton, 1996) and the United States (Blank, Charles, and Sallee, 2009) report minimal impact of legislating a minimum marriage age. Additionally, qualitative evidence from Africa shows societal backlash against international laws (Leclerc-Madlala, 1997). My study reveals that the negative impact of the international law, CRA, is driven mainly by respondents in majority Muslim clusters with deep-rooted child marriage traditions. This reinforces the argument that weakly enforced laws conflicting with established norms are not just inefficient but can also provoke backlash. According to

[2] Conversely, Bandiera et al. (2020) discovered that vocational and empowerment training for adolescent girls reduces the likelihood of early marriage or cohabitation, emphasizing the importance of empowering young girls in society.

Bursztyn, Egorov, and Fiorin (2020) and Bursztyn, González, and Yanagizawa-Drott (2020), individuals may face implicit threats when deviating from social norms, potentially resulting in various forms of enforcement. This research underscores the need for careful implementation strategies and local community engagement before introducing laws that challenge entrenched social norms. Importantly, this study is among the first to document adverse outcomes resulting from the implementation of an international age-of-marriage law in a developing country.

Next, Section 2.1 provides information on the local context and marriage policies in Nigeria. Section 2.2 describes the data and offers summary statistics, while Section 2.3 introduces the estimation strategy and Section 2.4 presents the results. In Section 2.5, the mechanisms and their implications are discussed, and finally, Section 2.6 concludes the study.

2.1 Marriage policy in Nigeria and the CRA

2.1.1 Local context

Nigeria, a multi-ethnic and culturally diverse federation, comprises 36 autonomous states along with the Federal Capital Territory. With a population surpassing 210 million, Nigeria ranks as the sixth-largest country globally. It falls under the lower middle-income category, with a GNI per capita of around \$2,000, as classified by (2021). Nigeria's performance across a range of human welfare indicators is considerably below average. Notably, it surpasses all other countries in terms of annual maternal deaths during pregnancy and childbirth, as reported by the Organization (2019). Furthermore, Nigeria accounts for approximately 10 percent of global newborn deaths (Lawn et al., 2014). The under-five child mortality rate in Nigeria, standing at 132 per 1,000 live births, is worse than that of significantly poorer countries (DHS, 2018). Additionally, the average life expectancy in Nigeria is 54 years, lower than the sub-Saharan African average of 61 years.

Nigeria exhibits a remarkable diversity in its social and cultural structure, marked by a multiplicity of factors such as religion, culture, legal systems, education, and ethnicity. This heterogeneity is profoundly manifested in its marriage customs and practices. As one of the most populous nation, Nigeria comprises over 250 ethnic groups (DHS, 2018). Among these, major religious groups include Islam and Christianity, each contributing significantly to the nation's intricate social landscape. The coexistence of these religious traditions, often in dynamic tension, has shaped diverse marital norms and practices across the country. Figure 2.2 depicts the prevalence of child marriages across all states, revealing a distinct pattern. Notably, the rates of child marriage closely align with the proportions of Muslim populations in states (as shown in Figure A1.3). Majority Muslim northern states exhibit significantly higher child marriage rates, while majority Christian states in the southern region exhibit remarkably lower rates. This geographic disparity underscores the influence of religious composition on the prevalence of child marriages in Nigeria. Educational disparities also play a role, with varying levels of access and attainment across regions. These factors interact to shape distinct marriage cultures, emphasizing the significance of considering heterogeneity when examining marriage dynamics in Nigeria.

2.1.2 Child Marriage and Marriage Laws in Nigeria

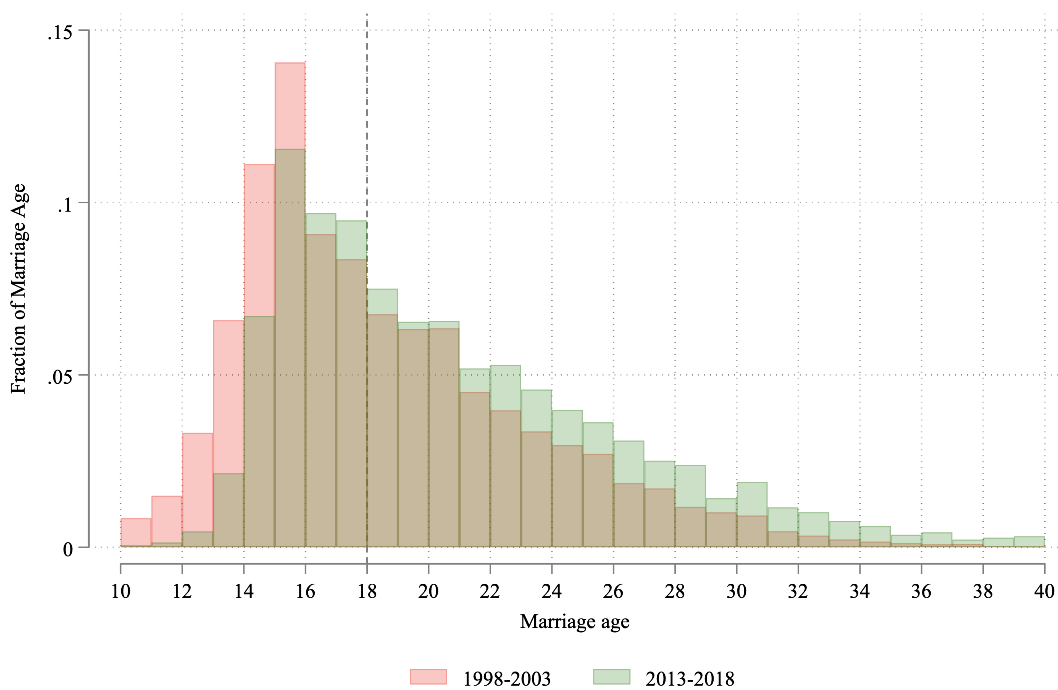


Figure 2.1: Fraction of Marriage Ages

Notes: This figure presents the distribution of marriage ages for two distinct time periods: 1998-2003 and 2013-2018, sourced from the DHS.

Child marriage is generally characterized as a union involving individuals under the age of 18, encompassing both formal marital bonds and cohabitation arrangements resembling marriage (UNICEF, 2018). In the initial phase of our investigation commencing in 2003, all regions of Nigeria permitted individuals below 18 years to enter into official marriages, albeit under certain conditions. Specifically, minors were required to meet a minimum age threshold and secure consent from their parents or legal guardians.

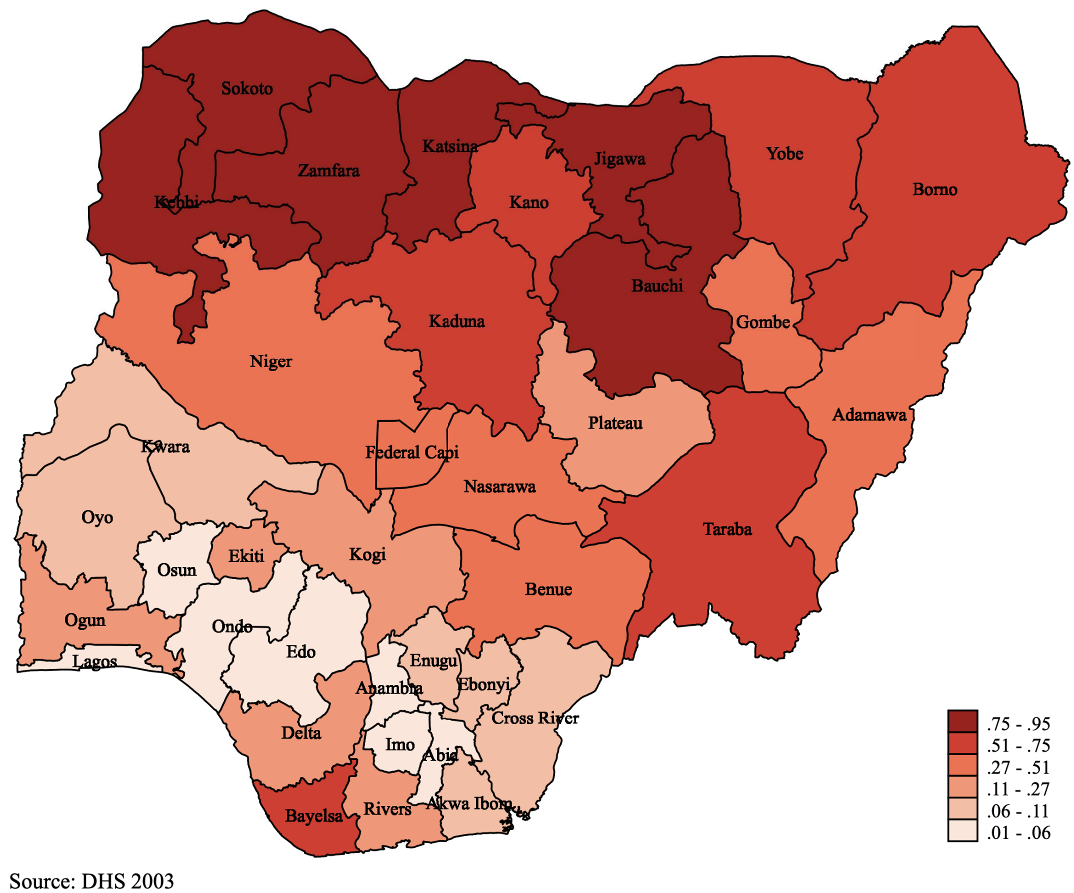


Figure 2.2: Pre-reform female child marriage rate by states

Notes: This map illustrates the staggered adoption of the Child Rights Act across 36 states and 1 federal capital territory in Nigeria.

Child marriage in Nigeria presents a compelling subject for investigation, considering its prevalence among Nigerian girls. As the most populous nation in sub-Saharan Africa, Nigeria bears the highest burden of child brides, with more than 3.5 million women being married before reaching the age of 18. DHS (2018) revealed that 42% of women aged 20-24 in Nigeria were married before turning 18, and a rate of 15% before the age of 15. Furthermore, Nigeria ranks as the 11th highest country in terms of child marriage prevalence. This prevalence is attributed to deeply entrenched customs and religious norms, making child marriage a pervasive phenomenon, particularly concentrated within certain ethnic and religious enclaves, predominantly in the Northern regions. Figure 2.2 illustrates alarmingly high child marriage rates in the Northernwest and Northerneast regions. This phenomenon is particularly pronounced in certain states, DHS (2003) indicates that over 90% of women aged 18 to 25 were married by age 18. This prevalence sharply contrasts with the less than 10% observed in some Southern states.

While these overall high child marriage rates underscore the need for intervention, it is crucial to address the heterogeneity across states when analyzing the reform aimed at abolishing child marriages.

The absence of a comprehensive national marriage law in Nigeria adds complexity to the issue at hand. Prior to the Child Rights Act (CRA), Nigeria lacked a uniform law governing the minimum marriage age due to its complex legal framework, which encompasses civil, customary, and religious laws (Imam-Tamim et al., 2016). The nation's legal history involves the incorporation of foreign marriage law systems, including Islamic and English law, resulting in a multitude of laws regulating marriage (Park, 1963). This legal diversity posed significant challenges when addressing child marriage. In Islamic law, marriage age is determined by factors such as puberty and maturity, which can vary across different traditions, often resulting in ages between 12 and 15. In contrast, although the Marriage Act recognizes individuals under 21 as minors it allows marriage with parental or guardian consent even at ages as young as 13 or 14. The subsequent Matrimonial Causes Act of 1970, while deeming marriages void if either party is not of "marriageable age," fails to specify this age threshold.

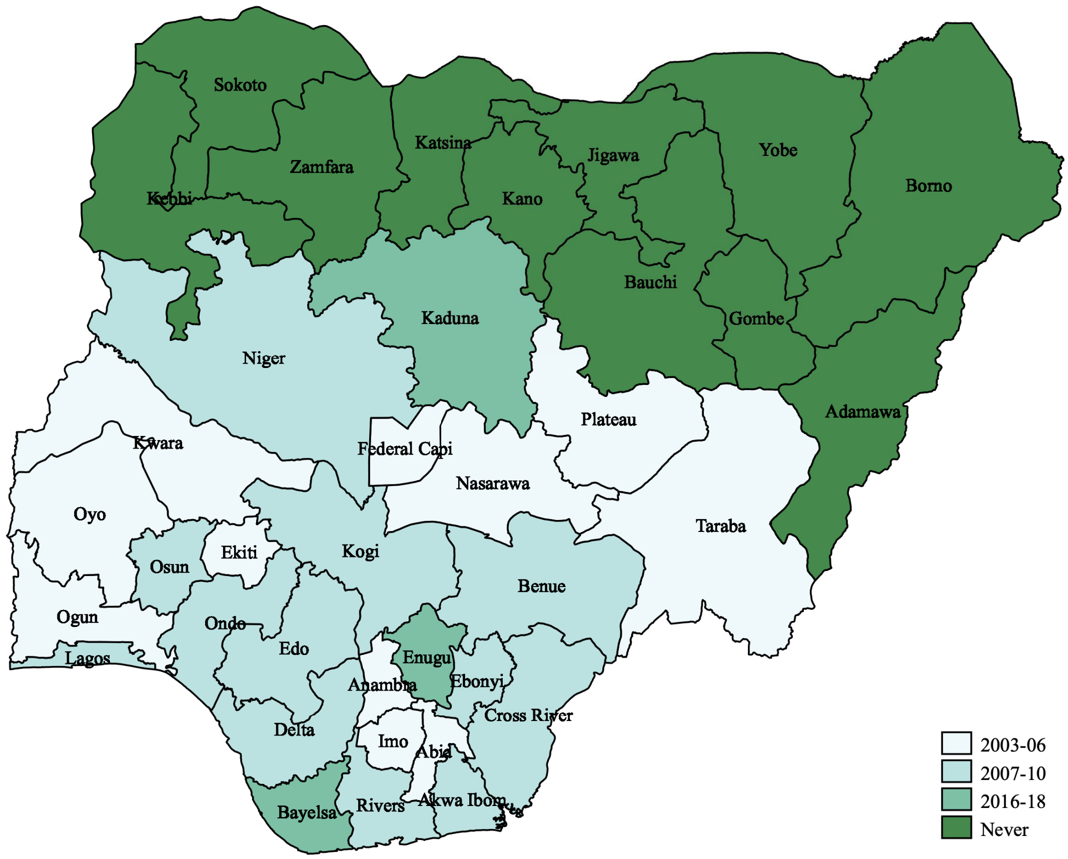
2.1.3 An overview of CRA

In 2003, Nigeria enacted the Child's Rights Act to comply with the United Nations Convention on the Rights of the Child.[3] Sections 21 and 23 of the CRA directly target child marriage, unequivocally setting 18 as the minimum marriage age and explicitly prohibiting parents from arranging marriages for their daughters below this age, thus outlawing child marriage and betrothal. Violations of these provisions carry severe penalties, including a fine of N500,000 (or approximately US$655) or a prison sentence of five years.[4] Furthermore, the act criminalizes the consummation of a marriage between a child under 18 years of age and her husband, punishable by imprisonment.

The matter of child protection in Nigeria is not exclusively or concurrently under the jurisdiction of the national government as per the Constitution. Therefore, it is the responsibility of each state, as sub-units of the federal government, to either apply the CRA as it is or pass it as a state law (Toyo, 2006). Despite the Federal Government's efforts to combat child marriage through the enactment of the Child Rights Act in 2003, its enforceability depends on individual states enacting the act under their own state laws. Consequently, state legislatures possess the authority to establish laws for the

[3] Emelonye (2014) argues that the acy was passed due to civil society advocacy and diplomatic pressure from international allies.

[4] The CRA additionally protects a range of rights, encompassing the right to survival and development, the right to identity, the freedom to engage in peaceful assembly, freedom of thought, conscience, and religion, the right to privacy, the freedom to movement, and the right to be free from discrimination.



Source: UN - Convention on the Rights of the Child

Figure 2.3: Map of State Adoption Years for Child Rights Act (CRA)

Notes: This cartographic illustration depicts the incidence of child marriage among women aged 18 to 25 during the year 2003, utilizing data extracted from the 2003 Demographic and Health Survey (DHS), a timeframe predating any interventions related to marriage reforms.

protection of children, aligning them with religious, cultural, and traditional values instead of adopting the Act. As a result, states adopted CRA in a staggered manner. As of 2018, 25 states have adopted the law, while 11 states under Sharia law have not yet done so. Figure 2.3 illustrates the adoption timeline of the Child Rights Act (CRA) by each state.

The concept of a minimum age for marriage, originating from the international context of the CRA, has implications for both state and Muslim personal law. It has stirred controversy, primarily because it is seen as an international intrusion into the private sphere (Nwauche, 2015). In Nigeria, the Supreme Council for Shariah, in conjunction with certain northern legislators opposed the CRA, deeming it incompatible with culture, tradition, and religion (Assim, 2020). This opposition is particularly pronounced in northern Nigerian states, where the CRA's provisions are perceived as conflicting with deeply rooted religious and cultural norms, especially among Muslim communities who object to the provision setting 18 years as the minimum marriage age, considering it contrary to Islamic precepts.

Conversations with journalist and Child Rights advocate Adégbìté (2023) have shed light on the perception that the CRA's campaign against child marriage aims to Westernize traditional practices and religious adherence. This perception has fueled resistance against the law's implementation, given child marriage's entrenched nature in society, resulting in individuals taking ideological stances for or against the Act. According to Toyo (2006), Bilkisu Yusuf, the former President of the Federation of Muslim Women Associations of Nigeria (FOMWAN), emphasizes that Islamic family law holds distinct rights notions, separate from those stated in the constitution. She asserts that reforms should originate within the Islamic legal system, a viewpoint supported by Imam (2006), who critiques the portrayal of international solidarity around women's rights, highlighting dissent among Muslims and the protests and campaigns in Nigeria. As noted by Toyo (2006), opposing groups have gone beyond mere disagreement; they have mobilized religious leaders, lobbied in the Sharia states of the northern region, and confronted members of the National Assembly regarding their support for the CRA. Furthermore, they have initiated an extensive media campaign, publicly identifying individuals who work for the CRA as perceived to be working against Islam's interests.

Figure 2.4: Marriage age among older and younger cohort of girls

Notes: This figure depicts the distribution of marriage ages categorized by girls' ages when the CRA was adopted. The data used in this figure are derived from the sample of ever-married women in the Nigeria DHS who were a minimum of 18 years old at the survey's time.

Using Nigeria DHS data from 2003, 2008, 2013 and 2018, Figure 2.4 shows the distribution of marriage ages for two distinct groups of women: those who were 12-15 years old and those who were 18-21 years old when the CRA was enacted in their respective states. It is important to note that these two groups faced different legal age requirements for marriage. The cohort of girls aged 12-15 encountered a minimum marriage age of 18, while there was no specific age requirement for the cohort of girls aged 18-21 when the CRA was implemented. The figure reveals an intriguing pattern in which the distribution of marriage ages shifted left for those aged 12-15 when the CRA was instituted, despite being fully exposed to a legal marriage age of 18. Although the figure indicates that the most common age at first marriage increased from 17 to 18 for the younger cohort, it also highlights that the younger group exhibits a higher likelihood of marrying between the ages of 15 and 17, which contradicts the intended impact of the CRA. Figure A1.4 provides additional support indicating the reform's ineffectiveness. There is no discernible discontinuity at the reform time, and the pre-reform decreasing trend in child marriage appears less steep afterward. This study aims to investigate this puzzling trend of younger marriage ages upon adoption of the CRA.

Studying this reform is crucial in order to understand the potential backlash effect it may generate, as it illuminates the complex interplay between international human rights standards and deeply ingrained cultural and religious traditions, shedding light on the challenges and tensions that arise when attempting to harmonize these seemingly conflicting values.

2.2 Data

This study uses the Nigeria Demographic and Health Survey, which is part of the larger Demographic and Health Surveys (DHS) program. The Nigeria DHS, conducted by the National Population Commission (NPC) in collaboration with the National Malaria Elimination Programme (NMEP) of the Federal Ministry of Health, provides comprehensive and representative data on various socio-economic and demographic factors for women aged 15-49 and men aged 15-59. The survey was conducted in 2003, 2008, 2013, and 2018, and covers a wide range of topics, including fertility, family planning, nutrition, maternal and child health, mortality, women's empowerment, violence, HIV/AIDS, and more.

With a large sample size of approximately 121,000 Nigerian women, the Nigeria DHS dataset is particularly valuable for this study as it offers reliable information on marriage, education, fertility, and family planning practices. Table 2.1 presents summary statistics derived from the data. To analyze the impact of the Child Rights Act (CRA) on marriage, we utilize the Nigeria DHS data to identify a respondent's year and month of marriage and state of residence, enabling us to link individuals to relevant marriage policies. An advantage of the Nigeria DHS is its inclusion of detailed information on religion and ethnicity, which are used as control variables.

Within the Nigeria DHS, women were surveyed regarding their marital status and "age at first cohabitation," a term referring to the age at which ever-married women entered into marriage, as documented by the DHS. In addition to examining the marriage age, following McGavock (2021) this study considers secondary outcomes regarding the distribution of marriage ages.

Table 2.1 presents summary statistics for 121,744 women based on data from the Nigeria DHS, encompassing survey waves from 2003, 2008, 2013, and 2018. It provides insights into various aspects related to women aged 15-49, distinguishing between majority-Muslim and non-Muslim clusters. In Nigeria DHS, each state comprises local government areas (LGAs), further divided into wards. Additionally, within each locality, there are smaller subdivisions known as DHS-clusters, with each cluster averaging 34 respondents. DHS- clusters with more than 50% Muslim respondents are classified as majority Muslim clusters.

In the first column, representing the statistics for all women regardless of their religious cluster, we observe several key trends. On average, women in this cohort marry at around 17.88 years of age. Approximately 29% of marriages occur before the age of 16, with an additional 14% happening between ages 16 and 17. Only about 56% of marriages take place after the age of 18, indicationg high rates of child marriage. Educational attainment is relatively low, with an average of 6.19 years of education. Employment rates stand at 62%, indicating that a significant proportion of women are engaged in the workforce.

In terms of women's characteristics, there are notable disparities between the women who reside in majority Muslim and majority non-Muslim clusters. Women in majority-Muslim clusters tend to be more prevalent in the North, reside in rural areas, and are typically younger on average. The majority-Muslim cluster also has a higher proportion of Muslim women and a lower proportion of Christians and traditionalists compared to the non-Muslim cluster. Regarding outcome variables, significant differences emerge in age at first marriage. Women in majority-Muslim clusters tend to marry at younger ages compared to their non-Muslim counterparts. Additionally, there is a higher incidence of marriages under the age of 16 in majority-Muslim clusters.

Education and employment indicators also highlight disparities. Women in majority-Muslim clusters tend to have fewer years of education on average and are less likely to be employed compared to those

Table 2.1: Summary Statistics - Females, Nigeria DHS Sample

	All		Majority Muslim		Majority non-Muslim		Difference
	mean	sd	mean	sd	mean	sd	b
Region							
North	0.59	0.49	0.90	0.30	0.33	0.47	0.56***
South	0.41	0.49	0.10	0.30	0.67	0.47	-0.56***
Rural	0.62	0.48	0.69	0.46	0.56	0.50	0.13***
Muslim	0.48	0.50	0.90	0.30	0.12	0.32	0.78***
Religion							
Christian	0.50	0.50	0.09	0.28	0.86	0.34	-0.77***
Traditionalist	0.01	0.10	0.00	0.07	0.01	0.12	-0.01***
Ethnicity groups							
Yoruba	0.14	0.35	0.10	0.29	0.18	0.38	-0.08***
Igbo	0.15	0.36	0.01	0.10	0.27	0.44	-0.26***
Hausa-Fulani	0.33	0.47	0.65	0.48	0.05	0.22	0.59***
Others	0.39	0.49	0.25	0.43	0.50	0.50	-0.26***
Outcome variables							
Age at first marriage	17.88	4.80	16.28	3.73	19.72	5.21	-3.45***
Marriage under 16	0.29	0.45	0.46	0.50	0.15	0.35	0.31***
Marriage from 16 to 17	0.14	0.35	0.18	0.38	0.11	0.31	0.07***
Marriage over 18	0.56	0.50	0.35	0.48	0.73	0.44	-0.38***
Education - Employment							
Education in years	6.19	5.61	3.43	5.16	8.57	4.84	-5.14***
No education	0.36	0.48	0.63	0.48	0.14	0.35	0.48***
Primary level	0.18	0.38	0.14	0.34	0.22	0.41	-0.08***
Secondary level	0.37	0.48	0.20	0.40	0.51	0.50	-0.32***
Higher	0.09	0.29	0.04	0.21	0.13	0.34	-0.09***
Employed	0.62	0.49	0.56	0.50	0.67	0.47	-0.11***
Other characteristics							
Majority Muslim cluster	0.46	0.50					
Under Sharia	0.38	0.48	0.71	0.46	0.10	0.29	0.61***
Ever-married	0.73	0.45	0.84	0.37	0.63	0.48	0.21***
Age	28.85	9.64	28.57	9.53	29.10	9.73	-0.53***
Age gap with husband	10.64	8.01	11.87	8.15	9.22	7.59	2.65***
Marr. to first birth (months)	22.74	26.68	27.15	29.11	18.06	22.91	9.09***
Number of children	2.55	2.46	2.92	2.56	2.24	2.33	0.68***
Domestic violence index	1.21	1.80	1.45	1.94	1.00	1.64	0.45***
Decision-making index	-0.55	1.84	-1.05	1.63	-0.07	1.91	-0.98***
Can ask to use condom	0.41	0.49	0.31	0.46	0.53	0.50	-0.22***
Can refuse sex	0.61	0.49	0.47	0.50	0.78	0.41	-0.32***
Observations	121774		56282		65492		121774

Notes: Summary statistics are derived for all women aged 15-49 from Nigeria DHS, spanning waves 2003, 2008, 2013, and 2018, and are separated for majority-Muslims and non-Muslim clusters. The last column reports the difference in means between these two samples. The domestic violence index is computed by adding together the binary variables related to questions about whether beating is justified in cases where the wife neglects children, argues with her husband, goes out without informing her husband, or burns the food. The decision-making index sums variables for healthcare, purchases, family visits, and personal earnings. Negative values indicate no decision-making power.

in non-Muslim clusters. Additionally, various other characteristics, including age gaps with husbands, the duration between marriage and the first birth, the number of children, and indices related to domestic violence and decision-making, all display disparities between the two groups, with more favorable outcomes observed among women residing in majority non-Muslim clusters. These statistics underscore the importance of considering regional and religious differences when studying various aspects of women's lives in Nigeria. Understanding these disparities can inform targeted policies and interventions to address the unique challenges faced by women residing in different clusters.

2.3 Empirical Strategy

This study aims to estimate the causal impact of the Child Rights Act (CRA) on marriage age and other outcomes for women in Nigeria. Specifically, it seeks to assess the impact of the reform by comparing the average age of women at marriage before and after the reform, taking advantage of the staggered implementation times of the reform across different states The conventional difference-in-differences (DiD) method (two-way fixed effects approach), introduced by Ashenfelter and Card (1985), is typically employed to assess public policies (Card and Krueger, 1995; Eissa and Liebman, 1996). Baker, Larcker, and Wang (2022) documents that in recent years, there has been a growing trend in using a generalized version of this estimation method (staggered DiD), which takes advantage of the staggered adoption of laws or regulations (e.g., across states or countries).

In this section, I begin by examining potential deviations from the identifying assumptions of the widely used two-way fixed effects (TWFE) approach that might arise in the context of this study. Subsequently, I suggest adopting the Callaway and Sant'Anna (2021) model as my primary methodology to address issues stemming from the use of TWFE in staggered reform settings. Furthermore in the following section, I assess the severity of this concern in this specific context by comparing the results obtained from TWFE with those from Callaway and Sant'Anna (2021), which addresses the "forbidden comparison" issue.

I use difference in differences model to estimate the impact of the CRA by comparing the average age of women at marriage before and after the reform leveraging the staggered adoption of the reform across different states to assess its effect on marriage age using the following specification:

$$Y_{ist} = \beta PostCRA_{st} + \gamma X_{ist} + \mu_s + \theta_t + \epsilon_{ist} \tag{2.1}$$

where Y_{ist} is the marriage age outcome of woman i residing in state s married in year t, specifically marriage age, and binary variables for marriage under 16, marriage from 16 to 17, and marriage over 18. $PostCRA$ serves as an indicator to determine whether a marriage occurred after the implementation of the reform in state s. Additionally, the vector X_{ist} includes several control variables, such as a rural dummy, a Muslim dummy, birth year and ethnicity group fixed effects.[5] Furthermore, μ_s and θ_t represent fixed effects for the state and marriage year, respectively. The coefficient β on the post-CRA dummy represents the treatment effect of the reform, indicating the average change in marriage age resulting from the implementation of the reform.

To address the potential influence of endogenous factors on marriage timing, such as economic crises or security issues, this specification incorporates year of marriage and state fixed effects. These controls help mitigate the impact of common factors that affect women married in the same year or residing in the same state on marriage age. Due to the survey design, women are interviewed either post-marriage or pre-marriage, which prevents the incorporation of controls associated with their family backgrounds that might impact their marriage timing. In the data, noticeable variations in marriage age trends emerge among women with distinct religious affiliations and those residing in different states (see Figure 2.2 and Figure A1.1). However, any systematic variations or changes in the distribution and trends of these factors across states, birth cohorts, ethnic and religious groups or over time are accounted for by incorporating state, birth year and ethnicity group fixed effects and Muslim dummy into the analysis.

Previous research investigating the effects of staggered reforms has frequently employed the TWFE approach (Huebener, Pape, and Spiess, 2020; Fauver et al., 2017). Similarly, prior studies examining the impacts of staggered child marriage reforms, such as those discussed by Bellés-Obrero and Lombardi (2023) and McGavock (2021), have commonly employed the TWFE approach. In the context of this study, the TWFE approach faces several challenges that limit its applicability and reliability. The unconditional parallel trends assumption requires that, in the absence of treatment, the outcome of interest would follow a similar trajectory across groups or cohorts. Firstly, it is likely that the unconditional parallel trends assumption is not met, and the typical conditional parallel trends assumption may be overly stringent in the context of this study. This is evident from the significant differences in observed characteristics, such as age, education, and religion, among individuals living in early-treated, late-treated, and never-treated states.[6] When the outcome trends depend on these covariates, a conditional parallel trend becomes more plausible. Consequently, the DiD estimate will be

[5]All ethnicities are categorized into the top three ethnic groups (Hausa-Fulani, Igbo, Yoruba) and others.

[6]Please refer to Table A1.1 for a comparison between never-treated and treated states. This table highlights that never-treated states generally have poorer outcomes concerning child marriage, education, and women's employment. Additionally, these states are more likely to have a higher population of Hausa-Fulani and Muslim communities.

biased if the control states' trends fail to capture the counterfactual outcome trends for the treatment states. Additionally, time-varying confounding factors, such as floods or epidemics, can further violate the parallel trends assumption.

Crucially, another challenge for the TWFE approach lies in the presence of dynamic and heterogenous treatment effects as it assumes static and homogenous treatment effects across treated units (Callaway and Sant'Anna, 2021; Borusyak, Jaravel, and Spiess, 2021; Sun and Abraham, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Athey and Imbens, 2022). Given the differential trends in marriage outcomes across religious groups and varying adoption timing and adherence to the reform among different states, heterogeneous treatment effects are likely to occur. The presence of heterogenous treatment effects raises concerns regarding forbidden comparisons between later-treated and early-treated units. In cases of treatment heterogeneity (as shown by Sun and Abraham (2021) and Borusyak, Jaravel, and Spiess (2021)), these forbidden comparisons can lead to issues, including TWFE coefficients showing the opposite sign of individual-level treatment effects. This issue arises due to negative weighting problems, as emphasized by Callaway and Sant'Anna (2021) and Goodman-Bacon (2021). When considering aggregation, negative weighting poses various challenges, with weights determined by group sizes and treatment variation within pairs. Units in the middle of the panel receive the highest weight. However, relying solely on the static Ordinary Least Squares (OLS) coefficient for aggregation fails to capture meaningful comparisons between units, especially in staggered settings with heterogeneous treatment effects. This can lead to biased TWFE estimates. To address these challenges, a common solution involves using an estimator that isolates "clean" comparisons between treated and untreated groups and aggregating the estimates using user-specified weights to obtain the target parameter of economic interest.

Another particular concern arises when earlier-treated units serve as controls for later-treated units under dynamic treatment effects. Given the implementation of reforms in large countries like Nigeria, it is likely that the treatment effect will exhibit different dynamics over time, as awareness increases with time. The changes observed in the outcomes of the earlier-treated units may reflect changes in their treatment effects over time, introducing dynamic treatment effects that violate TWFE assumption on static treatment effects. Additionally, Sun and Abraham (2021) demonstrate that event study estimates are biased when the reform has differential effects on different states. These factors collectively contribute to the substantial risks associated with employing the TWFE approach in this context.

I use Callaway and Sant'Anna (2021) (CS) method to address these issues arising from dynamic and heterogenous treatment effects. The specification follows Eq. (3.2) in Callaway and Sant'Anna (2021) and is set up as in equation 2.1. The CS method provides several benefits. Firstly, it accommodates arbitrary treatment effect heterogeneity and dynamic effects, addressing the limitations of TWFE, which can lead to negative weights due to forbidden comparisons. Furthermore, the CS method is more transparent regarding the units included in the analysis. It employs clean control units, ensuring that earlier treated units do not serve as controls for later treated units. In this study, I employ not-yet treated units as part of the control group. This approach, as suggested by Callaway and Sant'Anna (2021), provides greater flexibility compared to using only never-treated states. By incorporating not-yet treated units, which are more similar in nature, into the control group, we enhance the comparability of treatment and control groups.

Secondly, the CS approach imposes a more flexible parallel trends assumption, which is better suited for the Nigerian context.[7] This relaxation means that starting from period g, cohort g - consisting of the women in states that passed the CRA in year g - must follow the same trend as the not-yet treated groups if they had not implemented the CRA. However, before that, cohort g may have been following a different trend. Although Figure 2.5 ensures that the pre-trends of states adopting the law in different times are quite similar, this flexibility in the parallel trends assumption provides additional robustness.

Moreover, the method can incorporate covariates into the staggered difference-in-differences setup, allowing for covariate-specific trends across groups. This is particularly crucial in settings where differences in observed characteristics, such as residence based on majority religion (see Table 2.1), ethnicity, birth cohort, and religion, lead to non-parallel outcome dynamics. Given that the distribution of these observed characteristics differs among individuals in early-treated, late treated, and never-treated states, the inclusion of covariates enables a more plausible conditional parallel trend assumption. Instead of assuming that all groups follow the same pattern in how they change their outcomes when not treated, the assumption of conditional parallel trends suggests that groups with the same characteristics that don't change over time should have similar changes in their outcomes which is often a more flexible assumption. Following the specification in Equation 2.1, this assumption implies that in the absence of the CRA, individuals with the same religion, rural/urban residence status, birth cohort and ethnicity group would have experienced the same marriage trends, rather than assuming that all states would have experienced the same marriage evolution. While the parallel trends assumption cannot be tested directly, Figure 2.5 illustrates that states in different groups based on their treatment adoption years

[7] In contrast to Borusyak, Jaravel, and Spiess (2021), which relies on average pre-treatment periods, the CS approach only requires parallel trends from one period before the treatment.

display similar trends in marriage age before the reform. This suggests that these states would have likely experienced similar marriage age trends even in the absence of the reform. Another identifying assumption of CS is that the treatment anticipation is limited. For the purposes of this study, I assume that there is no treatment anticipation. In a large country like Nigeria, with diverse regions and communities, it often takes time for awareness of new laws and their implications to spread uniformly. Therefore, this assumption appears plausible. Additionally, Figure 2.5 provides further assurance that there is no anticipation effect, as there is no abrupt jump or decline observed around the reform cutoff.

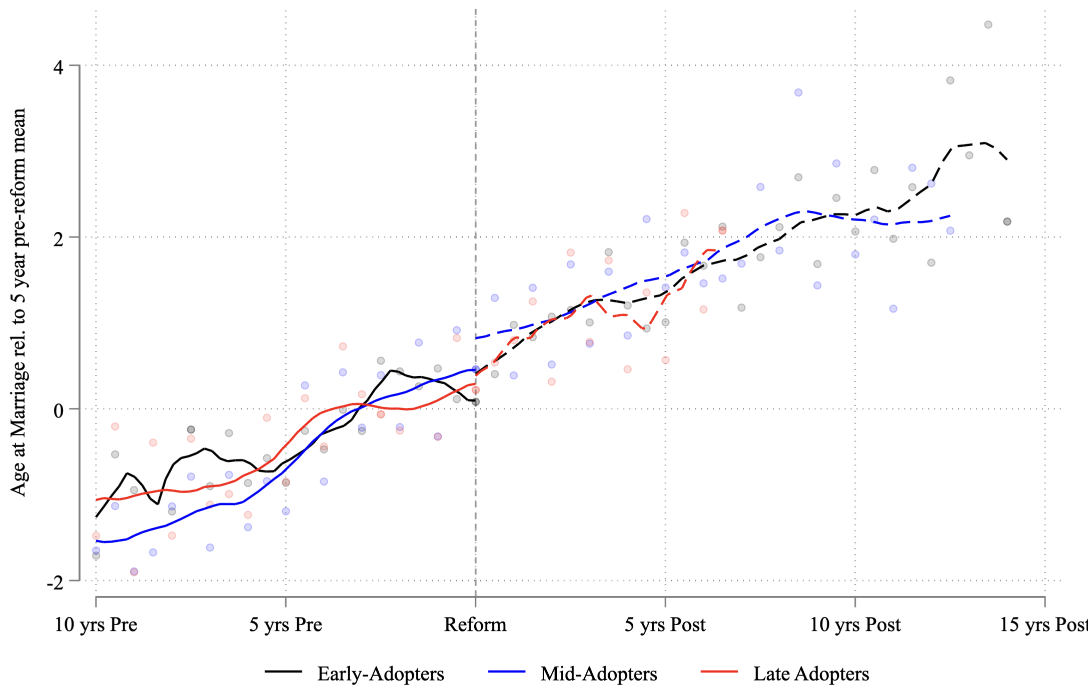


Figure 2.5: Average Age at marriage

Notes: This figure illustrates the age at marriage for three groups of states categorized by their years of reform adoption. Each data point represents the average age at marriage in relation to the mean age during the 5 years preceding the reform in that respective group, with pre-reform means normalized to zero across state groups. Lines are local polynomials fitted to the data. Source: Nigeria DHS.

Under the assumptions discussed above, CS identify a disaggregated causal parameter known as the group-time average treatment effect ATT(g,t) where $ATT(g,t) = E[Y_{i,t}(g)$ - $Y_{i,t}(\infty)|G_i = g]$.[8] This parameter represents the average treatment effect for a specific group g (where groups are defined as treatment cohorts) at a given time t, based on clean control units. CS method identifies the ATT(g,t), through a comparison of the expected change in outcome for cohort g between periods $t-1$ and t with

[8] Other key identifying assumptions include the "irreversibility of treatment," which is met as no state reverted the law, and "random sampling," which is maintained through the DHS sampling method. Additionally, the assumption of "overlap," which necessitates that for each treated unit with covariates X_i, there are at least some untreated units in the population with the same value of X_i, is also secured due to the large sample size.

that of a control group that has *not yet* received treatment at period t. One of the main advantages of this method is its generality and flexibility, which enables the construction of easy-to-interpret causal parameters. These parameters can be utilized to gain insights into treatment effect heterogeneity and to construct various other aggregated causal parameters. It extends easily to estimate weighted averages of the ATT, allowing for the estimation of ATT for all groups across all periods, ATT for each group or cohort over all periods, ATT for each period across all groups or cohorts, and event study parameters using all periods relative to the period of the first treatment across all cohorts.

Table A1.1 presents summary statistics for women included in the sample, revealing notable distinctions between those treated and those never treated. Women residing in states that did not adopt the CRA had a lower average marriage age, a higher likelihood of marrying before the age of 16, and a reduced likelihood of marriage after 18, in contrast to their counterparts in treated states. Moreover, a higher proportion of women with no schooling is observed among those in states that never embraced the CRA. These variations suggest that the implementation of the CRA predominantly took place in states with a lower risk of child marriage, contrary to the intended policy objective. Additionally, a greater representation of Muslim women is found among the group never exposed to the CRA, accompanied by slight age differences. Furthermore, a higher number of non-treated women resided in states operating under Sharia law. These disparities underscore the necessity of robust quasi-experimental methodologies for valid comparisons between outcomes of women exposed and unexposed to the CRA. To address this, I employ the double-robust estimator suggested by CS, which relies on less stringent modeling conditions and provides increased robustness against model misspecifications compared to the outcome regression (OR) or the inverse probability weighting (IPW) approaches. Furthermore, given the notable disparities observed between treated and never-treated units in Table A1.1, we adopt a rigorous approach by using not-yet treated units as clean controls. While Sun and Abraham (2021) restrict the use of not-yet treated units as controls, the method proposed by Callaway and Sant'Anna (2021) allows for the inclusion of not-yet treated units in the control group. This ensures a more comprehensive evaluation of the treatment effects while addressing potential confounding factors. Please refer to Table A1.3 for a summary of all assumptions and their respective discussions.

For all following analyses, the applied methodology adopts cluster-robust standard errors at the state level, as suggested by CS. As highlighted in the preceding section, summary statistics reveal notable distinctions between treated and untreated women, as well as between women residing in majority Muslim and majority non-Muslim clusters. Consequently, I employ the double-robust estimator for identification, as recommended by CS.[9]

2.4 Results

Within this section, I present findings based on the assumptions of no treatment anticipation and conditional parallel trends after controlling for observable variables.

The CS methodology not only takes care of the issue stemming from dynamic and heterogeneous treatment effects, it also offers the advantage of identifying a single average treatment effect coefficient, equivalent to the average treatment effect on the treated in the conventional DiD setup. The main results of this study in Panel A of Table 2.2 presents the overall average effect of CRA experienced by all women exposed to the reform.[10] Contrary to its designed purpose, the CRA has a negative treatment effect on marriage timing, leading to increased prevalence of child marriage. Instead of raising the marriage age as intended, it leads to a decrease of 0.65 years on average from the baseline average of 17.8 years. Additionally, it increases the likelihood of marriage before age 16 by 5.7 percentage points compared to the baseline average of 39%, while simultaneously decreasing the likelihood of marriage after age 18 by 5.1 percentage points from the baseline rate of 44%. However, there is no evidence that CRA affects marriages between the ages of 16 and 17. These findings reveal the complexity and unintended effects of the reform on marriage outcomes for women in Nigeria.

To emphasize the significance of treatment heterogeneity across groups and using the aggregation scheme provided by CS, I aggregate the group-time treatment effects based on treatment cohorts and present the results in Panel B of Table 2.2. In treatment cohorts 2007, and 2018 a positive effect of the CRA on the age of marriage. However, its impact is mostly insignificant in the cohorts after 2006 and negative for cohorts before 2006. These findings highlight the presence of treatment effect heterogeneity.[11] Women exposed to CRA earlier have significant negative average treatment effects, which are not seen in those treated later.

[9] Sant'Anna and Zhao (2020) shows that rather than selecting between the OR and IPW approaches, one can merge them to create doubly robust (DR) estimations for the ATT. In this context, doubly robust means that the resulting estimand can identify the ATT even if one (but not both) of the propensity score model or the outcome regression models is misspecified. As a result, the DR DiD estimand for the ATT inherits the benefits of each individual DiD method while mitigating some of their drawbacks.

[10] All CS regressions are conducted in STATA using the 'csdid' package developed by Rios-Avila, Sant'Anna, and Callaway (2023).

[11] Event-study plots in Figure A1.5 illustrate the dynamics of TWFE results discussed earlier, with a positive effect on marriage age but a negative effect on marriage distribution. These contrasting results further reinforce the argument that the TWFE approach is susceptible to treatment heterogeneity, leading to biased outcomes arising from negative weighting issues. Additionally, the pattern in the marriage age outcome demonstrates an increasing trend before the reform, indicating the presence of pre-existing trends. These pre-trends reinforce the use of the more relaxed conditional parallel trends assumption in the CS method.

Table 2.2: Aggregated Treatment Effects for all groups across all periods

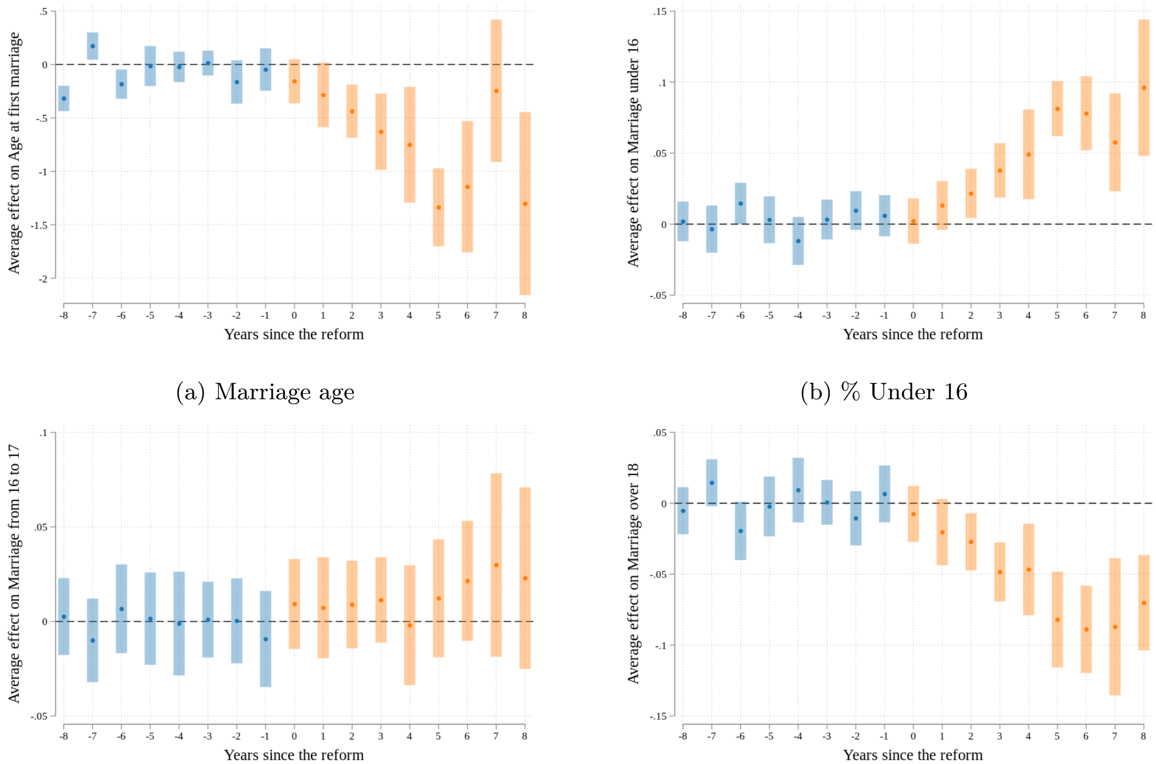
	Marriage Age	% Under 16	% at 16-17	% Over 18
Panel A: CS results				
ATT - All	-0.6510***	0.0570***	0.0078	-0.0517***
	(0.107)	(0.00735)	(0.0114)	(0.00956)
Panel B: CS results - by treatment cohort				
G2003	-2.022***	0.139***	0.0238	-0.122***
	(0.207)	(0.0173)	(0.0227)	(0.0159)
G2004	-3.255***	0.126***	-0.000183	-0.116***
	(0.690)	(0.0420)	(0.0455)	(0.0411)
G2005	-0.527***	0.0597***	-0.000400	-0.0612***
	(0.0752)	(0.0116)	(0.0146)	(0.0102)
G2006	-1.018***	0.0796***	-0.0140	-0.0431***
	(0.114)	(0.00957)	(0.0146)	(0.0129)
G2007	0.934***	-0.00824	0.0476	-0.0334
	(0.0936)	(0.00904)	(0.0316)	(0.0302)
G2008	-0.174	0.0349	0.0114	-0.00626
	(0.581)	(0.0307)	(0.0379)	(0.0273)
G2009	0.190	0.0278	-0.0181	-0.0125
	(1.103)	(0.0768)	(0.0899)	(0.0610)
G2010	-1.420***	0.0774***	-0.0188	-0.0564***
	(0.155)	(0.0150)	(0.0194)	(0.0153)
G2016	-2.576	0.0156	-0.0229	0.0535
	(2.015)	(0.113)	(0.152)	(0.117)
G2018	1.025***	0.0355	-0.0516	0.110
	(0.338)	(0.0526)	(0.0810)	(0.0922)
Panel C: TWFE results				
ATT - All	0.0212*	0.1510***	-0.0825***	-0.0728***
	(0.0123)	(0.0324)	(0.0193)	(0.0186)
Observations	86745	86019	85251	84018
baseline	17.82	0.387	0.181	0.442

Notes: The table presents aggregated treatment effect parameters based on the conditional parallel-trends assumption, and the results are clustered at the state level. Panel A reports the weighted average of all available group-time average treatment effects. Panel B reports tratment cohort specific effects by the timing when CRA was adopted. To estimate these effects, I employ the doubly robust estimator as discussed in Callaway and Sant'Anna, 2021. Panel C reports TWFE results for comparison.

In Table 2.2, I present the baseline results of the TWFE analysis for marriage outcomes in Panel C. These findings reveal a contradictory pattern: the reform is associated with a 0.02-year increase in the average marriage age, but it also raises the likelihood of getting married before the age of 16 by 15 percentage points while reducing the likelihood of getting married after 18 by 7 percentage points. Notably, the magnitude and direction of the marriage age effect differ substantially from the heterogeneity-robust CS method, suggesting potential issues related to weighting problems. This comparison underscores the critical importance of selecting an appropriate methodology tailored to the specific context. To gain deeper insights into this relationship and account for potential heterogeneity, Table A1.2 presents the results with an interaction term between the post-reform variable and a dummy indicator for clusters with a Muslim-majority population. Interestingly, the results indicate that the reform expectedly increases the marriage age significantly more for individuals outside of predominantly Muslim clusters. However, among those residing in predominantly Muslim clusters, the reform has a negative effect on marriage age. It is worth noting that contradictory patterns with other outcomes persist, underscoring the importance of considering potential treatment effect heterogeneity.

Prior studies have explored the effects of marriage age laws on marriage outcomes. For example, McGavock (2021) observed that a comparable marriage age reform in Ethiopia led to a marriage age increase of 0.032 years. Likewise, Bellés-Obrero and Lombardi (2023) investigated marriage age laws in Mexico and identified a 49 percent decrease in the monthly count of formal marriages per 1,000 girls of that age, equivalent to 0.695 fewer marriages. However, this decline was offset by an increase in informal unions, resulting in an overall null effect. Notably, it is important to highlight that both McGavock (2021) and Bellés-Obrero and Lombardi (2023) assumed homogenous treatment effects, which may lead to biased outcomes when treatment varies over time (i.e., staggered adoption), as discussed in relevant literature (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021; Athey and Imbens, 2022).

To assess how average treatment effects vary with the length of exposure to the reform I also conduct an event-study analysis. Figure 2.6 presents the event study plots for marriage age outcomes. In contrast to the positive treatment effect in Figure A1.5a, the results shown here are consistent, revealing a negative impact of the reform across all marriage outcomes once the issue of treatment heterogeneity is addressed. These findings suggest that the reform triggered a backlash within society. Figure 2.6 also corroborates the parallel trends assumption, as no pre-trends are observed in any outcomes except marriage age, for which the significance of the pre-reform period diminishes starting from 5 years prior to the reform.



(a) Marriage age

(b) % Under 16

(c) % 16-17

(d) % Over 18

Figure 2.6: Effect of the CRA on marriage outcomes

Notes: The figure presents coefficient estimates and their corresponding 95% confidence intervals obtained through the Callaway and Sant'Anna (2021) estimation approach. State-level clustered standard errors are computed using a doubly robust difference-in-differences estimator, employing stabilized inverse probability weighting. In all regressions, I account for state and marriage year fixed effects, birth year and ethnicity group fixed effects, along with binary variables indicating Muslim affiliation and rural residency. The outcome *Marriage age* represents the age at first marriage, calculated using birth year and month as well as marriage year and month. Additionally, the other outcomes are binary variables that indicate marriage occurring under the age of 16, at ages 16 or 17, or at age 18 or older. Source: Nigeria DHS.

The empirical strategy outlined above presents a potential limitation by confining the sample exclusively to ever-married women while establishing the treatment status based on the timing of marriage in relation to the implementation of the reform. Addressing this concern, I introduce a refinement to the analysis by narrowing the sample to women aged 25 and above. This age threshold, set at a point where marriage is nearly universal (encompassing more than 91% of the sample), is designed to provide a comprehensive representation of married women in the dataset. This adjustment seeks to mitigate potential bias arising from parents postponing their daughters' marriages due to the reform. The results of this adjusted analysis, presented in Table 2.3, reaffirm the robustness of the main findings, albeit with a reduced effect size.

Given the small number of states in the analysis (25 in the treatment group and 11 in the control group), along with the imbalance between treatment and control clusters, it is important to provide

Table 2.3: Aggregated Treatment Effects for each group across all periods for women aged above 25

	(1) Marriage Age	(2) % Under 16	(3) % at 16-17	(4) % Over 18
ATT	-0.178*** (0.0672)	0.0326*** (0.00546)	-0.0233*** (0.00785)	-0.00924 (0.00939)
Observations	69,021	69,021	69,021	69,021

Notes: The table presents aggregated treatment effect parameters for women aged above 25 based on the conditional parallel-trends assumption, and the results are clustered at the state level. Panel A reports the weighted average of all available group-time average treatment effects. To estimate these effects, I employ the doubly robust estimator as discussed in Callaway and Sant'Anna, 2021.

robustness checks that adopt a potentially more reliable approach for inference. Rather than relying on an asymptotic approximation to the distribution of the statistic of interest, bootstrap inference is employed to ensure robustness in the presence of limited state numbers and imbalances. MacKinnon, Nielsen, and Webb, 2023 argue that bootstrap inference tends to be more dependable than asymptotic inference in many cases. In Table 2.4, the estimation and aggregation of results for the main outcomes are presented, utilizing clustered bootstrapped standard errors at the DHS-cluster level. This approach is particularly valuable when examining heterogeneity in the effects of the Child Rights Act (CRA), given the concerns associated with the small number of states and the treatment-control imbalance. The results not only strengthen the main findings but also enhance the overall robustness of the analysis.

Table 2.4: Aggregated Treatment Effects for each group across all periods with clustered bootstrapped standard errors

	Marriage Age	% Under 16	% at 16-17	% Over 18
Panel A: CS results				
ATT - All	-0.6510*** (0.107)	0.0570*** (0.13055)	0.0078 (0.01152)	-0.0517*** (.00886)
Observations	86745	86019	85251	84018

Notes: The table presents aggregated treatment effect parameters based on the conditional parallel-trends assumption, and all inference procedures use clustered bootstrapped standard errors at the DHS-cluster level. To estimate these effects, I employ the doubly robust estimator as discussed in Callaway and Sant'Anna, 2021.

In the following section, I investigate particular communities within the society to identify where this backlash effect is more prominent.

2.5 Discussion

In this section, I discuss the importance of pre-existing local and religious norms when implementing international acts. The adoption of international human rights treaties is based on the normative assumption that they will universally guarantee rights. However, this assumption often neglects the influence of locally existing cultural and religious norms, as well as power dynamics, which can undermine the effectiveness of legal provisions. These norms are asserted by groups seeking to protect their interests (Toyo, 2006). Opposition to the Child Rights Act (CRA) in Nigeria primarily emerged during its incorporation into sub-national legislation, where culture and religion was invoked by populations feeling threatened. According to Mr. Uwemedimo Nwoko, the Attorney General and Commissioner of Justice in Akwa Ibom State, the primary challenges they face in implementing the act are tradition and religion, as reported in Ojelu (2019). Newspaper articles highlighted the Supreme Council for Shariah in Nigeria and northern legislators characterizing the Act as anti-culture, anti-tradition, and anti-religion (Assim, 2020). The core dispute centered around the Act's definition of a child and its perceived impact on prevalent child marriage practices, especially for girls. An article featuring the Speaker of Gombe State House of Assembly, Rt. Hon. Inuwa Garba, provided insight into the local perspective. While acknowledging the positive aspects of the CRA, Garba emphasized the need for a more modest approach, considering socio-cultural diversity and religious differences (Bulus, 2012). This sentiment reflected the broader resistance in the north, aligning with deeply rooted norms and ethics.

In response to the imposition of international law, certain groups may feel threatened and respond by becoming more conservative, while others may embrace the new law and become less conservative. This phenomenon aligns with the model of Acemoglu and Jackson (2017) that when laws contradict prevailing social norms, compliance tends to decrease among those who uphold traditional values. Moreover, they assert that such laws may backfire when they directly conflict with deeply entrenched social norms, leading to a divergence in attitudes and behaviors among different segments of the population. The observed backlash to the reform in this study may arise because some individuals adopted more conservative attitudes, and the reform itself provided a means for individuals to outwardly express their conservatism.

I argue that the UN-designed reform introduced an information asymmetry, with some groups adhering to traditional norms while others embraced 'Westernizing' customs. With diverging norms prevalent in society, conservative families may feel a compelling need to signal the purity and conservativeness of their brides by marrying them early. In Nigeria, as highlighted by Arowolo (2022), one of the primary reasons for child marriage is to ensure the 'purity' of the bride.[12] Referring to Buchmann et al. (2021)'s marriage model analyzing rural Bangladesh, situations with information asymmetry about

[12] Virginity holds a significant role in marriage customs, signifying purity and honor. Research by Feyisetan and Pebley (1989) and Olamijuwon and Odimegwu (2022) underscores the importance of the bride being a virgin when she meets her suitor. Maintaining virginity brings honor to the bride's parents, commands respect for the bride herself, and is a widely practiced tradition before marriage.

brides' quality can incentivize earlier marriages to signal conservativeness and docility. In this study, I document a backlash behavior in certain communities where there are strong incentives to signal adherence to traditions in the marriage market.

In areas where child marriage is deeply ingrained in the culture, respondents may have a stronger motivation to adhere to the norms after the introduction of CRA. Hence, in majority Muslim clusters, where religiosity and adherence to traditions are highly valued, families may choose to marry their daughters off at a younger age as a signal of their commitment to traditional norms, thereby opposing what they perceive as a new 'Westernizing' effort. Consequently, the backlash effect is likely to be primarily driven by majority-Muslim clusters where child marriage is deeply entrenched in tradition.

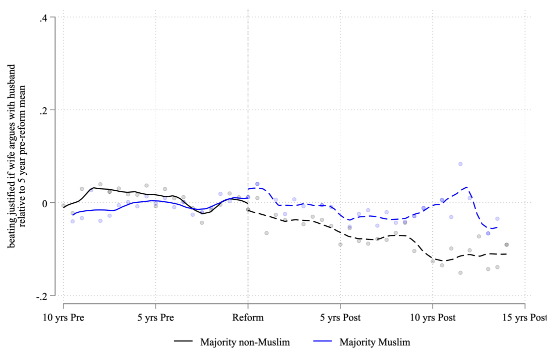
Table 2.5: Aggregated Treatment Effects by majority religion in the cluster

Panel A: All sample	Marriage Age	% Under 16	% at 16-17	% Over 18
ATT (majority non-Muslim cluster)	1.069***	-0.043***	-0.0224	0.106***
	(0.379)	(0.010)	(0.018)	(0.018)
Observations	40087	39987	47056	39676
ATT (majority Muslim cluster)	-0.810***	0.070***	0.0484*	-0.139***
	(0.093)	(0.013)	(0.025)	(0.027)
Observations	46658	46032	45346	44342
Panel B: Muslim sample				
ATT (majority non-Muslim cluster)	-2.265	0.217	-0.023	-0.211
	(1.404)	(0.221)	(0.203)	(0.138)
Observations	5961	5880	5815	5700
ATT (majority Muslim cluster)	-1.822***	0.072***	0.028	-0.121***
	(0.103)	(0.013)	(0.017)	(0.020)
Observations	43182	42568	41919	40909

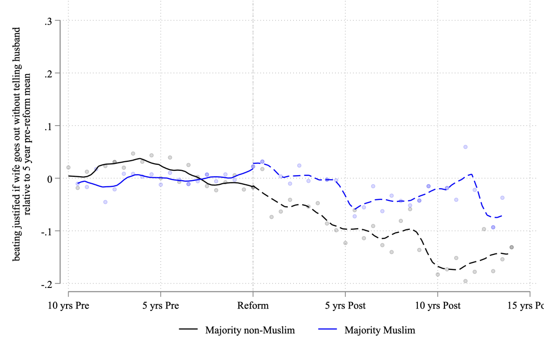
Notes: The table presents aggregated treatment effect parameters based on the conditional parallel-trends assumption, and the results are clustered at the state level. The first row presents the weighted average of all available group-time average treatment effects for women residing in majority Muslim clusters, while the second row provides the same information for women residing in majority non-Muslim clusters.

To provide evidence for the claim above, I conduct a separate analysis of women residing in majority Muslim and majority non-Muslim clusters in Panel A of Table 2.5. The findings reveal a significant disparity between the two samples: while the reform has the intended consequences on marriage timing for women residing in majority non-Muslim clusters (treated women marry 1 year later), a strong adverse effect is observed among women in majority Muslim areas (treated women marry 0.8 years younger). This backlash effect manifests as a negative impact on marriage age and a positive impact on marrying before the age of 16. Therefore, these results substantiate my assertion that the implementation of the UN-designed law in Nigeria leads to a counterreaction. This backlash effect is driven by the conflict between the law and the values and norms upheld by the majority Muslim clusters. As a consequence of this resistance, we observe a reversal in the trend of marriage age, which acts as a signal of the community's dedication to conservatism and religiosity.

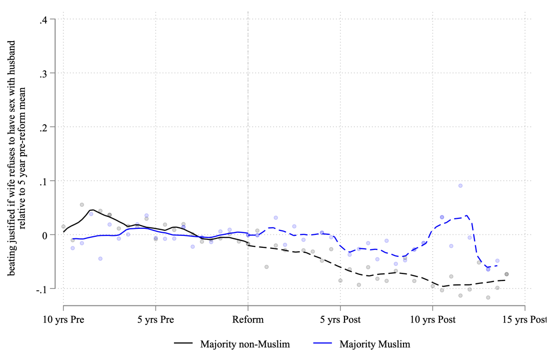
I also argue that the level of conservatism may vary depending on whether the respondent lives in a cluster where the majority shares these values. In regions where the individual adheres to the same religion or set of traditional norms as the majority, there may be a greater inclination to adhere to these beliefs due to the higher cost of deviating from social norms. Conversely, individuals living in areas where the majority follows a different religion may also feel a stronger need to adhere to their own traditions. Panel B of Table 2.5 illustrates that the backlash effect is more pronounced for Muslim individuals residing in majority Muslim clusters. However, although the size of the impact is larger in magnitude for Muslims who are in the minority within their cluster, the effect is not significant. Hence, these findings cannot definitively reject the presence of both effects discussed above.



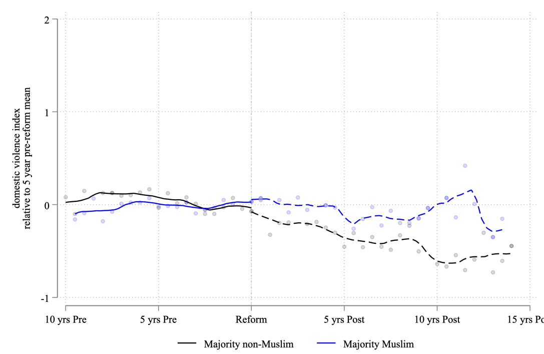
(a) if she argues with husband



(b) if she goes out without asking



(c) if she refuses to have sex



(d) domestic violence index

Figure 2.7: Trends in attitudes towards domestic violence by religion

Notes: These figures illustrate the attitudes towards domestic violence for two groups of women by the majority religion in the cluster they reside. Each data point represents the average support for domestic violence in relation to the mean support during the 5 years preceding the reform in that respective group, with pre-reform means normalized to zero across groups. Lines are local polynomials fitted to the data. Source: Nigeria DHS.

To further exemplify the shift toward conservatism, I show that the reform also leads to a negative shift in gender norms, particularly among respondents residing in majority Muslim clusters. I assess the impact on gender norms by examining women's attitudes toward domestic violence. These attitudes can serve as an indicator of evolving norms within the community. Figure 2.7 presents the trajectory of different measures of domestic violence over time, providing insights into this evolution. An intriguing pattern emerges: women residing in majority non-Muslim clusters witness a reduction in support for domestic violence around the reform cutoff, followed by a sustained decline over subsequent years. In contrast, women in Muslim majority areas exhibit a less pronounced decrease in support, notably compared to the 5-year pre-reform average, which widens the gap between the two groups. These trends suggest that following the reform, women in Muslim majority clusters display less progressive attitudes towards domestic violence against women. Also, I employ the CS method to examine the causal relationship between the reform and the domestic violence index. Figure A1.7 provides empirical evidence in line with the argument, showing that being affected by the CRA leads to positive effect in the justification of domestic violence. This further supports the notion that certain groups became more conservative in response to the CRA. This reinforcement of negative norms particularly holds true for majority Muslim areas, where prevailing gender norms are culturally more entrenched.

Table 2.6: Summary Statistics of Religiosity and Gender Norm Variables in World Value Surveys

	Muslim			Non-Muslim		
	Before	After	Difference	Before	After	Difference
Religion-very important	0.95	0.96	-0.01	0.91	0.89	0.02*
Child qualities-faith	0.77	0.78	-0.01	0.67	0.67	0.00
Religious person	0.95	0.96	-0.01	0.94	0.94	-0.00
Neighbor-different religion	0.20	0.22	-0.02	0.26	0.20	0.05***
Member of a religious org.	0.55	0.48	0.07*	0.73	0.47	0.26***
Men - job priority	0.67	0.72	-0.05*	0.54	0.57	-0.03
Problem if women earn more	0.66	0.81	-0.15***	0.67	0.79	-0.12***
Observations	1161	1233	2394	2857	1763	4620

Notes: Summary statistics are derived from World Value Survey data for Nigeria, spanning waves 3, 4, 6, and 7, and are disaggregated for Muslims and non-Muslims. The "Before" columns display average values prior to the reform's first introduction in 2003, while the "After" columns show post-reform averages. *Religion-very important* represents the proportion of respondents who considers that religion is very important in their life. *Child qualities-faith* represents the proportion of respondents who consider that religious faith should be encouraged for children to learn at home. *Religious person* represents the proportion of people who consider themselves religious. *Neighbor-different religion* corresponds to the proportion of respondents who would not like to have people of a different religion as neighbors. *Member of a religious org.* represents the proportion of individuals who are members of religious organizations. *Men - job priority* shows the proportion of respondents who think that when jobs are scarce, men should have more right to a job than women. *Problem if women earn more* presents the proportion of respondents who think that it is a problem if women earn more than their husbands. Variables are coded so that a positive difference indicates a shift toward less conservative religious beliefs or more positive gender norms.

In another analysis to investigate shifts in gender norms and religiosity, I employ data from the World Value Survey in Nigeria to compare social norms between Muslim and non-Muslim respondents both before and after the implementation of the CRA. Table 2.6 presents the average values for select variables related to religiosity and gender norms, separately for Muslims and non-Muslims before and after the CRA enactment.

The observations reveal that, on average, the importance of religion has slightly diminished among non-Muslims, while there is a small, statistically insignificant increase among Muslim respondents. Furthermore, the results suggest that non-Muslim respondents have become less opposed to having neighbors from different religions, whereas there is no noticeable change in this direction among Muslims. The data also indicates a decline in the membership of religious organizations for both groups, with a notably larger decline among non-Muslims.

Additionally, the analysis uncovers that Muslims continue to uphold stronger gender norms, as a larger proportion of them believe that men should have priority for job opportunities even after the reform. In summary, these findings suggest that, compared to non-Muslims, Muslim individuals appear to be moving towards a less progressive direction. These results align with the previously discussed findings indicating that, after the reform, gender norms have shifted in a less progressive direction for certain communities.

Lastly, I consider the potential influence of varying levels of public awareness concerning the CRA and its impact on marriage outcomes. Scholars like Awosola and Omoera (2008) and Toyo (2006), along with journalist Adégbìté (2023), assert that both supporters and opponents of the CRA utilized media campaigns to disseminate information about the act. To explore this aspect further, I conduct a separate analysis of treatment effects and their dynamics among respondents who own or do not own a TV or radio and among those who live in rural or urban areas. The outcomes, presented in Figure A1.6 and Table A1.4, reveal a discernible pattern: individuals who own these devices, and are thus more likely to be informed about the law, exhibit significantly negative outcomes. In contrast, the treatment effect is not as pronounced or significant for those without these devices. A similar pattern emerges regarding residence status, with 81% of urban dwellers having access to electricity compared to only 33% of respondents in rural areas.[13] The results in Table A1.4 indicate that urban residents have a more significant backlash reaction to the reform. These findings support the notion that a different factor related to awareness is not the primary driver of the main results.

2.6 Conclusions

This study delves into the far-reaching implications of an international law aimed at raising the minimum age for marriage in Nigeria. The analysis reveals a complex landscape of responses to this legal reform,

[13]Similar trends are observed for TV ownership, with 71% of urban residents owning a TV compared to just 28% of rural residents.

shedding light on the need for nuanced policy approaches. Using data from Nigeria DHS, contrary to the reform's intended effects, I show that the reform had a negative treatment effect on the marriage age.

Initially, I emphasize the significance of choosing the appropriate methodology for dynamic and heterogeneous treatments by comparing the results obtained through TWFE with those using Callaway (2021) method. Then, I demonstrate that the negative effect is primarily attributable to respondents residing in majority Muslim clusters where child marriage is deeply ingrained in the culture and remains highly prevalent. These findings suggest that in Nigeria, a highly diverse country encompassing various ethnicities, religions, and cultures, the international reform implemented by the UN, which contradicts pre-existing norms, triggers a backlash effect. I elaborate on this backlash, explaining that it stems from the desire to signal the quality of brides by adhering to religious and traditional norms, rather than succumbing to 'Westernizing' influences. Additionally, I illustrate that women residing in majority-Muslim areas tend to exhibit less progressive gender norms in their attitudes toward domestic violence. Furthermore, I substantiate these findings by presenting evidence that Muslim Nigerians experience fewer progressive shifts in gender norms based on data from the World Value Survey.

My findings hold particular relevance for other countries in Africa and Southeast Asia where child marriage norms and traditions align closely with those in Nigeria. Policymakers in these regions might consider an adjusted approach to international laws, involving local religious leaders and community figures as mediators to effectively communicate the essence of these reforms. While the focus of this study primarily centers on child marriage reforms, the implications extend to a broader context of implementing and internalizing international laws in developing countries. To recap, in highly diverse local contexts like Nigeria, it is imperative for policymakers to factor in prevailing local culture and norms to mitigate the risk of backlash effects and protect vulnerable populations from further harm.

Chapter 3

Infant Mortality Expectation and Fertility Choice in Rural Malawi

Population research has maintained a long-standing interest in explaining the complex relationship between child mortality and fertility. This interest stems from understanding the population-level impact of public policies targeting child mortality, and gaining insights into the underlying drivers of the demographic transition. Several prominent hypotheses for this relationship have emerged, including that child mortality influences couples' fertility behaviors through two distinct mechanisms: a "replacement effect" where parents adjust their reproductive behavior after experiencing the death of a child; and an "insurance" or "hoarding" effect, wherein parents, expecting high mortality risks, proactively increase the number of children beyond their desired level to safeguard against the possibility of child loss (Ben-Porath, 1976; Heer and Smith, 1968; LeGrand et al., 2003; Kalemli-Ozcan, 2003; Canning et al., 2013; Sah, 1991; Chowdhury, Khan, and Chen, 1976; Montgomery and Cohen, 1998; Wolpin, 1997; Preston et al., 1978). However, testing the hoarding effect empirically has been challenging due to the lack of data on parental *expectations* about child mortality. In this study, we address this gap by leveraging expectations data from rural Malawi to investigate the causal impact of infant mortality expectations on subsequent fertility.

Our data come from the Malawi Longitudinal Study of Families and Health (MLSFH), a longitudinal cohort study conducted in Sub-Saharan Africa (SSA) that gathers comprehensive demographic, socioeconomic, and health information from one of the world's poorest nations (Kohler et al., 2015).

Malawi's population trends, characterized by historically high infant mortality and fertility rates, along with recent declines, are similar to other Sub-Saharan countries, making it a relevant setting to investigate the fertility response to infant mortality expectations (see Figure 3.1). A unique feature of the MLSFH is that it collects probabilistic expectations from survey respondents about important health events, including infant mortality (Delavande and Kohler, 2009). This allows us to study the impact of expectations on fertility behavior without the need to impose unverifiable assumptions on the expectations that people hold (e.g., Manski, 2004), and identify the hoarding behavior hypothesized above.

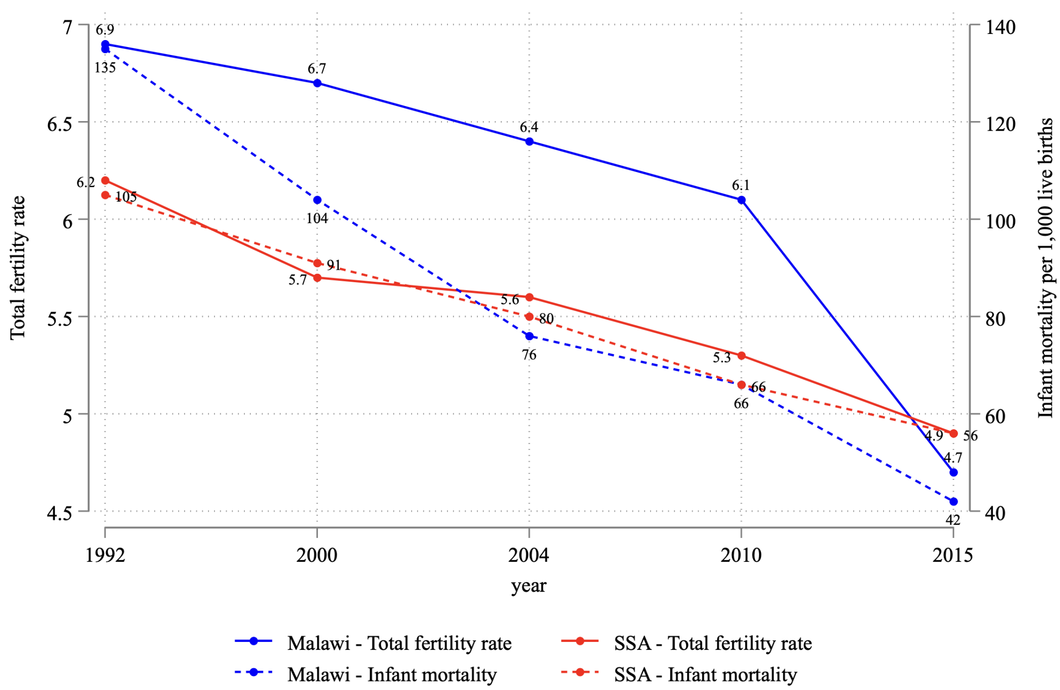


Figure 3.1: Fertility and Infant Mortality rate trends in Malawi and SSA

Source: Malawi DHS 2015-16 and World Bank

Respondents were asked the probability that a baby born in their community this month would die within one year. In all waves of the data from 2006, 2008 and 2010, the modal infant mortality expectation, held by almost a quarter of the respondents, stands at 1 chance out of 10, which aligns with the average of 73 deaths per 1000 live births in rural Malawi (MDHS, 2010). Yet, there is substantial heterogeneity in child mortality expectations (Figure 3.2), a common observation with expectations data collected in developed and developing countries (Bruin et al., 2023; Delavande, 2023). More than half of the respondents provide an expectation that is above Malawi's average. Notably, this variation remains largely unexplained by respondents' characteristics, emphasizing the importance of relying on expectations data rather than making assumptions about them. One exception is variation by region, where respondents living in the Southern region, with higher actual infant mortality rates, exhibit significantly higher child mortality expectations.

A general difficulty in estimating the causal effect of child mortality on fertility is that individuals may engage in behaviors or possess traits that can influence both the mortality risk of their children and their fertility (e.g., Wolpin, 1997). For example, a woman with a strong preference for health or a higher health endowment might choose to invest more in her own and family health, which can positively impact both her ability to bear children and the survival chances of her offspring. A similar concern arises when estimating the effect of child mortality expectations on fertility, as women who prioritize health may hold lower expectations of child mortality.

To deal with this potential issue, we use an instrumental variable approach. The instrument is motivated by research on the role of neighbours and friends in reproductive and sexual behavior (Montgomery and Casterline, 1996; Munshi and Myaux, 2006; Kohler, Behrman, and Watkins, 2007). As an instrument for the individual-specific infant mortality expectation, we utilize a spatially-weighted average of children's health status in neighboring households. By assigning greater weight to the health of children in closer proximity to the respondent, we aim to capture the impact of direct observation or social learning regarding children's health. The validity of this instrument is reinforced by the inclusion of village-level fixed effects, which control for unobserved time-invariant village-level factors that are common to all individuals within the same village.

Our main finding is that a 10 percentage points decrease in infant mortality expectations leads to a 14 percentage point reduction in the propensity for having an additional child in the next two years. This reduction is noteworthy, amounting to a 33% decline from the baseline rate of 43%. These results suggest that parents consider their infant mortality expectations when making fertility decisions. The magnitude of the effect is larger for older respondents who are close to have already achieved their desired family size. The results are robust to an imperfect instrumental variable method, where the assumption of strict exogeneity is relaxed (Nevo and Rosen, 2012).

To isolate the hoarding effect from the replacement effect more precisely, we exclude from our analysis respondents who have experienced child loss. Our results demonstrate that among parents who did not experience child mortality, a 10 percentage-point decrease in infant mortality expectations leads to an 11 percentage-point reduction in the propensity of giving birth within the next two years. We also find that respondents with higher infant mortality expectations are more likely to have more children than desired, indicating the presence of excess fertility, possibly driven by an insurance mechanism against child's death. Taken together, our findings provide compelling support for the hoarding hypothesis, which has been the subject of extensive debate in population research.

These results have potentially important policy implications. Firstly, they indicate that improvements in infant survival, if effectively communicated and understood by parents, have the potential to lead to reduced fertility rates. Secondly, our findings point to the possibility of empowering parents to make better-informed fertility choices by providing them with information about the mortality risk faced by children in their community. Many respondents appear to overestimate infant mortality risk as the median expectation of 20% in 2010 is larger than the infant mortality rate of 7.3% for rural Malawi (MDHS, 2010). Based on our estimates, if all respondents were to revise their infant mortality expectations to align with the rural Malawi average, the propensity to have another children within the next two years would decrease by 12.7 percentage points. This indicates the potential impact of information provision on fertility decisions and suggests the value of targeted interventions to improve the accuracy of parents' expectations. Previous studies have shown that information provision can have a substantial impact on subjective expectations (Ciancio et al., 2020) and health behavior (Dupas and Miguel, 2017; Delavande and Kohler, 2012; Kerwin, 2018; Chinkhumba, Godlonton, and Thornton, 2014).

Our work contributes to three main strands of literature. First, we build upon existing studies investigating the interplay between child mortality and fertility. An important focus has been on identifying replacement (fertility response to experienced child mortality) and hoarding (fertility response to expected child mortality) behavior. Here, we focus on hoarding and provide novel empirical evidence on the role of infant mortality expectations directly elicited from parents as a key factor in shaping fertility decisions. Past studies have found evidence of replacement behavior subsequent to child mortality (e.g., Ben-Porath (1976), Palloni and Rafalimanana (1999), Angeles (2010), and Herzer, Strulik, and Vollmer (2012)).

Hoarding behavior has been widely discussed in the theoretical literature (e.g., Sah, 1991; Kalemli-Ozcan, 2003; Wolpin, 1997). However, empirical identification of hoarding has proven challenging without imposing strong assumptions on child mortality expectations. Canning et al. (2013) conduct a similar analysis to ours, investigating the association between infant mortality expectation and fertility using 46 low and middle-income countries and more than 30 years of data. Nevertheless, their approach does not rely on subjective expectations data; instead, they assume that the actual experienced child mortality rate serves as an unbiased measure of infant mortality expectations. They find that a 1% decrease in the expected child mortality rate causes 0.61% fewer children born.[1] Bhalotra and Van Soest (2008) use a dynamic panel data framework to deal with unobserved heterogeneity in fecundity and health endowment. They conclude that, while there is evidence of replacement in India, hoarding behavior is not observed.[2] Some work relies on structural dynamic models with uncertain child survival (e.g., Wolpin (1984), Doepke (2005), and Mira (2007), with evidence of hoarding in Malaysia (Wolpin, 1984). In these models, the assumption is that households forecast future mortality rates exactly as researchers do, based on the extrapolated trend in mortality rates at some geographic level.

Another strand of the literature we contribute to is the study of the mechanisms for the demographic transition. The demographic transition refers to the change from a high fertility-high infant and child mortality environment to a low fertility-low mortality environment, that has occurred in all developed countries. Three main explanations have been proposed as potential triggers for this transition (Galor, 2012): the rise in income per capita (Becker, 1960; Murtin, 2013; Murphy, 2015; Fernandez-Villaverde, 2001), the rise in the demand for human capital (Becker, Cinnirella, and Woessmann, 2010; Murphy, 2015; Doepke, 2005), and the decline in infant mortality (Canning et al., 2013; Doepke, 2005; Fernandez-Villaverde, 2001). There is still an ongoing debate about the relative role of each of these, and other explanations in the historical demographic transitions. Our findings lend support to the idea that the decline in infant mortality plays a role in shaping the demographic transition in SSA today.

Finally, we also contribute to the growing literature using subjective expectations data to better understand decision-making under uncertainty without the need to rely on assumptions about expectations (e.g. Bachmann, Topa, and Klaauw, 2022). Drawing conclusions about the decision-making process from choice data and underlying assumptions regarding expectations poses challenges, as observed choices may align with multiple combinations of expectations and preferences (e.g. Savage, 1972; Manski, 1993). This line of research has demonstrated the feasibility of eliciting high-quality probabilistic expectations data from survey respondents, including those in low income countries. For instance, research has demonstrated that expectations data exhibit patterns of variation aligned with observable characteristics just as actual outcomes do, and expected outcomes have been strongly linked to future outcomes at the individual level. (Delavande, 2014; Delavande, 2023; Delavande, Giné, and McKenzie, 2011). Moreover, it has revealed substantial heterogeneity in expectations, emphasizing the importance

[1] They also rely on an instrumental variable approach and instrument the child survival rate experienced by an individual woman with the survival rate among firstborn children of other women in the village of that particular woman.

[2] The absence of correlation between health endowment (frailty) and fecundity suggests that women do not engage in hoarding, as this implies that women who anticipate a relatively higher risk of neonatal death do not preemptively reduce the length of their birth intervals.

of avoiding overly restrictive assumptions on individual expectations.

Expectations have proven valuable for drawing conclusions about decision-making processes across diverse domains in low and middle-income countries, including but not limited to areas such as education, migration, sexual behavior, and investment in human capital (e.g. Attanasio and Kaufmann, 2014; Delavande and Zafar, 2019; McKenzie, Gibson, and Stillman, 2013; Baranov and Kohler, 2018; Baranov, Bennett, and Kohler, 2015).[3] Of particular relevance is Shapira (2017), which studies the determinants of women's reproductive decisions in Malawi. The author develops a dynamic discrete-choice life-cycle fertility model that incorporates expectations regarding life horizon and child survival, taking into account a perceived infection hazard, which may diverge from the actual infection hazard. In counterfactual simulations, the model indicates that the presence of HIV leads to a decrease in the number of births.

The paper is organized as follows.Section 3.1 provides background information for Malawi, Section 3.2 describes our data (MLSFH) along with the key variables, Section 3.3 proposes our empirical strategy, Section 3.4 presents our empirical results and robustness checks, and Section 3.5 concludes.

3.1 Local Context

Malawi is one of the lowest-performing countries in terms of living standards, health, education, and literacy. In 2021, Malawi was ranked 169$^{\text{th}}$ among 191 countries and territories in Human Development Index.[4] In rural Malawi, comprising 85% of the population, individuals experience challenging living conditions similar to those found in other rural, low-income regions of Sub-Saharan Africa (SSA). These areas face common issues, including high morbidity and mortality rates, strained healthcare facilities, and often unmet nutritional requirements. The rural populace primarily relies on subsistence farming, primarily cultivating maize, while engaging in small-scale local market endeavors. Malawi's GDP per capita stands at approximately 2% of the global average. According to GBD Collaborators 2018 (Roth et al., 2018), life expectancy is 59.6 for men and 66.9 for women. People in Malawi also suffer from a high prevalence of the HIV epidemic; 10.4% of the population aged between 14 and 49 are estimated to be HIV-positive.

Malawi has had historically high fertility and high infant mortality rates (see Figure 3.1). According to the MDHS (2015) , the total fertility rate has dropped significantly from 6.7 children per woman in

[3] See (Delavande, 2023) for a recent literature review.

[4] The ranking can be found at `https://hdr.undp.org/data-center/human-development-index#/indicies/HDI`.

1992 to 5.7 children per woman in 2010 and 4.4 children per woman in 2015. Birth spacing has also followed a parallel trend; between 1992 and 2010, the median birth interval increased from 32.7 months to 36.1 months. After 2010, Malawians experienced a more substantial increase in birth spacing to 41 months in 2015-2016. The respondents' ideal family size has declined from 5.7 children in 1992 to 4.5 children in 2010 and 3.7 children in 2015. Infant and child mortality rates have also declined over the years. MDHS (2015) documents that infant mortality has declined from 134 deaths per 1,000 live births in 1992 to 66 deaths per 1,000 live births in 2010 and 42 deaths per 1,000 live births in 2015.

It is important to discuss whether fertility is a choice in this context. According to MDHS (2010), 98% of all women and 99% of all men know at least one method of contraception. In the 2006 MLSFH data, 54% of the females state that they have ever used family planning, which is close to the estimate of 60% from MDHS (2004). MDHS (2010) shows that ever-use of contraception has increased to 78% for married women.

Additionally, according to MDHS (2010), almost half of married women were using some form of contraceptive method. Only a small percentage (14%) reported an unmet need for birth spacing, while an even lower percentage (12%) reported an unmet need for birth limiting. In contrast, a relatively high percentage (74%) of women reported that their contraceptive needs were being satisfied. These findings suggest that couples have available options to control their fertility.

3.2 DATA

3.2.1 Malawi Longitudinal Study of Families and Health (MLSFH)

Our analyses utilize data from the 2006, 2008, and 2010 waves of the Malawi Longitudinal Study of Families and Health (MLSFH).[5] This study is conducted across three regions in rural Malawi. A comprehensive discussion of MLSFH's sampling procedures, survey methods, survey instruments, biomarkers, and attrition analysis can be found in Kohler et al. (2015). TThe MLSFH cohorts were specifically chosen to represent the rural population, as the majority of Malawians reside in impoverished rural conditions. Comparisons with the Malawi Demographic and Health Survey have demonstrated that the MLSFH sample populations offer a reasonably representative reflection of rural Malawi's population (Kohler et al., 2015; Anglewicz et al., 2009).

[5]Additional details about the MLSFH project can be found on the project's website at https://web.sas.upenn.edu/malawiresearch/

In 2008 and 2010, the MLSFH included 2,972 and 2,729 respondents, respectively, aged 17 to 59, who were asked about a wide range of demographic, health, and socioeconomic characteristics.[6] Our analyses focus on fertility reported in 2008 and 2010 for respondents with non-missing information on infant mortality expectation at the previous wave, GPS coordinates, basic covariates, and the outcome variables.[7]

The resulting analytical sample comprises approximately 2,700 observations (1,634 unique respondents), and their characteristics are presented in Table 3.1. In the analytical sample, we include 1,421 respondents from the 2008 wave and 1,286 respondents from the 2010 wave. The left panel of Table 3.1 provides the basic characteristics of respondents of reproductive age, including females aged 49 and below and males aged 59 and below, from the 2008 analytical sample. About 59% of the respondents are females, with approximately one-third falling within the age range of 20-29, a critical period for fertility decisions. A significant majority (over 85%) of the respondents have either received primary-level education or have no education at all. Moreover, a similar proportion of respondents (over 85%) are married. Table 3.1 also reveals that fertility, as measured by the occurrence of having a child in the last two years, has decreased in the analytical sample, declining from 40% in 2008 to 37% in 2010.

According to Table A2.2, we do not observe any remarkable differences between the characteristics of the survey sample and the analytical sample. Consequently, missing respondents do not appear to significantly alter the demographic characteristics of the sample on average. We conduct a robustness check on this sample selection in section 3.4.3 by including respondents with without GPS information or prior wave's expectation data.

Our analysis will make use of village indicators. Respondents are living in 115 different villages. In each district, a cluster sampling strategy was used in all villages within the selected Census Enumeration Areas. Household lists of the resident population were compiled one week before fieldwork, and a random sample of eligible women was selected. The sampling fractions were inversely proportional to village populations, ensuring a higher proportion of eligible women in smaller villages were sampled (Kohler et al., 2015). Figure A2.1 shows that more than half of the villages in our sample include 10 to 40 respondents.[8] While some villages are much larger, most of them include less than 60 respondents.

[6]These numbers represent the entire sample, but in this section, we present the analytical sample used in the regression analysis. Summary statistics for the entire sample are presented in Table A2.2.

[7]Among the 5,701 observations (3,643 unique respondents) within the relevant age groups across the 2008 and 2010 waves, 27% of them were lost because they did not participate in the previous wave, resulting in a lack of previous wave's expectations data. Additionally, a further 24% were lost due to the absence of GPS information, which is necessary for creating the instrumental variable.

[8]See Kohler et al. (2015) for the comparison of MDHS and MLSFH.

Table 3.1: Characteristics of the analytical sample by survey years

	2008			2010		
	mean	sd	count	mean	sd	count
Female	0.59	0.49	1421	0.58	0.49	1286
Age group						
less than 19	0.04	0.20	1421	0.00	0.00	1286
20-29	0.33	0.47	1421	0.31	0.46	1286
30-39	0.28	0.45	1421	0.30	0.46	1286
40-49	0.27	0.44	1421	0.29	0.46	1286
50-59	0.08	0.27	1421	0.10	0.30	1286
Education						
No schooling	0.20	0.40	1421	0.17	0.37	1286
Primary level	0.66	0.48	1421	0.66	0.47	1286
Secondary level	0.14	0.35	1421	0.16	0.37	1286
Higher level	0.00	0.04	1421	0.00	0.06	1286
Family						
Married	0.86	0.35	1421	0.87	0.34	1286
Number of children	4.10	3.48	1421	4.28	2.70	1286
Religion						
Catholic	0.16	0.37	1421	0.18	0.38	1286
Muslim	0.25	0.44	1421	0.25	0.43	1286
Indigenous Christian	0.15	0.36	1421	0.16	0.37	1286
Other Christian	0.35	0.48	1421	0.36	0.48	1286
Other religion	0.09	0.29	1421	0.05	0.22	1286
No religion	0.01	0.10	1421	0.01	0.08	1286
Region						
Central	0.28	0.45	1421	0.28	0.45	1286
Southern	0.35	0.48	1421	0.34	0.47	1286
Northern	0.37	0.48	1421	0.37	0.48	1286
Key variables						
Any child in the last 2 years (%)	0.40	0.49	1320	0.37	0.48	1166
Any birth in the last 2 years (%)	0.53	0.50	1421	0.47	0.50	1286
Past infant mortality expectation	2.47	2.10	1421	2.43	2.01	1286
Current infant mortality expectation	2.45	2.00	1417	2.54	1.85	1282
Past average kid health	1.98	0.32	1421	1.83	0.10	1286

Infant mortality expectation variables are measured between 0-10. Spatially-weighted average parental rating of child health (past average kid health) is measured between 1-5.

3.2.2 Fertility Choice

In this study, we assess fertility choices using two different outcomes. Each of these outcomes has its own set of advantages, but they both depend on the respondent's self-report and may therefore contain some level of noise. One of the primary fertility outcomes examined in this study is the occurrence of any live birth within the two-year period preceding the survey wave, as determined by the respondent's self-reported number of alive children at each wave of the MLSFH. The variable of interest, denoted as "*any child in the past two years*" (abbreviated as "*any child*"), is binary and takes the value one if the difference in the number of alive children reported between consecutive survey waves is positive, indicating an additional alive child, and zero otherwise, indicating no childbirth during that period.

The variable above may underestimate fertility if a respondent experienced a child's death exactly between the two surveys without the child's birth being recorded in the survey. To address this issue, we construct an additional binary outcome variable generated using the survey question regarding the total number of births ever reported by the respondent (or the total number of children fathered by male respondents), referred to as *any live birth in the last 2 years*, or shortly *any birth*. We also use family roster information to correct for unaccounted births. This binary variable indicates whether the total number of reported births in the subsequent wave is higher or if a birth is recorded in the family roster. We employ these two variables as the main outcomes for fertility.

Table 3.1 presents the data, indicating that there was a 40% and 37% occurrence of respondents having another child between the last two waves in 2008 and 2010, respectively, highlighting a high fertility rate. Furthermore, the *any birth* variable reveals an even higher level of fertility at 53% and 47%, emphasizing the significance of considering all births. Notably, our sample aligns with the reported decrease in fertility rates between 2008 and 2010 as documented in MDHS (2010).It is worth noting that the *any birth* outcome, while advantageous for encompassing all live births in an environment marked by high infant and child mortality, comes with the caveat of being measured with more noise. This arises from the fact that parents are generally more accurate in reporting the number of their living children compared to the total number of births they have experienced.

3.2.3 Infant Mortality Expectations

Since 2006, MLSFH has employed an interactive elicitation technique to elicit subjective expectations. This method, developed by Delavande and Kohler (2009), involves asking respondents to allocate a number of beans (up to ten) on a plate to express the probability that a particular event will occur. During the survey, interviewers provided a brief introduction to the technique. After any necessary clarifications, respondents were initially asked a trial question about the likelihood of winning in a local board game (Bawo), followed by a series of questions pertaining to economic and health outcomes.

Delavande and Kohler (2009) conducted an extensive analysis and assessment of the probabilistic expectations collected through the interactive elicitation technique. Their examination of the 2006 data yielded several noteworthy findings: (a) when asked about nested events, 99% of the respondents, demonstrated beliefs that align with the fundamental principles of probability theory when asked about nested events; (b) significant variation in subjective beliefs was observed across individuals across a wide range of domains; (c) subjective expectations exhibited systematic correlations with observable characteristics such as gender, age, education, and region of residence -these correlations mirrored how actual outcomes tend to vary with these variables (for instance, expectations regarding infant mortality displayed regional discrepancies akin to actual outcomes, and expectations about economic prospects varied in accordance with socioeconomic status); and (d) expectations about future events displayed similar variations across individuals as their real-life experiences did.

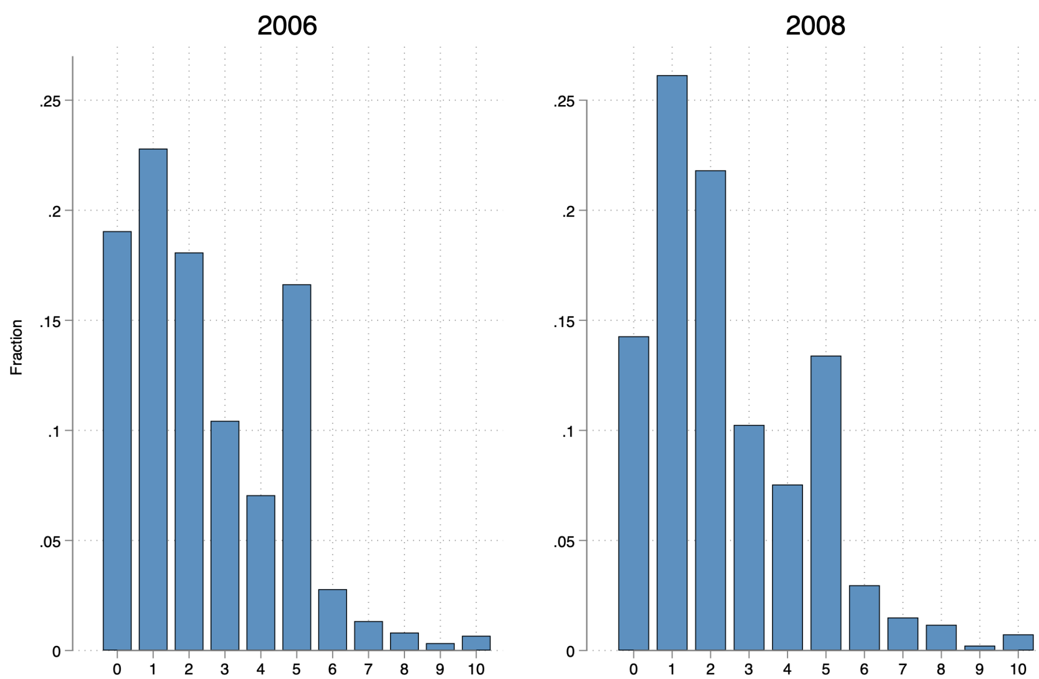


Figure 3.2: Distribution of infant mortality expectation by year

To measure infant mortality expectation, respondents were asked to **pick the number of beans that**

reflects how likely they think it is that a baby born in their community that month will die within a year. The distribution of data collected for infant mortality expectations in the first two waves of the analysis (2006 and 2008) is presented in Figure 3.2. In 2006 and 2008, subjective beliefs on infant mortality follow a similar distribution. In 2008, 80% of the respondents consider that a newborn baby's chance of dying is less than 50%, while 63% think it is less than or equal to 20%. The most frequently observed value in the data was "1" bean (10%), which aligns with the figures reported in the MDHS (2010), which stated 66 deaths per 1,000 live births. However, the data also reveals a high degree of heterogeneity in the responses, with an inclination towards overestimation compared to the population average.

Table 3.2 presents the findings from a descriptive regression analysis of infant mortality expectations in the year 2006, both for the entire sample and when stratified by gender. Column 1 reveals that women generally have higher infant mortality expectations. However, the influence of individual characteristics on these beliefs appears limited overall. Notably, the regional factor stands out as a significant predictor. Residing in the Southern region is associated with elevated infant mortality expectations in comparison to living in the Northern region. This observation aligns with the documented regional variations in infant mortality rates in Malawi, with reported rates of 79, 68, and 70 deaths per 1,000 live births in the Southern, Central, and Northern regions, respectively, as reported in MDHS (2010).

3.2.4 Child Health Status

Since infant mortality expectation may be correlated with some unobserved factors that also determine fertility, such as individual preference for health, we rely on an instrumental variable approach. We will explain the rationale for this instrument in detail in Section 3.3 but present the survey variable we utilize now as part of our data description.

For each household, we create an indicator for children's health. The respondents answering the family roster (which is the mother in 60% of the cases) is asked to answer the following survey question: **"How would you rate (NAME)'s health in general? (1 = Excellent, ... 5 = Very poor)"** for everyone in their household. We focus on their responses for the children aged less than 18 in their household.

To calculate the instrumental variable for each respondent, we follow these steps:

Table 3.2: Determinants of infant mortality expectation for the wave 2006

	Infant mortality expectation (0-10)		
Sample	ALL	WOMEN	MEN
Number of children	-0.016	-0.026	-0.007
	(0.016)	(0.032)	(0.017)
Female	0.174*		
	(0.101)		
Married	-0.144	-0.220	0.178
	(0.163)	(0.181)	(0.430)
Age group			
20-29	0.088	0.127	-0.399
	(0.213)	(0.237)	(0.621)
30-39	0.324	0.476*	-0.318
	(0.226)	(0.271)	(0.623)
40-49	0.275	0.325	-0.231
	(0.236)	(0.295)	(0.627)
Education			
Primary level	0.061	0.116	0.115
	(0.126)	(0.154)	(0.200)
Secondary level+	0.102	0.363	-0.086
	(0.204)	(0.289)	(0.283)
Region			
Central	0.155	0.320**	-0.036
	(0.119)	(0.156)	(0.187)
Southern	1.039***	1.156***	0.865***
	(0.165)	(0.216)	(0.257)
Wealth Quintile			
Quintile 2	-0.053	0.036	-0.121
	(0.139)	(0.181)	(0.216)
Quintile 3	-0.127	0.110	-0.425*
	(0.143)	(0.179)	(0.232)
Quintile 4	-0.114	0.097	-0.356
	(0.147)	(0.192)	(0.227)
Quintile 5	0.014	0.314	-0.390
	(0.154)	(0.195)	(0.245)
Constant	1.948***	3.708***	2.472***
	(0.344)	(0.347)	(0.730)
Observations	2,291	1,312	979
R-squared	0.040	0.048	0.045

Robust standard errors in parentheses. This regression also includes religion fixed effects. Base categories are '< 20' for the age group, 'no education' for education, 'Northern' for the region, and '2006' for the year. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

1 We add up the child health ratings provided by each respondent for all the children in their household.

2 We then sum the ratings of respondents who live within a specific distance from each other.

3 Finally, we divide this sum by the total number of children living within that particular distance to calculate the average instrumental variable.

This process ensures a spatially weighted average of neighboring households' children's health, with closer households having a greater influence on the final instrumental variable.

3.3 Empirical Strategy

Our empirical specification is as follows:

$$y_{iv} = \beta_0 + \beta_1 m_{iv} + \beta_2 X_{iv} + \gamma_v + year_{iv} + \epsilon_{iv} \tag{3.1}$$

where y_{iv} is the fertility outcome of individual i who lives in village v, m_{iv} is the reported subjective infant mortality expectation of individual i in the previous wave, a vector of covariates of X including the number of children, marital status, gender, education level, wealth, region, and religion, $year_{iv}$ is the dummy for year 2008 (2010 being the base year), and γ_v represents the village fixed effects. The coefficient of interest is β_1 which shows the extent to which respondents' fertility is affected by their infant mortality expectations. Village fixed effects, γ_v, eliminates unobserved village-level confounding factors that are common to all respondents in the same village. These fixed effects control some critical village-level confounding factors that simultaneously affect individuals' fertility decisions and infant mortality expectations.

In all specifications, while the outcome variable and covariates are measured at wave t, the infant mortality expectation variable is obtained from the preceding wave, $t-1$. Consequently, our regressions examine the relationship between fertility outcomes measured in 2008 (and 2010) and infant mortality expectations reported in 2006 (and 2008, respectively). This time lag is important to consider as fertility outcomes observed at time t reflect decisions made before time t, and therefore, they are not influenced by mortality expectations measured at time t. In our analysis, we pool respondents from waves 2008 and 2010 and cluster standard errors at the village level to allow for unobserved components in outcomes to be correlated within the village in all our results.[9]

To draw causal inference using the OLS estimation, the conditional mean of the error terms must be zero, given the values of independent variables. This assumption implies that unobserved variables should not jointly determine respondents' fertility decisions and infant mortality expectations in our context. Time invariant local shocks that affect both fertility choice and infant mortality expectation do not pose a threat on the identification as village fixed effects, γ_v, can address these potentially time-invariant spurious unobserved factors such as access to clean water and health facilities or a malaria outbreak within a village. Yet, some individual-specific unobserved variables included in ϵ_{iv}, such as unobserved individual health shocks and parental taste for health, might affect both fertility outcomes and infant mortality expectations. Hence the OLS may result in biased coefficients.

The direction of potential bias depends on the correlation between the omitted variables in the error term, ϵ_{iv}, and infant mortality expectation, m_{iv}, and the direction that these unobserved factors affect the fertility choice. One key unobserved factor that might bias the results is the respondent's preference for health. This variable might at the same time negatively affect infant mortality expectation (i.e., a parent with a higher unobserved preference for health, who also may invest more in a child's health, might expect other parents do the same and give a lower probability to infant mortality in the community), and positively impact the likelihood of having a child in the next two years (i.e., she may invest more in her health and have higher reproductive efficiency). In this case, OLS will tend to underestimate the impact of infant mortality expectation on fertility choice.

In order to address the issue of potential bias and to estimate the coefficient β_1, we propose utilizing an indicator of the health status of children living in households close to the respondent as an instrumental variable for her or his infant mortality expectation. The children's health status is reported by the children's parent. In particular, we construct an individual-specific spatially-weighted average health status of other children in a respondent's village residing within a 5km radius of the respondent. We exclude the children living in the respondent's household. The functional form $F(d) = e^{1-d}$ for the exponential weights, as used in prior works (Quillian, 2014; Bottazzi and Peri, 2003), is a function of the distance d and assigns higher weights to neighbors in closer proximity.[10] About 60% of residents within a village live within 5 km distance to each other, see Figure 3.6.

[9]Individual fixed-effects models are not viable in this context as we do not observe enough variation in expectations within individuals.

[10]Other decay functions used in the literature include the inverse and quartic function.

As a result, individual-specific spatially-weighted level average health status of other children is obtained. Note that every individual's "spatially-weighted level average health status of other children" observation is based on the views of other respondents who live within 5 km and places greater emphasis on the ratings of respondents who live closer.

The rationale for using this instrument is that individuals are likely to form their expectations about infant mortality based in part on the health status of children they observe in their communities. spatially-weighted average of other respondents' perceived health status of other children is likely to determine their infant mortality expectation via community interactions and social learning, while stressing the stronger relationship with neighbors living nearby. The social learning literature provides significant findings showing that individual decisions in farming and production technology (Bandiera and Rasul, 2006; Foster and Rosenzweig, 1995; Conley and Udry, 2010), health (Kremer and Miguel, 2007; Rao, Mobius, and Rosenblat, 2007; Dupas, 2014; Oster and Thornton, 2012), and family planning and fertility (Munshi and Myaux, 2006; Kohler, Behrman, and Watkins, 2001; Linnemayr, 2012) are strongly influenced by decisions of friends, family, and neighbors within the community. Fertility behavior is socially regulated in the traditional economy. Munshi and Myaux (2006) show that individuals are responsive to changes in the reproductive behavior of their community, and their fertility decisions strongly depend on the contraceptive prevalence in their own religious group within the village. Kohler, Behrman, and Watkins (2001) find that in some regions of southern Kenya, the prevalence of family planning in a network has a direct impact on respondents' choice to use family planning.

The information transmission via social learning typically decays from person to person. Mobius, Phan, and Szeidl (2015) and Duflo and Saez (2002) show that closer individuals have a higher impact on behavior compared to others. The spatially-weighted functions are mostly used in innovation and spillover (Bottazzi and Peri, 2003; McArthur and McCord, 2017), and segregation literature (Reardon et al., 2008; Quillian, 2014). Even when women have knowledge about the existing contraception methods within the community, their assessments of convenience and effectiveness are strongly affected by their close friends' and neighbors' experiences (Montgomery and Casterline, 1993). To capture this decaying feature of social influence and social learning on individuals' fertility and health-related behavior, we use the exponential decay average of child health ratings based on physical proximity.[11]

The first-stage is

[11] Relative weight is calculated using the formula $F(d) = e^{-d}$ where d is the distance.

$$m_{iv} = \pi_0 + \bar{h}_{iv}\pi_1 + X_{iv}\pi_2 + \gamma_v + year_{iv} + u_{iv} \tag{3.2}$$

where $\bar{h}_{iv}$ is the instrument defined above.

As reported in Table 3.3, the F-statistic in the first-stage regression demonstrates a strong correlation between the instrument and infant mortality expectation. Identification of the causal effect relies on three key assumptions: that the instrument is exogenous, satisfies the monotonicity condition, and does not exert any direct effect on respondents' fertility choices, other than through its effect on infant mortality expectation.

While the relationship between infant mortality expectation and fertility choice may be spurious, it is less likely that the average health ratings of other children, provided by other people, are correlated with the respondent's unobserved preferences that may influence her own fertility. Individual-specific health shocks or the respondent's health preferences for children are unlikely to influence the average rating of child health by other individuals in the village. Furthermore, common shocks experienced by all village residents are controlled for by including village fixed effects.

Furthermore, the exclusion restriction assumption is credible since other respondents' village level perceived average health status of children is not prone to affect an individual's fertility decisions via channels other than the infant mortality expectation. Again, village-level fixed effects capture some of the potential mechanisms that could lead this assumption to fail.

Although these assumptions are not testable, given that we include village-level fixed effects that capture local health shocks and access to health care and other facilities, we discuss that it is plausible that our instrument is valid. Also, a robustness analysis following is provided in Section 3.4.3 if the exogeneity assumption fails to hold.

3.4 Empirical Results

This section presents all results, including OLS, first-stage, and IV, along with the robustness checks.

3.4.1 Main Results

We focus on the causal effects of subjective infant mortality expectation on two fertility outcomes. To provide a basis for comparison, we initially present the OLS estimation results. Subsequently, we present the first-stage regression results. Finally, we discuss the IV estimation results that plausibly yield accurate estimates of the causal effects. Results for the outcomes, *any child in the last two years* and *any birth in the last two years*" are reported in Table 3.3..

In Table 3.3, the first and fourth columns display the OLS results for *any child* and *any birth*, revealing that infant mortality expectations exert only a minimal influence on fertility outcomes. The coefficients exhibit relatively small magnitudes and lack statistical significance, suggesting a weak relationship. Conversely, higher fertility is associated with factors such as having more children, being married, and being younger. It is important to acknowledge that the OLS results may suffer from downward bias, as detailed in Section 3.3.

In Table 3.3, Columns 2 and 5 provide the results of the first-stage regressions for both outcomes, where the dependent variable is infant mortality expectation. These results reveal a significant and positive impact of the instrument, spatially-weighted average child health (past average child health), on past infant mortality expectations. Specifically, the point estimates indicate that a 1-unit increase in average child health, such as transitioning from "poor" to "very poor" (where a higher average health perception implies that parents perceive children as less healthy), leads to a 1-unit increase in infant mortality expectations, equivalent to 10 percentage points. Furthermore, both models exhibit F-statistics exceeding the typically recommended threshold of 10, indicating the instrument's strength and relevance. As for the endogeneity test, we report the p-value for Wooldridge (1995) robust score. The significance of this score suggests that the variables in our model should be considered endogenous, providing support for the use of the IV method.

Columns 3 and 6 in Table 3.3 present the main results obtained using the IV method. For the *any child* outcome, the findings indicate that a reduction of 10 percentage points in infant mortality expectations leads to a significant 14 percentage point decrease in the likelihood of having an additional living child in the next two years. Moving to the IV results for the *any birth* outcome in column 6 of Table 3.3, this outcome, not influenced by experienced child mortality, albeit noisier in measurement, provides a more reliable source of information regarding the impact of expected infant mortality, as it takes all births into account rather than just the count of living children. Notably, these two outcomes

Table 3.3: Effect of infant mortality expectation on fertility

Outcome		**Any child**			**Any birth**	
	OLS	F-S	IV	OLS	F-S	IV
Past infant mortality expectation (0-10)	-0.002		0.138**	-0.003		0.181**
	(0.004)		(0.070)	(0.004)		(0.0883)
Past average child health (0-5)		0.981***			0.891***	
		(0.246)			(0.213)	
Number of children	0.044**	-0.004	0.044***	0.037***	-0.008	0.039***
	(0.017)	(0.017)	(0.016)	(0.014)	(0.017)	(0.012)
Female	-0.077***	-0.070	-0.066***	-0.059***	-0.085	-0.043
	(0.020)	(0.102)	(0.023)	(0.022)	(0.099)	(0.0269)
Married	0.246***	-0.0338	0.250***	0.311***	0.0220	0.306***
	(0.034)	(0.138)	(0.038)	(0.035)	(0.143)	(0.044)
Age group						
20-29	-0.018	-0.304	0.033	0.133**	-0.359	0.208***
	(0.053)	(0.273)	(0.063)	(0.056)	(0.274)	(0.071)
30-39	-0.159**	-0.183	-0.126	0.011	-0.216	0.061
	(0.079)	(0.321)	(0.081)	(0.074)	(0.322)	(0.081)
40-49	-0.358***	-0.215	-0.320***	-0.221***	-0.223	-0.169*
	(0.089)	(0.318)	(0.093)	(0.082)	(0.318)	(0.089)
Education						
Primary level	0.015	-0.292**	0.057*	-0.027	-0.254**	0.022
	(0.025)	(0.126)	(0.034)	(0.022)	(0.120)	(0.035)
Secondary level +	0.033	-0.417**	0.092*	-0.057	-0.372**	0.014
	(0.039)	(0.184)	(0.053)	(0.042)	(0.176)	(0.062)
Year						
2008	0.017	-0.127	0.016	0.039*	-0.114	0.037
	(0.022)	(0.100)	(0.023)	(0.022)	(0.099)	(0.0244)
Endogeneity test			0.063			0.029
F			15.88			17.52
Observations	2500	2500	2500	2707	2707	2707
R^2	0.191	0.095		0.210	0.090	

Notes: The column names *OLS*, *F-S*, and *IV* correspond to the results obtained from Ordinary Least Squares (OLS), first-stage, and Instrumental Variable (IV) regressions, respectively. Within the age and education groups, the reference categories are individuals younger than 20 years and those with no education, respectively. The base year for all analyses is 2010. Additionally, all regression models incorporate fixed effects for village, religion, and wealth level. The outcome variables under consideration are *any child in the next two years* and *any birth in the next two years*. The primary explanatory variable of interest is *past infant mortality expectation*, which is instrumented using *past average child health* as the instrumental variable. Standard errors clustered in village level are in parentheses. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$.

exhibit a significant correlation, with a pairwise correlation coefficient of 0.68. We observe that a 10 percentage point decrease in infant mortality expectation results in a 18 percentage point decrease in the propensity to have an additional birth within the next two years. The 4 percentage point difference between these two effects underscores the impact of experienced child mortality through infant mortality expectation on fertility outcomes. Overall, these results shed light on a fundamental demographic transition mechanism: the hoarding strategy. They underscore that parents are responsive to their subjective infant mortality expectations when making fertility decisions, and they take ex-ante measures based on these expectations.

Experienced infant mortality among respondents could potentially influence their tendency to adopt replacement strategies, resulting in increased fertility behavior.[12] While the *any child* outcome is likely to offer a less noisy measure of fertility, given the reduced likelihood of misreporting the number of living children, it does have the limitation of potentially underestimating fertility behavior in cases where parents experience both child loss and subsequent childbirth within a two-year period. As a result, the primary findings presented for the *any child* outcome in Table 3.3 do not include observed fertility behavior when parents experience child mortality. We will discuss the impact of experienced child mortality further in Section 3.4.2.

These findings are also consistent with our discussion that OLS tends to underestimate β_1 towards zero. Given that the outcome variable in this study is binary, we additionally present instrumental variable probit estimates of fertility outcomes in Appendix Table A2.3. These estimates suggest that at the median level of infant mortality expectation (=2), the average marginal effect of infant mortality expectation on the predicted probability of having an extra child is .11, very similar to linear regression coefficient of .14.

The regressions discussed above involve both male and female respondents, some of whom are married to each other. While it would be ideal to gain insights into household-level decision-making by analyzing the couple's fertility based on both husband and wife's expectations, this is not feasible due to the availability of only one instrument. It is worth noting that there is a low correlation of expectations within a couple (0.03). As a result, we reproduce our analysis using solely women respondents to gain a better understanding of their fertility choices and present the results in Table 3.4. Note that, in our

[12]Respondents who experienced child mortality can be partially identified by examining the difference between the number of births and the number of living children. When there is no difference between these two variables in any of the waves, we consider that those parents have not lost a child. When we observe consistent differences, such as an increase in the number of births between two waves by one unit while the number of living children remains the same, we infer that these parents potentially faced the experience of child mortality.

Table 3.4: Females - Effect of infant mortality expectation on fertility

Outcome		**Any child**			**Any birth**	
	OLS	F-S	IV	OLS	F-S	IV
Past infant mortality expectation (0-10)	-0.009		0.134**	-0.007		0.144**
	(0.006)		(0.064)	(0.005)		(0.063)
Past average child health (0-5)		1.135***			1.035***	
		(0.346)			(0.293)	
Number of children	0.071***	0.017	0.069***	0.055***	-0.002	0.055***
	(0.011)	(0.039)	(0.013)	(0.010)	(0.038)	(0.013)
Married	0.111***	-0.012	0.115***	0.136***	0.032	0.133***
	(0.034)	(0.177)	(0.038)	(0.032)	(0.174)	(0.040)
Age group						
20-29	-0.148	-0.651*	-0.038	0.033	-0.709*	0.155
	(0.093)	(0.374)	(0.128)	(0.090)	(0.367)	(0.109)
30-39	-0.358***	-0.531	-0.264**	-0.190**	-0.536	-0.092
	(0.096)	(0.425)	(0.129)	(0.084)	(0.418)	(0.108)
40-49	-0.604***	-0.608	-0.499***	-0.481***	-0.595	-0.373***
	(0.097)	(0.428)	(0.138)	(0.086)	(0.418)	(0.114)
Education						
Primary level	0.011	-0.293*	0.056	-0.044	-0.295*	0.004
	(0.038)	(0.175)	(0.048)	(0.035)	(0.171)	(0.043)
Secondary level	0.090	-0.032	0.097	-0.079	-0.019	-0.073
	(0.056)	(0.282)	(0.066)	(0.069)	(0.276)	(0.077)
Year						
2008	0.017	-0.127	0.016	0.039*	-0.114	0.037
	(0.022)	(0.100)	(0.023)	(0.022)	(0.099)	(0.024)
Endogeneity test			0.046			0.031
F			10.76			12.50
Observations	1492	1492	1492	1587	1587	1587
R^2	0.238	0.138		0.258	0.133	

Notes: The column names *OLS*, *F-S*, and *IV* correspond to the results obtained from Ordinary Least Squares (OLS), first-stage, and Instrumental Variable (IV) regressions, respectively. Within the age and education groups, the reference categories are individuals younger than 20 years and those with no education, respectively. The base year for all analyses is 2010. Additionally, all regression models incorporate fixed effects for village, religion, and wealth level. The outcome variables under consideration are *any child in the next two years* and *any birth in the next two years*. The primary explanatory variable of interest is *past infant mortality expectation*, which is instrumented using *past average child health* as the instrumental variable. Standard errors clustered in village level are in parentheses. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$.

data, only 8% of the women state that they are not able to make any household decisions, and more than 67% think that they have some power to decide when and where to travel. Also, 68% of the women report that it is acceptable to refuse unprotected sexual intercourse if they do not want to get pregnant. These suggest that women have some authority to control the fertility decisions of the couple.

Our analysis of the female sample reveals positive and significant results in the first-stage regression, with F-statistics greater than 10, and the endogeneity tests confirm the endogeneity of expectation for both outcomes. We find that the impact of infant mortality expectation on fertility decisions in the female sample is consistent with the results obtained from the whole sample, both in terms of precision and magnitude. This finding suggests that women play a significant role in the decision-making process when it comes to fertility in couples. Our results indicate that the subjective expectations of women regarding infant mortality are an important factor that shapes their decisions in this regard.

3.4.2 Further Analysis

In this subsection, we further analyze the impact of infant mortality expectations on fertility to support our finding of hoarding behavior across different sub-samples.

Hoarding vs. Replacement Behavior

Our primary outcome, *any child*, is determined by comparing the number of living children between consecutive waves. Relying solely on the count of alive children can lead to an underestimation of fertility when a respondent experiences infant or child mortality and subsequently has another child between survey waves. While the *any birth* outcome considers all births, it may still be influenced by the replacement effect resulting from experienced mortality, making it challenging to isolate the impact of expectations on fertility. Consequently, the primary findings presented in Table 3.3 not only capture hoarding behavior but also reflect the impact of the replacement effect. In this subsection, we explore three methods aimed at distinguishing hoarding behavior from replacement behavior, thereby elucidating the role of expectations in shaping fertility behavior.

First, we introduce an indicator for *experienced child mortality* based on questions about the total number of births and living children reported by respondents. This variable equals 1 if the difference between the number of births and the number of living children increases by at least one unit between two waves. We then incorporate this variable as an additional control in our primary specification to mitigate the replacement effect that emerges after experiencing child mortality.

Secondly, we create an indicator of *excess fertility* using data from the 2006 wave of the survey, which includes information about participants' desired number of children. We generate a binary variable by comparing each respondent's reported number of living children to their stated desired number of children. This variable is assigned a value of 1 when a respondent has more living children than their desired target, signifying excess fertility beyond their ideal family size. It acts as an indicator of hoarding behavior, drawing attention to instances where individuals have more children than they desire and enabling further investigation into fertility behavior.

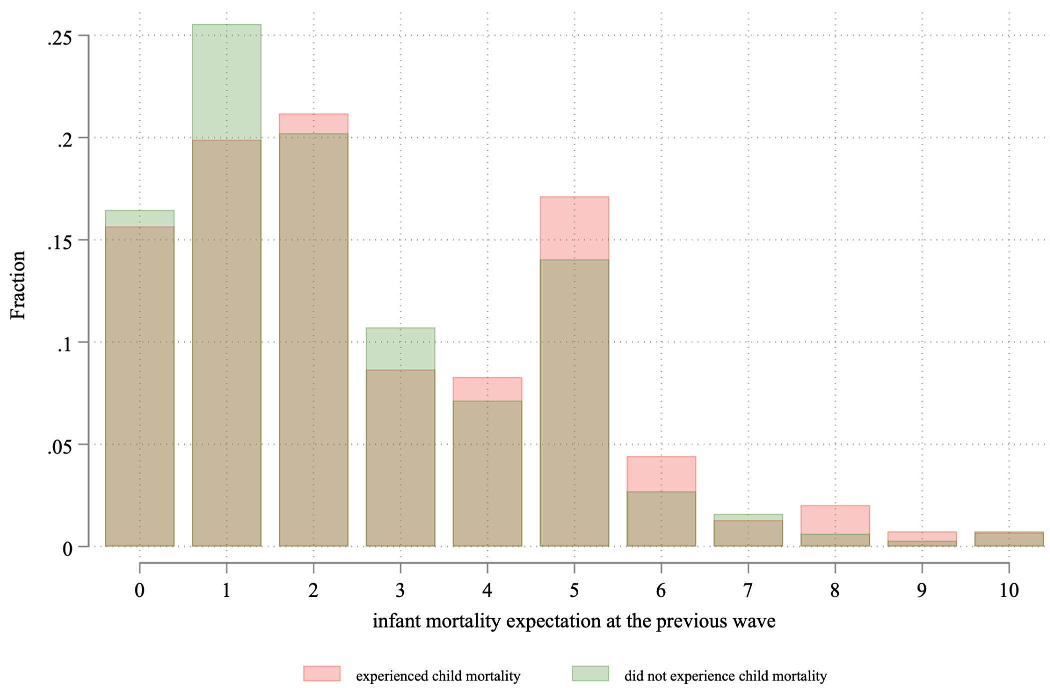


Figure 3.3: Distribution of infant mortality expectation by experienced child mortality

*Notes:*In this histogram, we distinguish respondents who experienced child mortality by examining their reported total number of births and living children. Within our analytical sample, approximately 13% of respondents experienced child mortality.

In Panel A of Table 3.5, we present the results for two main outcomes and the *excess fertility* that incorporate the effect of experienced child mortality on the overall sample. The coefficients for the first two outcomes suggest that expected infant mortality has a significant positive impact on the probability of having another child and giving birth in the next two years. As expected, these coefficients exhibit a smaller magnitude compared to the results presented in Table 3.3. Thus, we contend that our findings in Table 3.5 rule out the impact of infant mortality expectation on fertility through replacement behavior.

Table 3.5: Disentangling replacement and hoarding behavior (IV)

	Fertility Outcome		
	Any Child	**Any Birth**	**Excess Fertility**
Panel A: All sample with child mortality control			
Past infant mortality	0.102*	0.097*	0.090**
expectation (0-10)	(0.055)	(0.056)	(0.041)
Experienced child	-0.056*	0.315***	0.200***
mortality	(0.032)	(0.039)	(0.039)
F statistic	12.69	15.25	11.39
Observations	2,149	2,298	2,049
Panel B: Respondents who did not experience child mortality			
Past infant mortality	0.112*	0.098*	0.074
expectation (0-10)	(0.057)	(0.054)	(0.047)
F statistic	13.17	15.95	12.24
Observations	1,920	2,003	1,788

Notes: Standard errors clustered in village level are in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. Results presented above are from IV regressions where the outcomes are different fertility measures. In Panel A, experienced child mortality dummy is equal to 1 if the respondent reports a different number of total birth than alive children. In Panel B, the sample is restricted to respondents who did not experience child mortality. All regressions include number of children, gender, marital status variables and age group, education, village, religion and wealth level fixed effects. The key variable is *past infant mortality expectation*, instrumented by *past average health perception*. The F-statistics from the first-stage regressions are documented in the table.

In column (3) of Table 3.5, we examine the effect of infant mortality expectations on the *excess fertility* outcome. Our analysis reveals that an increase of one unit in infant mortality expectation leads to a 9 percentage point rise in the probability of having more children than desired. This finding corroborates the hypothesis that parents tend to overshoot their target family size when they have high infant mortality expectations, as is consistent with the notion of hoarding behavior.

It is also noteworthy that experienced child mortality exhibits a positive correlation with the *any birth* and *excess fertility* outcomes, implying that affected parents are more inclined to give birth within the next two years. As expected, experienced child mortality is negatively associated with the *any child* outcome, as this outcome is generated by using the number of alive children.

Finally, to provide additional evidence for hoarding behavior, it is crucial to fully account for the impact of replacement behavior on fertility. As mentioned earlier, a group of respondents who did not experience infant/child mortality can be identified by comparing variables for the total number of births and living children.[13] By restricting the analysis to this group of respondents who did not experience child mortality, the impact of subjective expectations on fertility is not confounded by replacement behavior. Parents who experience child mortality and have another child in the following wave tend

[13]It should be noted that some families who did not experience mortality may not be included in this group due to inconsistent fertility reporting.

to have higher infant mortality expectations, which could potentially inflate the estimate. Figure 3.3 illustrates that respondents who have experienced child mortality are more inclined to believe that the probability of an infant's mortality is greater than 20%. To address this issue, regressions for all three outcomes are run exclusively for this subsample. Results in Panel B of Table 3.5 provide strong evidence of a positive and significant effect of infant mortality expectations on fertility. Specifically, a 10 percentage point reduction in infant mortality expectation corresponds to an 11 percentage point decrease in the likelihood of having a child in the following two years. The absence of replacement behavior in the sub-sample examined in the first two columns further supports the presence of hoarding behavior in rural Malawi. Although the coefficient sign is positive for the *excess fertility* outcome, it is no longer statistically significant, presumably due to reduced precision resulting from the smaller sample size.

In conclusion, although we face data limitations that prevent us from precisely pinpointing child mortality, we are able to detect replacement behavior by examining the difference between the number of births and the count of living children. The results from this subsection suggest that the fertility decisions of respondents align with hoarding behavior.

Own Mortality Expectation

An individual's own mortality expectation can impact fertility, as it can affect people's decisions about when to have children and how many children to have. In a context where there is limited access to formal social security systems, individuals who expect to have a longer lifespan may prioritize having more children as a way to ensure intergenerational support.

Unobserved (realized or anticipated) health shocks that shape own mortality expectation may potentially influence infant mortality expectations. In our sample, the correlation between own and infant mortality expectation is 0.16. To ensure that our main result is driven by variations in infant mortality expectation rather than own mortality expectation, we augment our main specification with data on own mortality expectations. For this, we use the question "Pick the number of beans that reflects how likely you think it is that a man your age who is healthy and does not have HIV will die within a ten-year period beginning today."

In Table 3.6, we present the results for two fertility outcomes separately for the all and female samples. Our findings suggest that infant mortality expectation has a similar effect on fertility outcomes, albeit

Table 3.6: Impact of infant mortality expectation on fertility - controlling own mortality expectation

	All Sample		Female Sample	
Fertility Outcome	**Any Child**	**Any Birth**	**Any Child**	**Any Birth**
Past infant mortality	0.118*	0.159*	0.117**	0.124*
expectation (0-10)	(0.066)	(0.084)	(0.059)	(0.063)
Own mortality	-0.012	-0.015	-0.020**	-0.018*
expectation (0-10)	(0.009)	(0.012)	(0.010)	(0.010)
F statistic	21.98	22.56	13.44	14.90
Observations	2,454	2,657	1,466	1,559

Notes: Standard errors clustered in village level are in parentheses. ***: p <0.01, **: p <0.05, *: p <0.1. Results presented above are from IV regressions for all sample and female sample where the outcomes are two different binary fertility measures capturing fertility in the last two years. Own mortality expectation is measured similarly to infant mortality expectation where 0 means that individual is certain that they will not die in the next 10 years. All regressions include number of children, gender, marital status variables and age group, education, village, religion and wealth level fixed effects. The key variable is *past infant mortality expectation*, instrumented by *past average kid health*. The F-statistics from the first-stage regressions are documented in the table.

with slightly smaller magnitude. This result provides evidence that the impact of infant mortality expectation on fertility is not driven by own mortality expectations. The negative relationship found between own mortality expectation and fertility in the female sample aligns with the previous discussion that women who anticipate living longer are more inclined to have children.

Heterogeneity Analysis

To gain a more comprehensive understanding of fertility behavior, we conduct some heterogeneity analysis by examining the effects of infant mortality expectation on fertility outcomes within specific demographic groups: age, wealth, and education.

The observed fertility decline due to lower infant mortality expectations may result from either postponement of childbearing by young individuals or cessation of childbearing by older individuals. To explore this, we conducted separate regressions for respondents younger and older than 30 years. The result by age is presented in Column 2 of Table 3.7.[14] The finding in Panel A suggests that the elasticity of fertility to infant mortality expectations is higher for older respondents. This is likely due to older parents having achieved their desired family size, while younger parents are more active in pursuing fertility regardless of their beliefs about infant mortality. Figure 3.4 supports this argument, showing that 25% of respondents older than 30 have more children than their desired family size.

The elasticity of fertility with respect to infant mortality expectations may also differ by socio-economic status (SES). In particular, it may be more costly for low-SES parents to end up with too few children

[14] Note that the instrument is weak for the younger group in Panel B.

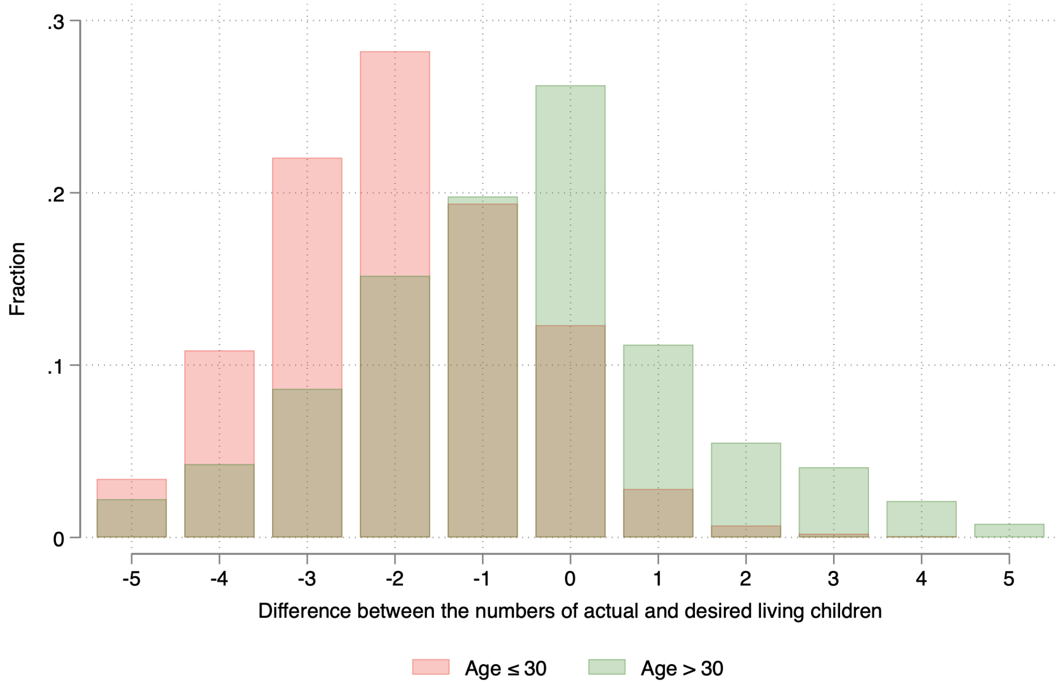


Figure 3.4: Distribution of (number of living - number of desired) children

as they may not get enough support in old age, while it may also be costly to end up with too many children as they may not be able to provide for them. We look at the heterogeneity of the main effect by wealth and education. We use a household's wealth index as an indicator of its overall standard of living.[15] For education, we consider respondents with or without primary education. Columns 2 and 3 of Table 3.7 show a larger elasticity of fertility to education for lower-SES respondents.[16]

Policy Counterfactual

We investigate the potential effect on fertility of a public health campaign providing information about child mortality rates. The simulations assume full compliance, meaning that all respondents fully revise their expectations to the rural Malawi average of 73 per 1000 (0.73 per 10). The results, therefore, represent an upper bound for any policy treatment effects.

We calculate the predicted probability of having a child in the next two years based on the IV probit results presented in Table A2.3. We do this for various scenarios where all individuals in the sample

[15]The wealth index is determined by considering factors such as the household's possession of certain assets (e.g., TVs and bikes), the materials used to construct their home, and their access to clean water and sanitation facilities.
[16]Again, the instrument is weak for the specifications in Panel B.

Table 3.7: Any child outcome - Heterogeneity analysis based on age, wealth, and education

Panel A - Sample:	**Age≥30**	**Wealth Q≤3**	**Education≤1**
Past infant mortality	0.219***	0.152**	0.166**
expectation (0-10)	(0.072)	(0.076)	(0.081)
F statistic	10.99	10.15	12.71
Observations	1,606	1,368	2,104
Panel B - Sample:	**Age<30**	**Wealth Q>3**	**Education>1**
Past infant mortality	-.0003	.043	-0.074
expectation (0-10)	(.100)	(0.128)	(0.148)
F statistic	7.96	4.95	0.71
Observations	898	1,136	400
χ^2	5.44	0.88	1.53
Prob> χ^2	0.019	0.349	0.217

Notes: Standard errors clustered in village level are in parentheses. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$. Results presented above are from IV regressions where the fertility outcome is the anychild born in the last 2 years. All regressions include number of children, gender, marital status variables and age group, education, village, religion and wealth level fixed effects. The key variable is *past infant mortality expectation*, instrumented by *past average kid health* where the average is calculated using exponential decay function and respondents within 40 km. Education ≤1 pertains to primary school or less. The F-statistics from the first-stage regressions are documented in the table. The lower section of the table presents the χ^2 value from testing the hypothesis that the coefficient in Panel A is equal to the coefficient in Panel B.

have infant mortality expectations equal to different values of p, where p takes on values in the set $\{\text{actual infant mortality rate } (=0.73), 0, 1, 2, ...10\}$, while keeping all other variables fixed. This approach enables us to make predictions under counterfactual scenarios of infant mortality expectations, including the situation where everyone's expectation is assumed to change to the actual level of infant mortality (0.73). To achieve this, we replace the collected infant mortality expectations with the actual rate, and the model generates predictions accordingly.

Figure 3.5 presents a coefficient plot illustrating the estimated probability of having a child in the next two years across various counterfactual scenarios of infant mortality expectations. This visualization brings attention to a notable difference between the counterfactual probability of having a child when individuals maintain their median reported expectations (=2) and the counterfactual probability when respondents update their infant mortality expectations to match the actual rate (=0.73). On average, compared to having the median infant mortality expectation, adjusting expectations to align with the actual infant mortality rate is associated with a significant decrease in the probability of having an additional child by 0.127 ($p = 0.012$). This represents a substantial reduction from the baseline average of 39%. These findings emphasize the crucial role of well-designed information campaigns and policies in shaping individuals' subjective expectations.

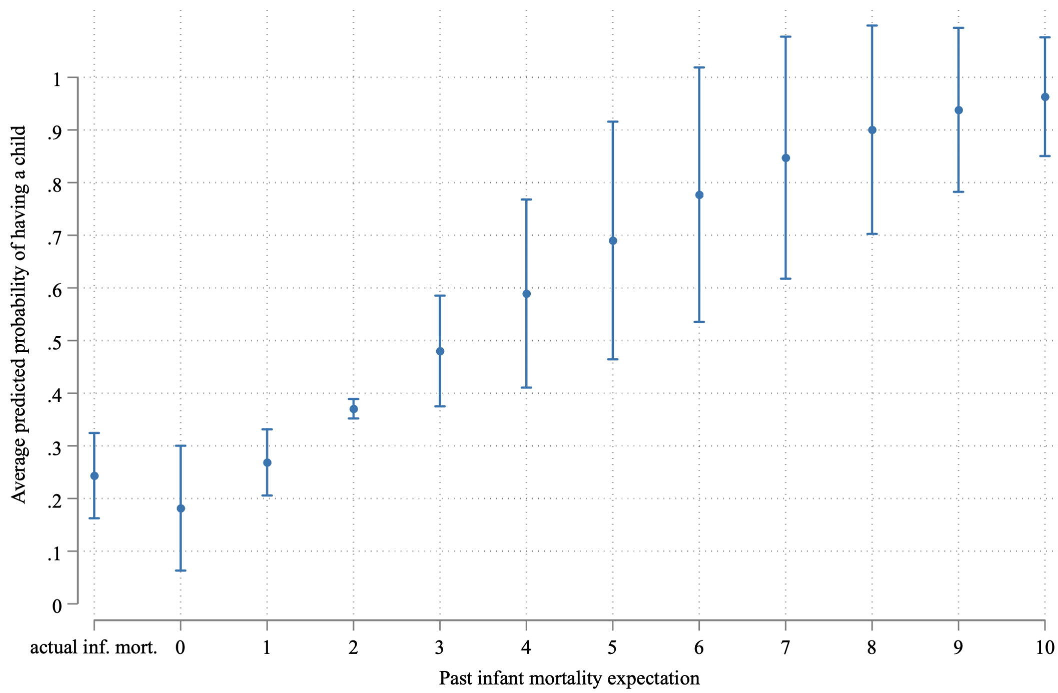


Figure 3.5: Counterfactual probabilities of having a child at each expectation point

Notes: This figure depicts a coefficient plot illustrating the estimated probability of having a child in the next two years based on the IV probit estimate presented in Table A2.3. Each coefficient on the plot is accompanied by 95% confidence intervals, and it corresponds to the predicted probability of having a child in the next two years. assuming that infant mortality expectation is equal to p where $p \in \{\text{actual inf. mort. } (=0.73), 0, 1, 2, ...10\}$ while holding all other variables fixed. The first point is under the assumption that everyone updated their expectations to the actual infant mortality rate (0.73 out of 10).

3.4.3 Robustness Checks

In this subsection, we first delve into the difference in magnitude between the OLS and IV coefficients, following the approach outlined in Oster (2019). Next, we conduct a robustness check, as suggested by Nevo and Rosen (2012), which relaxes the strict exogeneity assumption inherent in the instrumental variable method. Furthermore, we evaluate the sensitivity of our results to the sample selection by expanding the number of respondents in the regression by using an alternative measures of the average child health variable as an instrument, which does not rely on GPS information and previous wave survey participation. Finally, we present our findings under various decay functions.

Selection on unobservables

Finally we briefly discuss the difference in our OLS and IV (-0.002 and 0.138, respectively) estimates in Table 3.3. As discussed earlier, due to omitted variable bias OLS results are likely to be biased downwards. Following Oster (2019), under the assumption that the selection on unobservables (such as taste for health) is proportional to the selection on observables (such as number of children, marital status, age group, and wealth) the proportionality ($\frac{\text{selection on unobservables}}{\text{selection on observables}}$) that justifies our IV estimate is 1.95. In other words, as long as selection on unobservables is 95% larger than selection on observables it is enough for the true effect to have the size of the IV estimates. This ratio is not unexpected as fertility decisions depend on a complex interplay of cultural, social, economic, and healthcare-related factors, most of which are unobserved to the researcher. Hence, the difference in magnitude of OLS and IV coefficients is not unreasonable. Our analysis also reveals a proportionality of 0.56 that generates a null effect, implying that the selection on unobservable factors on fertility is approximately half that of observable factors. As we previously discussed, given the availability of observable determinants of fertility selection on unobservables likely accounts for a more substantial portion.

Using the above methodology, Ciacci (2021) calculates that the difference between OLS and IV estimates in the seminal paper by Acemoglu, Johnson, and Robinson (2001) where these estimates are not too far apart from each other, requires a ratio larger than 1,000. Hence, we conclude that the discrepancy in our estimates is credible.

Imperfect IV method

The IV estimation requires the instrument to be strictly exogenous. However, Nevo and Rosen (2012) propose an imperfect IV method designed for not perfectly exogenous instruments. They replace the zero correlation assumption between the instrument and the unobserved error term with an assumption related to the correlation's sign, which leads to convenient and estimable bounds in the linear IV model.

A comprehensive discussion of the assumptions and their relevance to our study can be found in Appendix Section 5. In brief, these assumptions suggest that the instrument should exhibit lesser endogeneity compared to the infant mortality expectation. Additionally, the instrument should be weakly correlated with the omitted error term in the same direction as the infant mortality expectation.

As discussed in Appendix Section 5, the covariance between the expectation and the instrument is positive, $\sigma_{m_{iv}\bar{h}_{iv}} > 0$. Hence, we only have one-sided bounds. For *any child in the last two years* outcome, the correlation between the error term and infant mortality expectation, $\rho_{m_{iv}\epsilon} \leq 0$. This relationship yields a lower bound. Below, Table 3.8 presents the one-sided bounds for the main outcomes and the lower bounds of their confidence intervals for both the entire sample and the female sample.

Table 3.8: Bound analysis of β_1

Outcome variable:	**Any child**		**Any birth**	
Sample	All	Female	All	Female
Lower bound of Estimator	0.138	0.134	0.181	0.144
Lower bound of CI	-0.005	0.036	-0.016	0.003

We have one-sided bounds due to the positive correlation between the instrument and the endogenous variable. The first row presents the calculated lower bound, while the second row provides the lower bound of the confidence interval for this estimate.

Table 3.8 shows that all of the bounds are the IV point estimates which are in the expected direction with assumption 2. Although not presented, bounds are identical under the case when A2 does not hold.[17] Hence, the validity of A2 is not required for this bounding analysis. While the lower bounds of the confidence intervals are slightly below zero for the entire sample, these lower bounds of the estimators themselves bolster our argument. For the female sample, the lower bounds of the confidence intervals contribute to enhancing the robustness of our findings. Thus, wven without the strict exogeneity assumption, we can conclude that a decrease in infant mortality expectation has a significantly negative impact on the propensity of giving birth in the next two years.

Sample selection

As previously mentioned, a subset of survey respondents lacks past infant mortality expectation data due to either their non-participation in the previous wave or the absence of GPS information, which is essential for instrument calculation. Consequently, these individuals were excluded from the regression analysis presented in Table 3.3.

In this subsection, we present two alternative analyses. First, for those respondents without GPS information, we generated the instrument by using only the village's average child health ratings without employing a kilometer bandwidth. The results can be found in Appendix Table A2.4. Despite this methodological variation, with a sample closer to the representative group, the main result remains robust, and the effect size is larger.

Next, we expand our analysis to include respondents who were initially excluded due to their non-participation in the previous wave. We use their current wave expectation and instrument it with the current village-level average child health rating. The results in Table A2.5 suggest an even larger

[17] A2: the instrument should exhibit lesser endogeneity compared to the infant mortality expectation.

effect for the *any child* outcome.[18] This finding reinforces our main results by demonstrating their consistency when applied to a larger and more representative group of respondents.

Alternative bandwidths and decay functions

Next, we check the sensitivity of our result to instrumental variables generated under different decay functions and distance bandwidths. Table A2.6 documents results for instruments created using 5 and 10 km bandwidths with exponential (as in our main specification), inverse[19] ($F(d) = \frac{1}{1+d}$), and quartic[20] ($K(z) = \frac{15}{16}(1-z^2)^2$ where $z = \frac{d}{bandwidth}$) decay functions.

Although the inverse decay function does better as the weights decrease more rapidly, our first choice of function, the exponential decay performs best as it attributes non-negligible weight only to the first couple of intervals which is more suitable considering that people observe the behavior of others who live nearest to them much more often.

For 5 km bandwidth, we observe that specifications using instruments with exponential and quartic decay functions provide significant and positive estimates. As presented in Figure 3.6, less than half of residents in a village lives within 5 km to each other on average. Hence, we also create instruments using 10 km bandwidth which encompasses 85% of respondents in the same village. For 10 km, exponential and inverse decay function specifications support our result. We can conclude that, although the selection of decay function and distance bandwidth matters, we find strong support for our main results suggesting that lower infant mortality expectation causes lower fertility under different specifications.

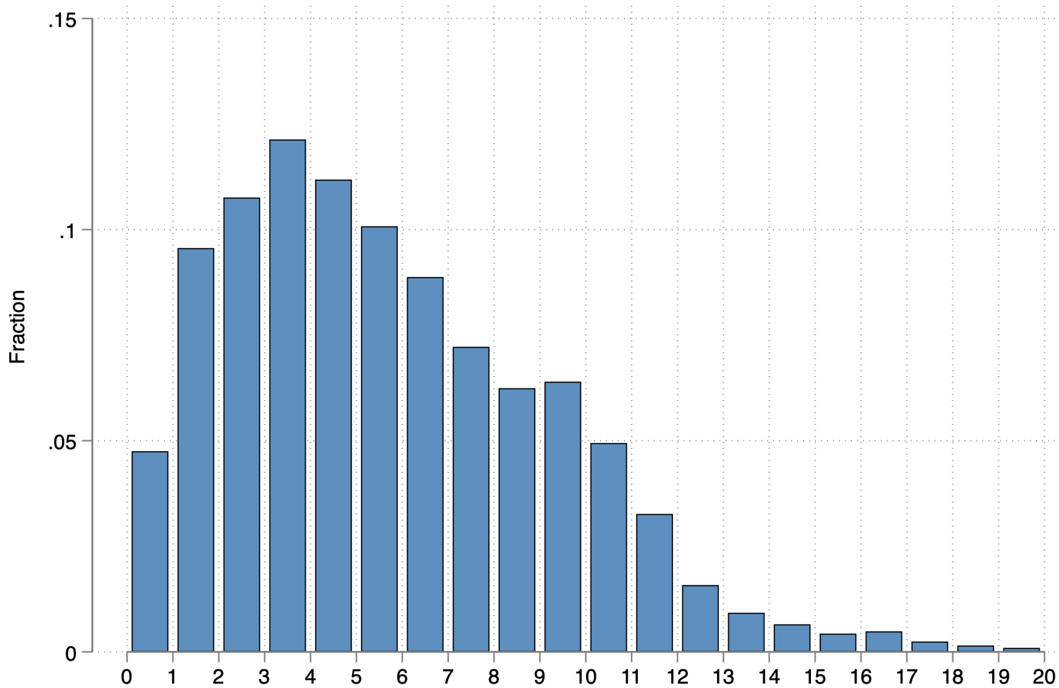
3.5 Conclusion

Understanding the decision-making process of fertility is of paramount importance in comprehending the demographic transition, both in developed and developing countries. This study delves into the role of subjective expectations in determining the likelihood of childbirth in rural Malawi, a region representative of rural SSA low-income countries. Given the declining mortality rates in these nations,

[18]The first-stage result for the *any birth* outcome suggests that the instrument is weak for that specification.

[19]Bottazzi and Peri (2003) argues that the inverse function does better as the weights decrease more rapidly, which is more suitable for R&D literature.

[20]Reardon et al. (2008) relies on a quartic distance-decay function arguing that it plausibly corresponds to patterns of social interaction.



Notes: The histogram illustrates the distribution of averaged distances for all respondents within a village. These distances were calculated by averaging the individual distances from each respondent to others within the same village.

Figure 3.6: Distribution of average distances within villages

fertility determinants have emerged as critical factors in shaping the trajectory of the demographic transition.

Our study stands as the first to investigate the causal link between infant mortality expectation and fertility using observations of expectations data. Filling a gap in the literature, we demonstrate that parents are responsive to expectations in their fertility choices. Our findings reveal that a 10 percentage point decrease in subjective infant mortality expectations leads to a substantial 14 percentage point decrease in the likelihood of having a child within the next two years. This result underscores the significance of subjective expectations in fertility choices and confirms the hoarding strategy as a contributing mechanism to the demographic transition in SSA. Moreover, our findings underscore the importance of incorporating subjective expectations data in existing surveys. Without this data, identifying parents' fertility strategies and disentangling different mechanisms of the demographic transition would not have been possible.

In terms of policy implications, our analyses indicate the potential benefits of an information intervention about the actual infant mortality rate to help some couples in making better-informed fertility decisions.

However, it is worth noting that not all expectations are easily modifiable (Ciancio et al., 2020). Therefore, a comprehensive approach to information dissemination is essential, taking into account the specific context and factors influencing parental decision-making.

Chapter 4

Expertise, Signaling, and Learning in Fish Auctions

One fundamental question in economics is how the agents in a market act based on the structure and the way the market works. In most of the literature, markets are studied as price-setting mechanisms that match demand and supply. However, a market can be considered as an intricate, evolving organization of interacting participants that may favor one side of the market. Gatti, Gallegati, and Kirman (2000) highlights the following fundamental issues: the heterogeneity between the participating agents in a market, how these agents interact, and the dynamic mechanism that controls the evolution of agents. Theoretical results relying on assumptions about individuals that do not take the above issues into account may not be able to explain some of the realized aggregate behaviors in the market. Disregarding the heterogeneity and interaction of agents can undermine the theoretical model and lead to potential inaccuracies in empirical analysis.

Auctions are ancient economic institutions that comprise a substantial share of economic activities in many sectors, including seafood, wine, flowers, artwork, and treasury bills. Our main interest in this paper is not restricted to fish auctions; we believe that some of the insights from this study of the Sydney Fish Market (SFM) can be applied to other markets. SFM provides insights into evolving market structures and an understanding of the drivers of interactive market processes. Hence, studying fish auctions in this context can improve our perception of how market participants interact with and learn from each other and how their heterogeneity in knowledge helps spread information through the market. A significant benefit of our SFM analysis is the extensive dataset covering 27 years of transactions. This unique dataset enables us to trace bidders from their initial entry into the market, a feature often absent in other auction data contexts. This capability, in turn, allows us to create an expertise measure and exploit the bidder heterogeneity for our research.

In this paper, we examine how prices change over time in auctions of homogenous seafood products, using the auction transactions data from SFM. At SFM, a heterogenous group of participants bids in sequential Dutch auctions, where they interact, exchange information, and adapt their decision-making based on what they learn from each others' bids. Our objective is to unravel the intricate web of bidder heterogeneity and bidder interactions, shedding light on their profound influence on market outcomes. Fish markets serve as an ideal setting for our study due to the perishable nature of fresh seafood, which necessitates its sale within a single day with no delay options, making speedy decision-making necessary. Within this context, our paper investigates the bidding behavior, how bidders use their own information in their decision-making, and whether they take information received from other bidders into account before their bidding decision. Taking bidder heterogeneity and signaling into account, we demonstrate that prices follow a non-monotonic trend, and expertise plays a key role in shaping this trend.

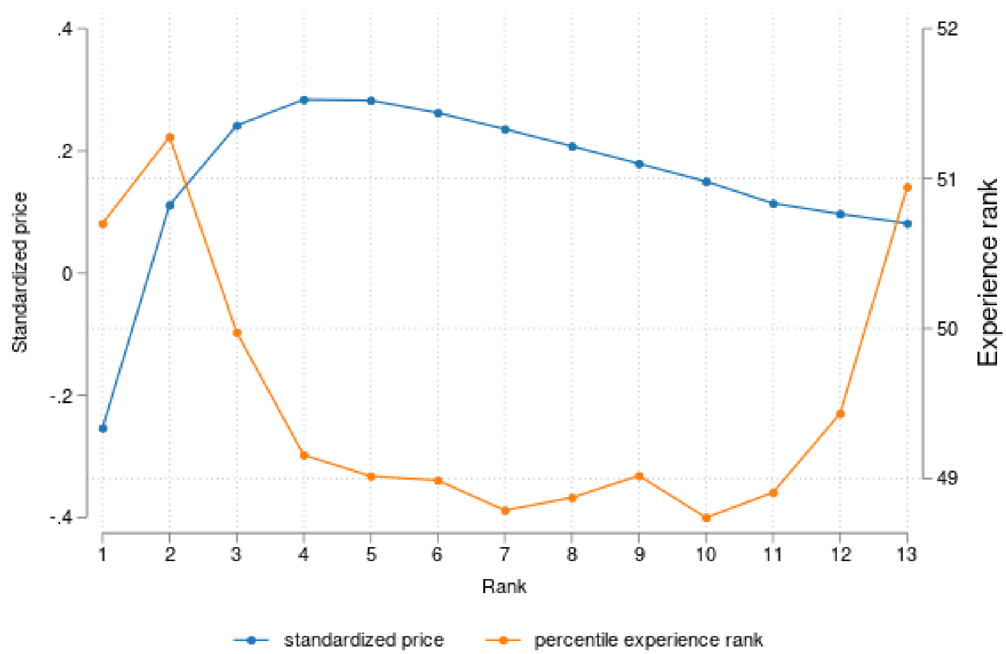


Figure 4.1: Standardized price and experience by rank

Notes: The left y-axis represents the average standardized price, indicating the number of standard deviations a point deviates from the average price of the lot at each round. Meanwhile, the right axis displays the mean experience rank at each round.

Figure 4.1 displays the average standardized price (on the left y-axis) that shows how many standard deviation away a point is from the average price of the lot at each rank and mean experience rank (on the right y-axis) at each rank. Very interestingly, we observe that on average prices follow a non-monotonic trend; while the bidder in the first rank pays significantly less than average, prices remarkably increase until rank 4, then slowly and consistently declines. Remarkably, when we look at the trend of experience over the course of ranks we notice that it mirrors the price trend. Although this figure does not provide any causal evidence, it presents an interesting puzzle where more experienced bidders are less likely to pay higher than the average and first bidders are more experienced and on average pay less. In this paper, we investigate the observed price dispersion illustrated in Figure 4.1 for homogeneous seafood. Our aim is to explore the mechanisms underpinning this dispersion and establish a connection between this dispersion and the heterogeneity in bidders' levels of experience. Additionally, we endeavor to discern its relationship with bidders' interactions within the market and their learning process from experienced bidders' bids.

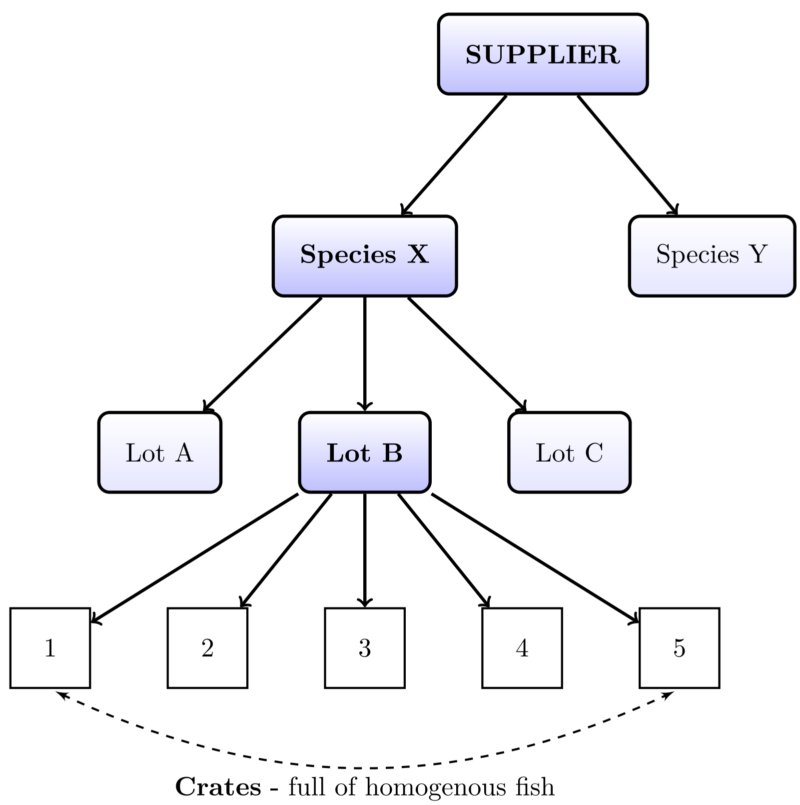


Figure 4.2: Structure of the Lots

Notes: This diagram illustrates the division of seafood catches into fully homogenous crates. Please note that, for the sake of space, only one species and one lot division are depicted here.

One key advantage of the auction setting used in SFM is that suppliers' catch of the day for each species is separated into lots based on their quality, size, and processing type. This division results in homogeneous lots, each of which is further divided into crates and then sold in sequential auctions. Figure 4.2 illustrates this division into lots and subsequently into crates. This homogeneity within each sequential auction provides us with an identification strategy that enables us to compare prices of homogeneous products sold in different rounds within the auction to bidders with varying levels of experience. The methodology we propose entails comparing prices between crate 1 and crate 2 (and more broadly, crates sold in subsequent rounds), all while controlling for other key observable variables.

In line with the estimation approach outlined by Berg, Van Ours, and Pradhan (2001), and by taking advantage of the homogeneity within lots, we incorporate lot fixed effects. Our analysis reveals a departure from the theoretical findings presented by Milgrom and Weber (1982): prices for homogeneous products do not adhere to a martingale pattern, and we observe a non-monotonic price dispersion in sequential auctions. Then benefiting from the bidder heterogeneity stemming from different levels of knowledge and experience, we show that bidders with more experience pay less than others even at the rounds where a price increase is more likely. Then we test if bidders benefit from this asymmetry by using the information signal emanating from the first bidder in a sequential auction. We find that when the first bidder is an experienced agent, the following bidders are more likely to bid higher than usual. In contrast, when the first bidder is not experienced, the price increase in the initial rounds is mitigated. These findings indicate that agents in the market are aware of the informational asymmetry and use it in their decision-making process by interacting with each other.

Our research delves into multiple aspects of the empirical literature on sequential auctions and market frameworks. We enhance the discourse on price dynamics in sequential auctions. Previous insights, such as those by Milgrom and Weber (1982), highlighted patterns like the "declining price anomaly" across various auction contexts like seafood, wine, and art.[1] To our knowledge, we use the largest available live auction data set and identify a non-monotonic price trend, challenging these patterns.

Furthermore, we shed light on auctions marked by asymmetric information, particularly in the seafood auctions. Despite all products being uniformly visible, auctions often involve both experienced and novice bidders competing for identical products in the same lot. Hence, it is reasonable to consider that information is distributed asymmetrically among the bidders. Our findings show that experienced bidders have different strategies, typically securing lower prices. Additionally, our research underscores the significance of information transmission in auctions, highlighting that initial bids, especially from

[1] Beggs and Graddy (1997) for art auctions; Ashenfelter and Genesove (1992) for real estate auctions; Chanel and Gérard-Varet (1996) for jewelry; and Pesando and Shum (1999) for Picasso prints.

experienced participants, influence the direction of subsequent bids.

Our paper is structured as follows: Section 4.1 provides a summary of relevant literature to which our study contributes. Section 4.2 outlines the market and auction dynamics within SFM. Section 4.3 details the data used in our empirical analysis and offers summary statistics for key variables used in the empirical analysis. Our empirical strategy is presented in Section 4.4, followed by the empirical results in Section 4.5. Lastly, Section 4.6 wraps up with a recap of our key contributions and highlights potential avenues for future research.

4.1 Related Literature

4.1.1 Price Dynamics

Milgrom and Weber (1982)'s model of sequential auctions for identical objects demonstrates that expected prices in each auction round remain the same. This result arises from two counterbalancing factors: the decreasing number of bidders and the declining count of objects throughout the sequence. Assuming risk-neutral bidders, these effects negate each other, leading prices to follow a martingale. Bidders with higher valuations find greater option value in waiting for subsequent auctions, causing them to moderate their initial bids. Consequently, all gains from delaying are neutralized. While this model primarily focuses on second-price auctions with two items, it's applicable to Dutch auctions and those featuring more than two objects.

Contrary to the above theoretical outcome, empirical studies do not offer consistent support. The 'declining price anomaly' was first pinpointed by Ashenfelter (1989) during sequential auctions of identical wine units. Several authors, including Ashenfelter and Genesove (1992), McAfee and Vincent (1993), and Ginsburgh (1998), have reported declining prices ranging from 0.25 to 1.5 percent in such auctions. The first strand of research attributes the decrease in prices to differences in bidder risk preferences, as outlined by McAfee and Vincent (1993). On the other hand, the second line of research emphasizes the role of information transmission and learning across sequential rounds Jeitschko (1998). Ginsburgh (1998) detects the anomaly in wine auctions and justifies it by the presence of absentee bidders, which does not align with the theory. Gallegati et al. (2011) documents the declining price anomaly in the Ancona fish market and explains it through evolving buyer behaviors that depend on the remaining supply, a threshold time, and the price of the last transactions.

Studies most closely aligned with ours in terms of auction structure, setting, and methodology include Berg, Van Ours, and Pradhan (2001) and Lu et al. (2019), both of which offer insights into the declining price anomaly observed in Dutch auctions for roses. While Berg, Van Ours, and Pradhan (2001) does not delve into the mechanisms behind this price dynamic and leaves it for future research, Lu et al. (2019) explains the declining trend via bidders' adaptive learning. Their study uncovers that by concealing the identity of the winner, it is possible to considerably mitigate the declining price trend in successive rounds. It's worth noting that, excluding these two studies, a majority of the literature primarily employs descriptive methods, often comparing mean prices per round for non-homogenous items.

Donald, Paarsch, and Robert (2006) developed the closest theoretical model to the SFM setting. According to their model, when agents demand at most one unit, prices follow a martingale pattern; however, if they demand multiple units from a good, the average price will increase over the course of the auction. In the SFM, bidders have the option to bid for more than one unit from a lot. This theoretical result lacks empirical support. Nonetheless, we document a price increase in the first four rounds of sequential auctions, partially aligning with their findings.

Our primary contribution predominantly arises from the dataset. This dataset ranks among the most extensive in terms of both the number of observations and the years it spans, particularly within the context of live auctions. This unique dataset provides valuable insights into the evolution of bidders over time, tracing their bids from entry to exit. In our approach, we incorporate lot fixed effects and introduce additional controls like experience and remote bidding status to determine price and rank. We further include the maximum rank fixed effects to enhance robustness in addressing potential concerns related to the endogeneity of the total rounds in a sequential auction. This approach builds upon the methodology developed by Berg, Van Ours, and Pradhan (2001) and contributes to a more robust analyses in the field of price dynamics literature.

4.1.2 Bidder Heterogeneity and Learning in Sequential Auctions

In the context of auctions, agent heterogeneity is predominantly analyzed through informational asymmetry. Engelbrecht-Wiggans and Weber (1983) and Hörner and Jamison (2008) model common-value sequential auctions with one informed and one uninformed bidder. Their models suggest that the uninformed bidder realizes a higher payoff, as the informed one cannot utilize his information without exposing it in subsequent stages. Since they focus on infinitely-repeated first-price auctions, their theoretical framework does not directly apply to SFM auctions. In SFM, it's rare for a bidder to participate more than once in a sequential auction, so concerns about revealing information are minimal.

Pezanis-Christou (2000) empirically analyzes Dutch auctions in a fish market with a model of two distinct bidder types having asymmetric preferences. While he observes that different bidder types indeed pay different prices, the overall trend remains unaffected by this asymmetry. In his study, bidder heterogeneity originates from their preferences. Whereas in our empirical model, the primary source of heterogeneity arises from varying levels of market and price knowledge acquired through experience. Hendricks and Porter (1988) explores the influence of asymmetric information on federal auctions for drainage leases. Consistent with our findings, their research reveals that firms with informational advantages achieve higher returns. Similarly, in an alternate context, Wang (1999) finds that floor traders, who have a comparative advantage in terms of knowledge, can better assess the presence of adverse information and are less sensitive to market volatility.

In our approach, heterogeneity and information asymmetry are determined using bidder experience. We highlight the pivotal role of experience in bidding. Goes, Karuga, and Tripathi (2010) employs a different measure of expertise by considering the time spent by each bidder in online auctions. They conduct an analysis of bidder heterogeneity, taking into account factors such as demand characteristics, experience, and winning status. This analysis reveals that bidders' willingness to pay and their bidding strategies exhibit variations depending on their level of experience. Similarly, our study also underscores the significance of experience as a key factor in shaping bidding behavior. These insights question the convention of common knowledge and bidder symmetry in traditional auction theory.

Additionally, our work augments the literature on learning within sequential auctions. Although bidding behavior in single-unit auctions receives comprehensive attention, studies on sequential auctions are more limited. In sequential auctions for homogeneous goods, bidders often derive their decisions from previous winning bids. Using sequential online auctions for identical items, Goes, Karuga, and Tripathi (2010) investigates how bidders learn and update their willingness to pay in a sequential auction environment. By actively participating in auctions, bidders accumulate and continuously update their information. They document that a bidder's decision is influenced by their experience from previous auctions, presenting this as evidence of bidder learning. In this study, the learning source is other bidders' bids from previous rounds in a sequential auction. We document that bidders consider earlier bids when making decisions, and the experience level of the first bidder determines the direction of subsequent bidders' bids.

Lastly, Jeitschko (1998) explores information transmission and learning in a sequential auction. In his model, bidders with independent private values learn their opponents' types from winning bids. He argues that this learning has two impacts: one directly influencing the bidder's strategy and the other operating through the anticipation effect. In our paper, we uncover evidence supporting the former, leading us to conclude that information disseminated through others' bids is a crucial factor for comprehending bidders' strategies in sequential auctions and elucidating market trends.

4.2 Context - Sydney Fish Market

Sydney Fish Market is Australia's leading seafood market, facilitating the sale of more than 13,000 tonnes of seafood, valued at approximately AUD 150,000,000,[2] annually. As the second-largest fish market in terms of variety and the third-largest in terms of volume worldwide, SFM holds significant prominence in the fish industry. Since 1989, SFM has employed Dutch auctions to sell fresh and frozen seafood products, aiming to enhance the efficiency of fish sales and rapidly attain premium prices (Sydney Fish Market, 2022).

Dutch auctions are a unique mechanism used in various markets, particularly in the sale of items with uncertain or perishable values, such as flowers, seafood, and even certain financial instruments. In a Dutch auction, the seller starts with a high asking price and gradually lowers it over time until a buyer accepts the price or a predetermined reserve price is reached. Bidders indicate their willingness to purchase at the current price by signaling their interest, and the first bidder to do so secures the item at that price. Dutch auctions are known for their simplicity and efficiency, as they enable quick price discovery and accommodate various buyer preferences.

In SFM, starting at 5:00 am every weekday, except for public holidays, and utilizing three identical auction clocks working simultaneously, SFM conducts Dutch auctions that commence with a price slightly higher than the anticipated value of the seafood product and decrease until a bid is placed. Bidders can arrive at the market before the auctions begin to inspect the products brought by suppliers on the auction floor. Trained and experienced auctioneers set an initial price per kilogram, typically

[2] All prices from this point onward are in Australian Dollars (AUD).

around 2 to 5 dolars higher than the expected final price. These auctioneers represent SFM, which takes a share of the sellers' revenues, aligning their objective with maximizing the selling price. Under the Dutch auction system, approximately twenty tonnes of seafood (equivalent to around 1,000 crates) are sold every hour, with an average of 50-55 tonnes of fresh and live seafood sold each day (Sydney Fish Market, 2022). There are three auction clocks selling products simultaneously, and each bidder's terminal features three bid buttons, enabling them to participate in all three auctions.

In the market, products are sold in 'lots' (see Figure 4.2 for the lot structure). These lots are pivotal to our identification strategy, with lot fixed effects being the primary empirical approach. Each lot consists of homogeneous seafood, divided into multiple crates from one supplier, one species, one size, and one processing type. A lot is randomly divided into crates, which the auctioneer sells sequentially. Bidders do not know in advance which crate from the lot they will receive. On average, it takes two to three minutes to auction off one lot. Since all aspects related to the supplier and species are identical within a lot, the only sources of variation stem from the bidders' characteristics, such as differences in experience, loyalty, demand elasticity, and the order in which they win the auction.

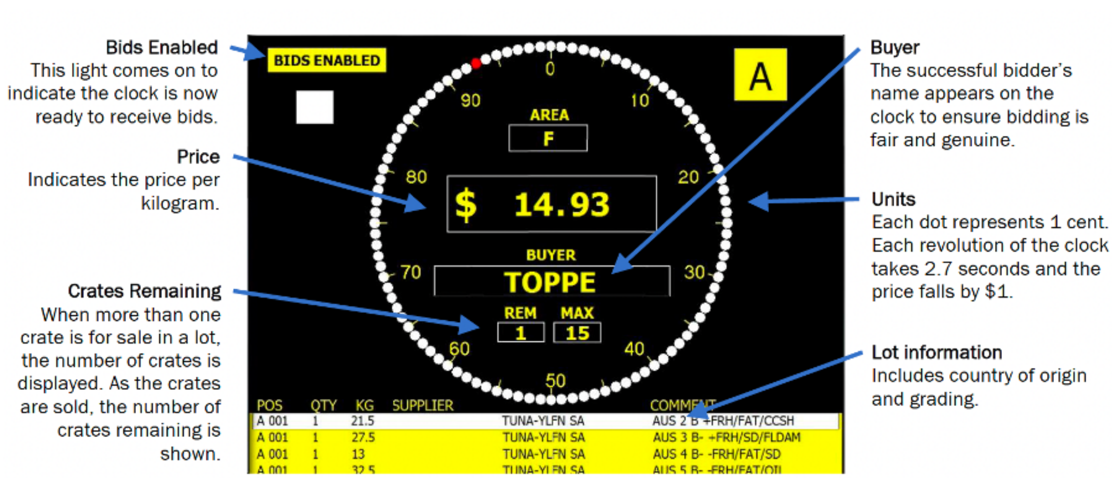


Figure 4.3: The auction clock, source: Sydney Fish Market, 2022

At the starting point of each lot auction, the auctioneer decides at a starting price that is slightly higher than the anticipated bid prices and sets the clock (in Figure 4.3) in motion. Each revolution of clock takes 2.7 seconds and corresponds to $1 price decrease. As the price shown on the clock declines, bidders can press the button and stop the clock on the price at which they want to place their bid. Then the winner chooses the number of crates he wants to purchase from the lot. The identity of the winner and number of crates sold are displayed on the clock. If there are more crates to be sold in the lot, the clock ticks backward to the point where it is $1 higher than the last bid, and the auction continues. This process is repeated until all crates are sold in the lot.

There are 350 registered active buyers in the market, and on average, 150 buyers actively trade every auction day. SFM also allows remote bidding from anywhere in Australia and New Zealand, so buyers no longer need to be at the market while bidding. Especially after COVID measures, there has been an increase in the number of remote bidders. The daily average number of remote bidders in 2021 is 69,[3] almost half of all buyers, 146. Seafood is accepted to the auction hall starting from 6 pm one day before, and buyers start viewing the products from 4:30 am on the auction day. All products are sold on a first-in first-sold basis. A supplier who arrives earlier sells all his products before the next one starts selling.

4.3 Data

All information on the clock (see Figure 4.3), along with the date of sale, transaction time, supplier and buyer code, supplier region, and quality and process information of some species, are available in the data. The SFM data capture all the auction transactions made from 03/01/1995 to 29/04/2022. In terms of the large period it spans and its comprehensiveness, the SFM data provides a unique opportunity to better test some hypotheses in the literature and understand bidding behavior that cannot be predicted by the theory.

Each transaction involves two decision variables for the bidder: price and quantity of crates. The rest can be categorized as follows: characteristics of the fish sold (species, process, condition, and size), characteristics of the crate (lot number, weight and type), transaction date and time, supplier information (region, type), identifiers for the agents, remote bidding status (based on the seat number), and clock type.

In Table 4.1, we present an overview of our data.[4] In this example, we observe six different transactions, each containing information about the supplier, bidder, species, lot, as well as product details, size, condition, and bidder decision variables, including price and quantity. While specific species include details about size and process, premium species such as mud crabs or sashimi-grade tunas include condition information. Notably, unlike most prior studies that focus on single-unit auctions, our setting allows bidders to bid for more than one unit.[5]

[3] However, Erik Poole, the Innovation & Technical Manager at Sydney Fish Market, noted that this number had significantly declined by 2023, attributing it to the absence of COVID-related restrictions.

[4] Please note that due to space constraints, not all available variables are included.

[5] The maximum bidding quantity is typically limited to 15 units for most species.

Date	Time	Supplier No	Bidder No	Lot No	Species	Size	Condition	Price	Quantity
29/01/15	05:51	113301	104622	309	68	M		2.75	2
29/01/15	05:53	133402	56317	591	125		B	14.41	1
29/01/15	05:54	113301	135550	310	28	L		15.94	1
29/01/15	05:54	113402	110111	592	125		A	16	1
29/01/15	05:54	113402	110111	593	125		A	16	1
29/01/15	05:55	113301	8642	311	58	X		3.47	2

Notes: This table presents a snapshot from the data with anonymized supplier, bidder, and species identifiers.

Table 4.1: A Sample Entry in the Data

	count	mean	sd	min	max
Supplier No.	4,887			40	159811
Bidder No.	2,093			2323	703872
Species Code	706			1	9999
Lot	8,205,505		.	1	8,207,631
Maximum Rank	12,334,654	4.40	7.00	1	96
Price	12,334,654	9.12	9.44	.01	1313.5
Crate Weight (Kg)	12,334,654	17.70	8.63	0.2	922
Crate Quantity	12,334,654	1.54	1.75	1	2040
Hours	9,721,021	6.40	1.06	0	21
Remote bidder	12,334,654	0.02	0.13	0	1
Total transaction of bidder	12,334,654	27223.19	31944.69	0	265598
Pc. rank of experience	12,334,654	50.50	28.88	1	100
Observations	12,334,654				

Notes: The first four rows provide summaries of the number of suppliers, bidders, species, and lots within our dataset, identified by unique identifiers. *Maximum Rank* signifies the total number of rounds within a sequential auction for a lot, *Hours* represents time in hh:mm format, *Remote Bidder* is a binary variable denoting bidding status, *Total transactions of bidder* counts all the transactions a bidder has from their entry to the last recorded point in the data, and *Pc. rank of experience* ranks each active bidder on a given day based on their total number of transactions and assigns them a percentile rank.

Table 4.2: Summary Statistics

	Max. Rank =1		Max. Rank >1		Difference	
	mean	sd	mean	sd	b	se
Maximum Rank			8.83	8.84		
Price	10.58	11.26	7.23	5.81	3.35***	(0.00)
Crate Weight (Kg)	16.04	9.38	19.85	6.99	-3.81***	(0.00)
Crate Quantity	1.27	1.53	1.90	1.95	-0.62***	(0.00)
Hours	6.40	1.10	6.40	1.01	0.01***	(0.00)
Remote bidder	0.02	0.13	0.02	0.14	-0.00***	(0.00)
Total transaction of bidder	27,287.33	32,326.76	27,139.81	31,440.89	147.52***	(18.28)
Pc. rank of experience	50.80	28.90	50.11	28.85	0.69***	(0.02)
Observations	6,971,634		5,363,020		12,334,654	

Notes: This table compares the above variables between single-unit auctions in the market (maximum rank = 1) and multi-unit auctions (maximum rank > 1).

Table 4.3: Descriptive statistics by maximum rank

Table 4.2 and 4.3 provide summaries of the descriptive statistics for our sample. In total, our dataset comprises 12,334,654 auction transactions for fresh seafood. However, only 5,363,020[6] of these transactions were conducted in sequential auctions, while 6,971,634 transactions were completed as single units. Nevertheless, these single-round auctions are not relevant for understanding how prices evolve in sequential auction rounds. Therefore, in this paper, we focus exclusively on this sub-sample of multi-unit sequential auctions.

Within the dataset's timeline, we observe 4,887 suppliers and 2,093 bidders participating in the market, bidding for 706 different species. While the overall average for the maximum rank is 4.40, for the sample of interest, the average is 8.83, and the median maximum rank is 6. The average price in the data is $12, with relatively high variation; prices can reach as high as $500 for live seafood like mud crabs and rock lobsters. As expected, prices are significantly higher for single-round transactions. This is mainly because premium species, such as crabs and tuna fish, are almost always sold via single-lot auctions, whereas smaller and cheaper species that come in large batches are more likely to be sold in multiple rounds. The overall average crate weight is 19.85 kilograms, slightly higher for transactions made in sequential auctions. As bidders can bid for more than one unit (crate), the average crate quantity for a transaction is 1.54. Although over 96% of the transactions occur between 5 am and 8 am, we observe transactions taking place from 12 am to 9 pm. The average transaction time for all transactions is around 6:24 am. Approximately 2% of all transactions were conducted via remote bidding, with this system first introduced in 2016, but not becoming prevalent until COVID restrictions were put in place in March 2020.

Experience plays a significant role in explaining price dispersion. In this paper, as a novelty, we define experience based on the total number of transactions a bidder has participated in. On average, we observe that a bidder in our sample has been involved in 27,223 transactions. Since our primary focus is on relative experience, we rank all active bidders in a day according to their total number of transactions. For simplicity in interpretation, we assign them their percentile rank among the active bidders on that day based on their experience level. Additionally, we note that bidders in the single-unit auctions are slightly more experienced on average.

[6] Please refer to Appendix Figure A3.1 for the distribution of maximum rank among multi-unit lots.

4.4 Empirical Strategy

In this section, we introduce our empirical strategy, building on Berg, Van Ours, and Pradhan (2001) and Lu et al. (2019).

Many studies evaluating price dynamics in sequential auctions simply compare the means of realized prices in each round or use OLS regression (Ashenfelter and Genesove, 1992; Ginsburgh, 1998). There are two main concerns that may confound the results of a simple regression of the price on the rank number of the transaction within the lot.

Firstly, the total number of rounds within a lot (maximum rank) varies between different lots, even for the same species. This factor is unlikely to be exogenous, as it depends on the bidding behavior and the prices realized in previous rounds of the lot. Suppose that, due to a shock observed by bidders but unobserved by the researcher, bidders decide to buy in bulk from a particular lot, creating more competition and higher prices. This shock impacts the number of ranks and the prices within the sequential auction of a lot. Consequently, the coefficients of low-rank numbers are biased upwards, whereas the coefficients of higher-rank numbers are biased downwards.

Secondly, as the observed prices within a sequential auction are plausibly dependent, unobserved price shocks, such as unexpected weather affecting the number of catches, can impact all prices in a sequential auction. Even if all sequential auctions had the same number of rounds within a lot, a simple regression would generate biased estimates due to this dependence.

Following Berg, Van Ours, and Pradhan (2001), we use a lot-fixed effects model to alleviate both of these concerns. In SFM, suppliers' products are sold via lots that contain crates of homogenous seafood. By utilizing lot fixed effects, we can fully eliminate unobserved heterogeneity that arises from demand and supply shocks and seasonality. The following econometric model allows us to compare the bidding behavior and prices in different rounds of a sequential auction of a lot.

$$logp_{ij} = \alpha_i + \beta_j r_{ij} + \epsilon_{ij} \tag{4.1}$$

where p_{ij} is the price paid per kilogram of fish in the transaction with rank number (sale order) $j = 1, ..., J_i$ in the sequential auction lot $i = 1, ...N$. α_i is the lot-specific fixed effect that captures the observed and unobserved heterogeneity between lots. r_{ij} is the dummy variable indicating the rank number of the transaction within a lot. The coefficient of interest β_j shows the price change within a lot in round j (r_{ij}) relative to the first sale in the lot (r_{i1}). Finally, the remaining variation in the outcome variable is captured by the random variable ϵ_{ij}.

Furthermore, to provide extra robustness, they take the first differences of consecutive rounds in a lot in equation (1) to cancel out the fixed effects from the model. Then the model becomes:

$$log\frac{p_{ij}}{p_{ij-1}} = \beta_j^* + \epsilon_{ij}^* \tag{4.2}$$

where $\beta_j^* = \beta_j - \beta_{j-1}$, and $\epsilon_{ij}^* = \epsilon_{ij} - \epsilon_{ij-1}$. The constant term, β_j^*, is the logarithmic price difference between the consecutive rounds. Berg, Van Ours, and Pradhan (2001) argues that this model has two advantages. First, it addresses the first potential issue by controlling the confounding factors that may affect transaction price and the maximum number of rounds. Second, factors that may bias results, such as the potential dependence of prices within a sequential auction, and unobserved heterogeneity within and between lots, are no longer a threat under this specification.

While Equation 4.2 serves as the baseline model, we enhance this model by adding additional controls to explain the price difference between consecutive rounds:

$$\begin{aligned} log\frac{p_{ij}}{p_{ij-1}} &= \gamma_1 + \gamma_2(Available_{ij-1} - 2) + \gamma_3(Rank_{i,j} - 2) \\ &+ \gamma_4(Rank_{ij} - 2)^2 + \gamma_5 RelWeight_{ij} \\ &+ \gamma_6 RelQuantity_{ij} + \gamma_7 Remote_{ij} \\ &+ \gamma_8 RelExperience_{ij} + \nu_{ij} \end{aligned} \tag{4.3}$$

where $Rank_{ij}$ indicates the rank number,[7] $Available_{ij-1}$ is the number of remaining units at the beginning of round $j-1$ of the lot i.[8] Berg, Van Ours, and Pradhan (2001) adds the $Rank_{ij}$ variable in continuous form to the first-differenced model to discern the price dynamics over the course of a sequential auction.

While we follow Berg, Van Ours, and Pradhan (2001) and Lu et al. (2019) by adding the above controls, we contribute to the empirical strategy by incorporating the following variables to explain

[7] This variable and its square are only used in the pooled regressions, as they do not vary in regressions where we separately analyze price changes in each round.

[8] We control this variable to distinguish the impact of the remaining number of units from the rank effect. The base auction for comparison has two units sold in two rounds, hence we subtract 2 from these variables.

the price dispersion caused by factors other than the round of the sale. The remaining variables indicating the relative difference come from first differencing observed characteristics $X^*_{ij} = X_{ij} - X_{ij-1}$ where X includes the weight of the crates, the quantity of crates bought, remote bidding status, and percentile experience rank. Specifically, $RelWeight$ represents the weight of the unit in round j relative to the one sold in round $j-1$ ($Weight_{ij} - Weight_{ij-1}$), *RelQuantity* is the relative number of units bought ($Quantity_{ij} - Quantity_{ij-1}$), *Remote* denotes the relative status of remote bidding, and *RelExperience* reflects the relative level of percentile experience rank compared to the previous round's winner ($Experience_{ij} - Experience_{ij-1}$ where *Experience* denotes the percentile experience rank of the bidder on the day). All of these variables are observed by the bidders except experience; however, as most bidders see each other in the market most days, they have an understanding of the winner's experience.

To our knowledge, this model, enabled by our extensive dataset, represents the first instance of incorporating these variables into the empirical model to assess the influence of bidder heterogeneity in terms of knowledge, demand, and bidding status. This approach proves valuable, as it allows us to consider that the price difference between consecutive rounds may not be solely attributable to the rank effect. Bidder heterogeneity is of importance in sequential auction settings, as bidders with different level of knowledge likely to participate at different stages. In our model, we incorporate bidder heterogeneity by considering their relative experience and whether they engage in remote bidding. We also account for variations in their demand by examining differences in the number of crates. Additionally, we take into account rank level differences that can influence prices, such as the remaining number of units and the transaction's weight. By doing so, we eliminate the influence of bidder heterogeneity and many potential factors, allowing us to obtain a more precise estimate of the rank effect on price dynamics. Furthermore, this approach helps us understand the impact of experience on price.

Before proceeding to the results, we present an analysis of the assumptions concerning the variance-covariance matrix of the error terms. We employ the Breusch-Pagan test to assess the null hypothesis of constant variance among the residuals. The test rejects the hypothesis of homoskedastic errors ($p < 0.001$). To address this issue, we utilize heteroskedastic-robust standard errors. Additionally, we conduct the Breusch-Godfrey test to examine higher-order serial correlation. This test rejects the null hypothesis of no serial correlation ($p < 0.001$). Consequently, in line with Lu et al. (2019), we cluster standard errors at the species level, allowing error terms within sequential auctions for the same species to be correlated.[9]

[9] Our results remain robust when considering alternative clustering settings, including bidder, supplier, and date.

4.5 Empirical Results

In this section, we begin by presenting our primary results, which illustrate the influence of sale order on price dynamics. Subsequently, in our pursuit of understanding the factors that contribute to these observed price dispersion, we delve into the impact of bidder experience on price dynamics. Finally, we conduct an analysis of the effect of bidder learning from the initial bids and underscore the significance of bidder heterogeneity.

4.5.1 Effect of Sale Rank on Price Dynamics

In this subsection, we investigate the impact of sale rank on price dynamics. As discussed in Section 4.1.1, much of the empirical literature points out a declining price trend in sequential auctions. However, we find that prices first increase and then decrease in a sequential auction for homogeneous seafood (please refer to Figure 4.1 for the average trend). Our model departs from previous work because we have information on bidders' identities and expertise levels, which we incorporate into the estimations. Consequently, our estimates for price differences between consecutive rounds are net of bidder heterogeneity.

Table 4.4 provides the results for pooled regressions, where we do not conduct separate analyses for each rank. In the initial regression without any controls, as outlined in Equation 4.2, the results are presented in the first column. Notably, we observe a positive and statistically significant coefficient for the intercept term. This implies a significant overall price increase between consecutive rounds. However, while this model provides a general understanding of the average price change between consecutive rounds and serves as a baseline for comparison to analyze the differences when incorporating bidder-related controls, it is not the primary specification we report for price dynamics. In column 2, following Equation 4.3 with additional controls, we observe that the coefficient nearly doubles in magnitude. Furthermore, to account for potential curvilinearity between prices and rank numbers within a sequential auction, following Lu et al. (2019) we introduce $Rank^2$ to the model, and the results are presented in column (3) of Table 4.4. Here, we notice that the coefficient becomes three times larger compared to the model with no controls, highlighting the significant influence of bidder-related controls on average price changes.

Although there is a significant price increase between consecutive rounds, factors such as crate weight, crate quantity, and bidder experience tend to mitigate this increase. We delve deeper into the impact

Variable	(1)	(2)	(3)
Intercept	0.0009***	0.0016***	0.0025***
	(0.00027)	(0.00038)	(0.00045)
Available		0.0001***	0.0001***
		(0.00002)	(0.00002)
Difference in crate weight		-0.0025***	-0.0026***
		(0.00027)	(0.00026)
Difference in crate quantity		-0.0025***	-0.0025***
		(0.00019)	(0.00019)
Difference in remote bidding		0.0051***	0.0051***
		(0.00044)	(0.00044)
Difference in experience		-0.0048***	-0.0048***
		(0.00037)	(0.00037)
Rank		-0.0003***	-0.0007***
		(0.00005)	(0.00007)
$Rank^2$			0.00002***
			(0.00000)
Observations	4,134,149	4,134,149	4,134,149
R^2	0.000	0.014	0.015

Notes: The first column represents a basic log difference regression with only an intercept term. In the second column, the results include the controls presented in the model. The third column includes additional results incorporating the control variable $Rank^2$ to account for a potential curvilinear relationship between price change and round number. The *Intercept* in this table represents the change in log prices between consecutive rounds. This table is based on the pooled sample, which means the coefficient represents the average of all price changes between consecutive rounds. Heteroskedasticity-robust standard errors, clustered by species, are presented within parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4.4: Pooled Sample: Effect of Rank on Price Dynamics

of experience in the following subsection. Additionally, remote bidding is associated with a more pronounced price increase, implying that remote bidders are inclined to pay higher prices than live bidders between consecutive rounds. Moreover, the positive coefficient on the number of remaining available units suggests that a more substantial price increase occurs when fewer units are left in the lot. Furthermore, the negative coefficient on the rank variable indicates that the magnitude of price increase tends to diminish over time, emphasizing the need for a more in-depth analysis of each rank.

Although the results in Table 4.4 show that overall prices tend to increase, the negative point estimate for the rank variable suggests that whole dynamics may indicate a decline after some rounds. Thus, to present our main results, we run separate regressions for each rank to check the impact of rank on price dynamics. Our preferred specification is with maximum rank fixed effects. Only the results up to 13th rank are presented.[10]

[10] More than 95% of sequential auctions end within 13 rounds.

Panel A: Rank 2 to 7						
Rank numbers	1→2	2→3	3→4	4→5	5→6	6→7
Intercept	0.0024***	0.0029***	-0.0000	-0.0017***	-0.0027***	-0.0028***
	(0.00019)	(0.00010)	(0.00011)	(0.00012)	(0.00013)	(0.00015)
Available	0.0004***	0.0002***	0.0001***	0.0000***	0.0000*	0.0000
	(0.00004)	(0.00002)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Difference in crate weight	-0.0033***	-0.0004	0.0001	-0.0008	0.0001	0.0007
	(0.00035)	(0.00027)	(0.00033)	(0.00050)	(0.00025)	(0.00048)
Difference in crate quantity	-0.0036***	-0.0024***	-0.0022***	-0.0019***	-0.0018***	-0.0016***
	(0.00027)	(0.00018)	(0.00018)	(0.00017)	(0.00015)	(0.00014)
Difference in remote bidding	0.0069***	0.0052***	0.0047***	0.0044***	0.0043***	0.0044***
	(0.00079)	(0.00053)	(0.00050)	(0.00058)	(0.00050)	(0.00077)
Difference in experience	-0.0078***	-0.0052***	-0.0042***	-0.0039***	-0.0028***	-0.0031***
	(0.00068)	(0.00042)	(0.00036)	(0.00032)	(0.00022)	(0.00025)
Observations	1,228,871	665,969	448,021	328,832	252,198	199,188
R^2	0.020	0.016	0.015	0.014	0.016	0.012
Panel B: Rank 8 to 13						
Rank numbers	7→8	8→9	9→10	10→11	11→12	12→13
Intercept	-0.0022***	-0.0017***	-0.0017***	-0.0015***	-0.0013***	-0.0015***
	(0.00025)	(0.00027)	(0.00024)	(0.00025)	(0.00023)	(0.00031)
Available	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Difference in crate weight	-0.0004	-0.0018	-0.0008	-0.0024	-0.0000	0.0003
	(0.00049)	(0.00200)	(0.00117)	(0.00235)	(0.00048)	(0.00034)
Difference in crate quantity	-0.0015***	-0.0015***	-0.0014***	-0.0014***	-0.0014***	-0.0014***
	(0.00015)	(0.00015)	(0.00014)	(0.00013)	(0.00014)	(0.00013)
Difference in remote bidding	0.0041***	0.0043***	0.0043***	0.0048***	0.0042***	0.0035***
	(0.00063)	(0.00068)	(0.00083)	(0.00069)	(0.00081)	(0.00073)
Difference in experience	-0.0031***	-0.0027***	-0.0025***	-0.0029***	-0.0022***	-0.0022***
	(0.00028)	(0.00022)	(0.00030)	(0.00031)	(0.00031)	(0.00037)
Observations	160,052	130,669	107,562	89,294	74,828	62,836
R^2	0.013	0.014	0.015	0.015	0.016	0.012

Notes: This table provides a separate analysis of the log price change for each rank to investigate price dynamics. Panel A displays results from Rank 2 to 7, while Panel B presents results for Rank 8 to 13. The *Intercept* term represents the causal effect of the rank number on the price change. Heteroskedasticity-robust standard errors, clustered by species, are presented within parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4.5: Effect of Rank on Price Dynamics

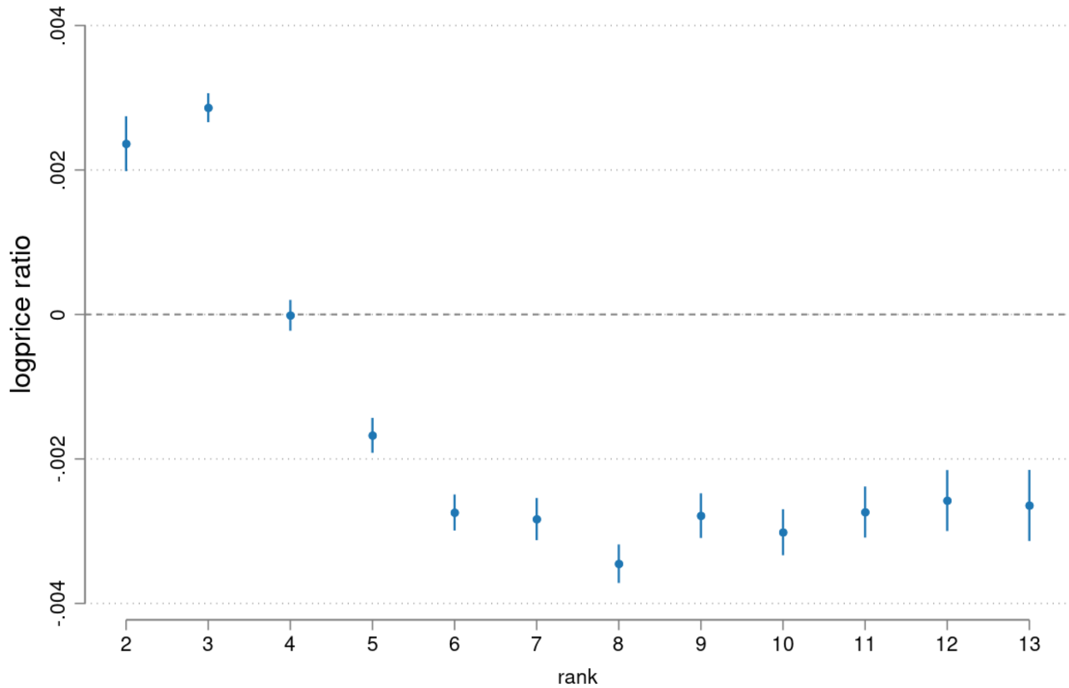


Figure 4.4: Rank Effect on Price Dynamics

Notes: This figure visually represents the price dynamics in sequential auctions relative to the rank number. Each point corresponds to the coefficient of the *Intercept* as shown in Table 4.5, and is accompanied by 95% confidence intervals.

To gain a more detailed insight into price dynamics, we conduct separate regressions for each rank, following equation 4.3.[11] Table 4.5 presents the results for the model described in equation 4.3 for each specific rank number, and Figure 4.4 provides a graphical representation of the coefficients derived from these regressions. The point estimates for the intercept term indicate that prices tend to increase in the first three rounds, after which they consistently decline. This finding implies that, contrary to what previous literature suggests, prices exhibit a non-monotonic trend, as evidenced in Figure 4.4, where each point estimate compares prices across consecutive sale rounds. Thus, in contrast to theoretical expectations, prices do not adhere to a martingale pattern; instead, they exhibit an inverted U-shape.[12] To our knowledge, this finding is a first in the sequential auctions context.

Other variables in the regression exhibit a more consistent pattern. We do not observe any reversals in direction, and the magnitudes of most variables do not exhibit significant changes; the majority of point estimates remain relatively stable after the second round. As depicted in Table 4.4, the impact of remote bidding and the quantity of available units consistently leads to higher prices, while greater

[11]Berg, Van Ours, and Pradhan (2001) also presents their primary findings using a similar approach.

[12]Please refer to Figure A3.2 which follows equation 4.1 for a visual representation of this inverted U-shape. In this plot, the point estimate for each rank (round) indicates the log price comparison with the first round sale.

bidder experience consistently results in lower prices. Interestingly, crate weight does not appear to have a substantial impact, but higher crate quantity is associated with lower prices.

As previously mentioned, the maximum number of ranks is likely to be endogenous, given its influence on both bidding behavior and the sale order. In the model presented in equation 4.2, sequential auctions that conclude in j_0 rounds do not impact the estimation of price changes in rounds $j > j_0$. In order to provide a better understanding of the impact of maximum rank and perform a robustness check, we provide results for each maximum rank less than 11 in Appendix Figure A3.3. Notably, we observe that the non-monotonic trend persists for each maximum rank, reaffirming our primary finding.

4.5.2 Effect of Experience on Price Dynamics

In this subsection, we analyze the impact of bidders' experience on their bidding behavior and price dynamics. We measure experience as the daily percentile rank of each bidder in terms of their total transaction numbers among all active bidders for that day. To the best of our knowledge, previous studies that focus on live auctions have not documented bidder expertise in sequential auctions.[13] Bidders with more transaction experience are better equipped to accurately assess the price level corresponding to a particular lot's quality. Our contribution to the literature on information asymmetry and bidder heterogeneity lies in incorporating experience into our model and examining its impact on bidder decisions. This innovative approach to measuring expertise also enables us to isolate the rank effect on price dynamics by controlling for the influence of experience on prices.

In Table 4.4, under each model specification, we observe that higher experience leads to a lower price difference between consecutive rounds. This suggests that when there is a positive and large difference in experience, the price increase is mitigated. To analyze the impact of experience at each rank separately, Figure 4.5 visualizes the results from Table 4.5. It is evident that at all rounds, experience plays a significant role in mitigating price increases. However, its impact is more pronounced in the first three ranks, where the price increase is observed (See Figure 4.4 for the price increase). The impact of experience is smaller in magnitude after the 4^{th} round, where the price increase is no longer present. Hence, experience plays a more remarkable role in the ranks where we observe the unexpected price increase. This decline in the impact of experience can also be attributed to bidders' learning through observing previous bids, which reduces the information asymmetry stemming from differing levels of experience.

[13] Goes, Karuga, and Tripathi (2010) measures experience using the time spent on online auctions.

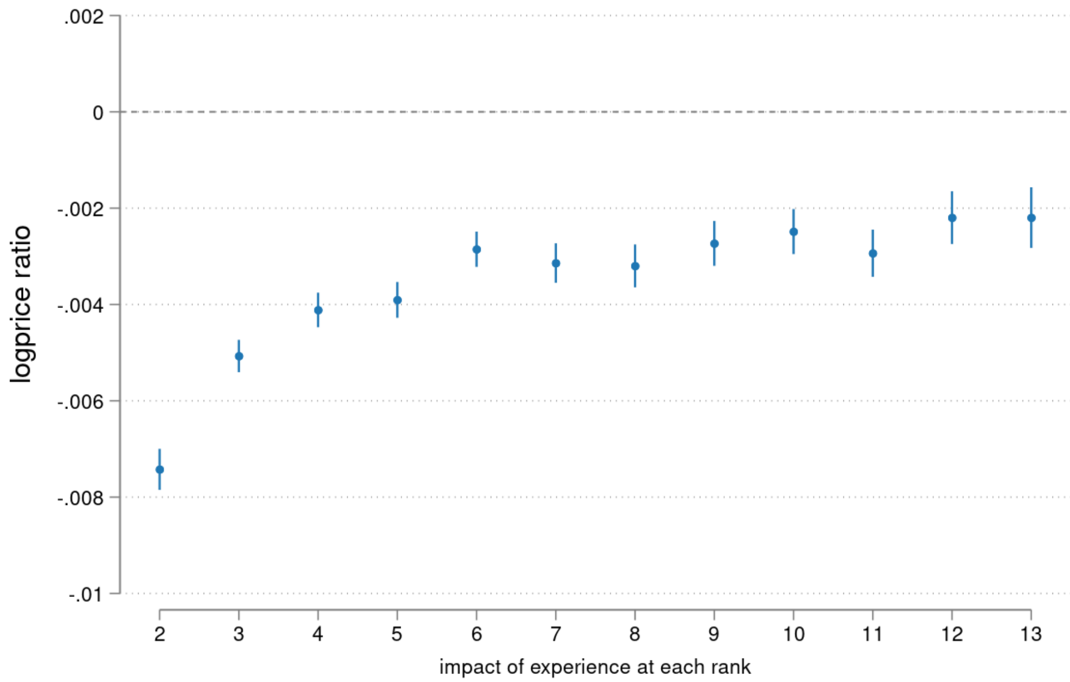


Figure 4.5: Experience Effect on Price Dynamics

Notes: This figure visually represents the effect of difference in *pc. experience rank* on price dynamics in sequential auctions for each rank number. Each point corresponds to the coefficient of the *Difference in experience* as shown in Table 4.5, and is accompanied by 95% confidence intervals.

To further investigate the role of relative experience on price trends, we categorize the difference in experience ($\text{experience}_{ij} - \text{experience}_{ij-1}$) into five equal categories, where a higher number of groups implies a higher positive difference. The median group, which serves as the base group for comparison, represents the category with the least difference in experience between consecutive bidders, indicating that bidders in this group have somewhat similar experience levels. Table 4.6 presents the results of the pooled regression. In column (1), we display the results of the regression based on equation 4.3, excluding the experience variable. This specification helps us understand the impact of controlling for experience on price. In column (2), we control for the continuous relative experience variable.[14] The coefficient of the intercept remains unchanged, and the sign of experience indicates that more experienced bidders pay less compared to the previous bidder.

In column (3) of Table 4.6, we present the results for a regression that includes experience as dummy variables for the relative experience groups. The median group, consisting of bidders with similar experience levels, serves as the base group for comparison. The results indicate that when a bidder is less experienced, the price difference with the previous rank is positive, whereas it becomes negative

[14]This regression is identical to the estimated model in Table 4.4, column (3).

	(1)	(2)	(3)
Intercept	0.0025***	0.0025***	0.0018***
	(0.00045)	(0.00045)	(0.00047)
Difference in experience		-0.0048***	
		(0.00008)	
Relative experience groups			
1: $(-99 <= RelExp <= -60)$			0.0042***
			(0.00031)
2: $(-60 < RelExp <= -20)$			0.0029***
			(0.00023)
3: $(-20 < RelExp <= 20)$: **The base group**			
4: $(20 < RelExp <= 60)$			-0.0007***
			(0.00012)
5: $(60 < RelExp <= 100)$			-0.0029***
			(0.00032)
Observations	4,134,149	4,134,149	4,134,149
R^2	0.016	0.017	0.017

Notes: The first column exhibits the outcomes of the regression with all controls, except for the difference in the *pc. experience rank* variable. In the second column, the results incorporate the difference in the *pc. experience rank* variable as well. The third column introduces difference in experience measure as relative experience group indicators, using the median relative experience group as the reference for comparison. The *Intercept* in this table represents the average change in log prices between consecutive rounds. This table is based on the pooled sample, which means the coefficient represents the average of all price changes between consecutive rounds. Heteroskedasticity-robust standard errors, clustered by species, are presented within parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4.6: Pooled Sample: Effect of Experience on Price Dynamics

when the bidder is more experienced. Furthermore, we emphasize that the magnitude of price change increases with the difference in experience level between consecutive bidders. Therefore, we can conclude that the impact of relative experience intensity depends on the size of the experience level discrepancy. Additionally, the difference between the *Intercept* coefficients in column (1), where no experience measure is controlled, and column (3), where we include relative experience groups, suggests that price dispersion is one-third smaller when experience is taken into account. This underscores the importance of considering bidder heterogeneity when studying price dynamics in sequential auctions.

To gain further insights into the influence of experience under varying levels of asymmetric information, we conduct separate analyses on two distinct species groups: those characterized by higher price uncertainty and those characterized by lower price uncertainty. We postulate that experience may exert a more pronounced effect in auctions with higher uncertainty, where bidders have greater opportunities to exploit their knowledge advantage. We determine the price uncertainty of species-process pairs based on the average daily price variance. Species falling within the top quartile of this measure are classified

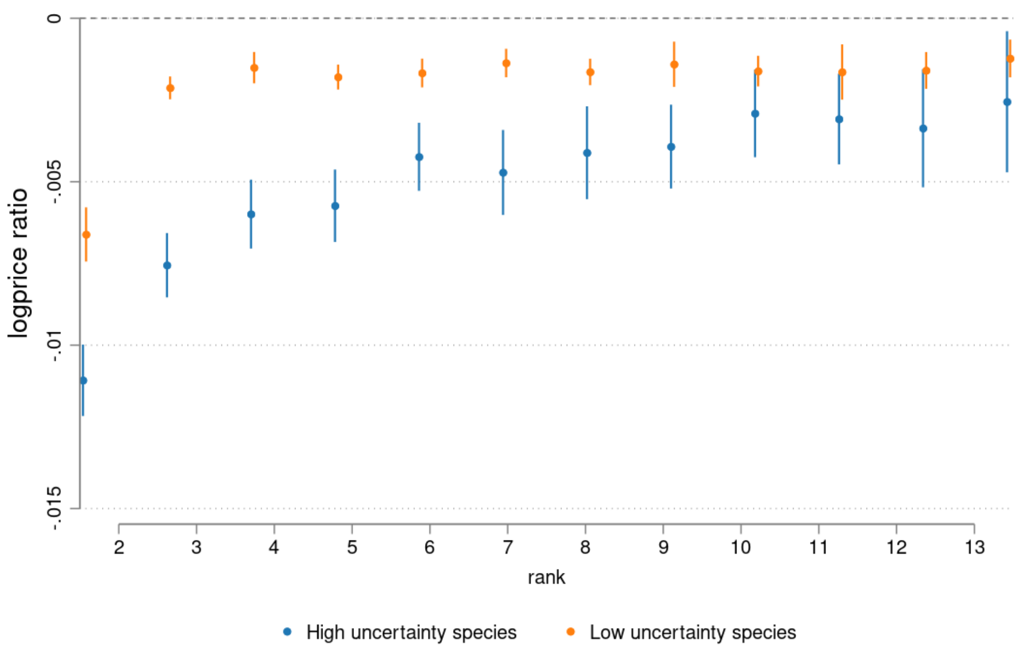


Figure 4.6: Effect of Experience on Price Dynamics by Uncertainty

Notes: This figure visually represents the price dynamics in sequential auctions relative to the rank number separately for species with price variance in the top quartile and species with price variance in the bottom quartile. Each coefficient point corresponds to the estimates of *Intercept* in Table A3.1, and is accompanied by 95% confidence intervals.

as 'high uncertainty species,' while those in the bottom quartile are classified as 'low uncertainty species.' This classification remains robust even when accounting for seasonality, as the uncertainty measure relies on daily price variances.

In Figure 4.6, we present the coefficients on experience for each sales order, following Equation 4.3.[15] This analysis confirms that, overall, experience leads to lower bid prices. However, for species facing high price uncertainty, the coefficient is at least twice as large as that for species with low price uncertainty. This suggests that experience plays a more substantial role in bidding when there is a higher level of information asymmetry, granting experienced bidders a distinct advantage. Furthermore, we observe that this difference begins to diminish after the 6th rank, indicating that the first 5 rounds have already provided sufficient information to reduce uncertainty about the lot's price. Consequently, experience no longer plays a pivotal role in price determination after round 5, as learning from previous bids becomes increasingly influential.

[15]Regression outcomes can be found in Table A3.1.

4.5.3 Signaling via First Bidder Experience

In the previous subsections, we first establish that prices follow a non-monotonic trend in sequential auctions for homogenous seafood. Then we show that the level of price dispersion depends on bidders' relative experience levels compared to the previous bidder. To have a deeper understanding of how prices evolve based on bidder heterogeneity, in this subsection, we focus on the learning behavior using the first bidder's bid in the lot as a signal to others. The bidders in SFM tend to know and interact with each other as they gather together in SFM almost daily. Hence, when an experienced (or a more knowledgeable) bidder makes the first bid in a sequential auction, it is plausible to think that this can have an impact on the competition, information acquired by other bidders, and hence the price dynamics. A more experienced bidder's bid is more likely to give a stronger signal, especially when there is uncertainty about the quality of the product and the price range a product might have, and this can impact others' bids. In this section, we investigate this claim.

	First bidder's experience quartile			
Rank numbers	**1**	**2**	**3**	**4**
$1 \rightarrow 2$	-0.0071***	0.0018	0.0050***	0.0077***
	(0.00078)	(0.00095)	(0.00066)	(0.00089)
Observations	295,117	308,692	321,391	303,671
$2 \rightarrow 3$	0.0003	0.0024***	0.0030***	0.0042***
	(0.00055)	(0.00050)	(0.00042)	(0.00045)
Observations	143,986	164,759	178,051	179,173
$3 \rightarrow 4$	-0.0007	-0.0001	0.0005	0.0005
	(0.00041)	(0.00034)	(0.00035)	(0.00037)
Observations	92,812	110,568	120,580	124,061

Notes: This table offers a detailed examination of log price changes for ranks 2 to 4, categorized by quartiles of the first bidder's experience rank. The coefficients shown reflect the impact of the rank number on price changes for each quartile of first bidder experience, starting with sequential auctions led by the first bidder from the highest experience quartile and so forth. Heteroskedasticity-robust standard errors, clustered by species, are presented within parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4.7: First bidder signaling

Figure 4.7 and Table 4.7 present the point estimates for the intercept term from the model in equation 4.3 separately for each case where the first bidder is in the top and bottom quartile in percentile experience rank. While the coefficients do not differ significantly after rank 4, notable disparities are observed in the first 3 ranks. When the first bidder is among those in the lowest experience quartiles, prices immediately start declining, and coefficients are smaller in size than the baseline case in the first 4 rounds. This difference is noteworthy because, unlike any other price dynamics results presented in this study, this result implies a declining price trend. Hence, when the first bidder is inexperienced, contrary to our other results, but in line with the literature's documented findings, we observe declining

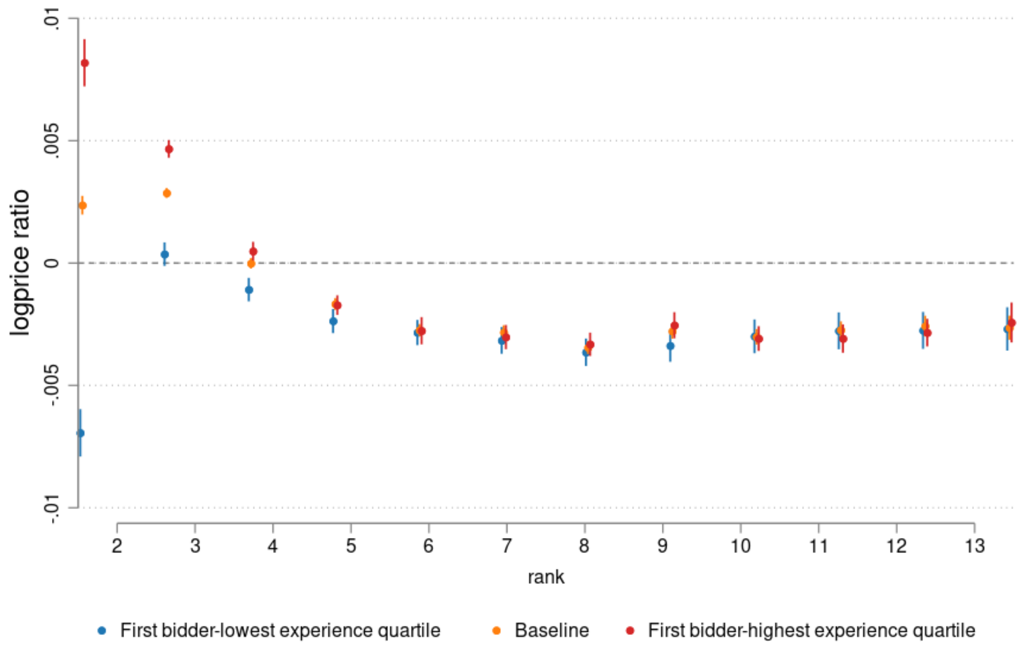


Figure 4.7: Price Dynamics by the first bidder experience

Notes: This figure visually depicts the price dynamics in sequential auctions, focusing on the rank number. It presents separate trends for sequential auctions initiated by the first bidder from the lowest experience quartile and those by the first bidder from the highest experience quartile. It also includes the baseline results presented in Figure 4.4 for reference. Each coefficient point is accompanied by 95% confidence intervals.

prices. However, when the first bidder is among the top quartile of experience rank, prices follow a stronger increase than in our baseline model. While this finding supports the non-monotonic price dynamics, it also highlights the importance of the first bidder's identity, as the price increase is more pronounced in the first 3 ranks when the first bidder is more experienced.

Results in Figure 4.7 and Table 4.7 verify the claim that bidders take the first bidder's experience into account and adjust their bids accordingly. When there is uncertainty regarding the quality or price of a particular lot, bidders are inclined to rely on the signal provided by the first bidder before forming their decisions. When the first bidder is an experienced agent in the market, in the first four rounds, other bidders continue to bid with a markup on the previous bidder's bid. Conversely, when the first bidder is inexperienced, they consider this and gradually reduce their bids. This suggests that the strength of the signal depends on the bidder's experience. While consecutive bidders after an experienced bidder are willing to pay a price premium for the information they receive, this is not the case for the inexperienced first bidder. As expected, the differences in results are no longer evident after the fourth round. As the sequential auction progresses, the significance of the first bidder's identity and the strength of their signal diminish.

These findings provide a unique perspective on the literature concerning price dynamics, emphasizing the role of information diffusion through the utilization of first bidders' experience levels. Many previous studies have consistently reported a declining price trend. However, our approach differs significantly in that it leverages the lot system, enabling us to compare bids for fully homogeneous products where bidders can obtain signals from one another. In cases where this feature is not considered, such as when running a pooled regression for all ranks, our model reveals an overall increasing price trend. Nevertheless, by focusing on consecutive bids for homogeneous seafood, where agents can receive information from each others' bids, our findings reveal non-monotonic price dynamics. Moreover, we document how this variability is influenced by experience and the process of learning from signals provided by others.

4.6 Conclusions

In this study, we analyze the price dynamics of sequential auctions within the context of the Sydney Fish Market (SFM), examining the factors that influence price trends. Exploring the complexity of seafood species, where factors like size and quality can fluctuate due to unpredictable weather conditions, presents a challenge due to endogeneity and omitted variable bias. However, our use of the lot fixed effects method, along with several controls, provides a robust method. This approach not only enhances the precision of our results through more homogenous comparisons but also, by accounting for demand effects and bidder heterogeneity, it addresses the limitations in prior studies that may have overlooked certain underlying determinants..

Our exploration reveals several key findings. Firstly, challenging the theory proposed by Milgrom and Weber (1982), we find that prices for homogeneous products in sequential auctions do not follow a martingale but exhibit a non-monotonic pattern. This novel insight challenges existing literature, which often lacks the lot system present in SFM auctions, providing a robust identification strategy.

Secondly, we introduce a unique metric for bidder experience based on transaction numbers. Experience significantly influences price dynamics, with more experienced bidders being better equipped to achieve lower prices in sequential auctions. This influence is particularly prominent in the early ranks, reflecting a learning behavior among bidders as the sequential auction progresses. Moreover, we demonstrate that in settings where information asymmetry is more pronounced, especially in auctions of species with greater price variability, experience exerts a more substantial impact on price determination.

Thirdly, to analyze the learning behavior among bidders, we highlight the significance of the initial bidder's experience level in shaping subsequent bidding behavior. When led by a more experienced bidder, others tend to place higher bids in the following rounds. Conversely, when initiated by a less experienced bidder, this increasing bidding trend is no longer present, and bidders start to shade the previous bid, showcasing how bidders actively interpret and respond to signals from other agents in the market.

In conclusion, this study underscores the profound impact of information asymmetry on auction outcomes. Although we primarily focus on seafood auctions, the insights acquired can resonate more widely, offering a nuanced understanding of auction mechanisms, the significance of information dissemination, and the influence of experience on determining market outcomes. Future research endeavors could consider expanding the scope beyond fish auctions to encompass other goods markets and analyze the impact of experience and learning on prices in markets where prices are not fixed. For instance, delving into the auction dynamics of fresh produce or flowers, or security auctions might reveal if similar bidding behaviors and price trends are prevalent. The effect of experience and learning are likely important in any other market setting where agents can observe each others' behavior. A cross-market comparison would provide a richer understanding of whether the patterns observed in seafood auctions are unique or if they reflect a broader phenomenon. Another intriguing avenue for exploration could involve examining the disparities in bidding behavior between remote and live bidding. In this study, we illustrate that remote bidders typically pay higher prices than live bidders for similar products. This discovery may also be linked to the significance of information acquisition through observing other market participants. Research that delves into the underlying factors explaining these distinct behaviors in the market would offer valuable insights.

Chapter 5

Concluding Remarks

The thesis concludes by bringing together the key findings from the three chapters and subsequently discusses areas for future research.

Chapter 2 provides a detailed analysis of the multifaceted implications of the Child Rights Act in Nigeria, a legal reform aimed at raising the minimum age for marriage. The analysis reveals a complex landscape of responses to this legal reform, shedding light on the need for nuanced policy approaches. Using data from Nigeria DHS, contrary to the reform's intended effects, I show that the reform had a negative treatment effect on the marriage age. Initially, I emphasize the significance of choosing the appropriate methodology for dynamic and heterogeneous treatments by comparing the results obtained through TWFE with those using Callaway and Sant'Anna (2021) method. Then, I demonstrate that the negative effect is primarily attributable to respondents residing in majority Muslim clusters where child marriage is deeply ingrained in the culture and remains highly prevalent. These findings suggest that in Nigeria, a highly diverse country encompassing various ethnicities, religions, and cultures, the international reform implemented by the UN, which contradicts pre-existing norms, triggers a backlash effect. It further highlights the imperative for policy approaches that are not only sensitive to local dynamics but also adept at navigating them. The findings have implications beyond Nigeria, resonating with regions that share similar child marriage norms and traditions. While the focus of this study primarily centers on child marriage reforms, the implications can extend to a broader context of implementing and internalizing international laws in developing countries. To recap, in highly diverse local contexts like Nigeria, it is imperative for policymakers to factor in prevailing local culture and norms to mitigate the risk of backlash effects and protect vulnerable populations from further harm.

Understanding the decision-making process of fertility is of paramount importance in comprehending the demographic transition, both in developed and developing countries. Chapter 3 delves into the role of subjective expectations in determining the likelihood of childbirth in rural Malawi, a region representative of rural SSA low-income countries. The findings illuminate a compelling connection: a 10 percentage point reduction in infant mortality expectations yields a substantial 14 percentage point decrease in the likelihood of having a child within the next two years. Moreover, our findings underscore the importance of incorporating subjective expectations data in existing surveys. Without this data, identifying parents' fertility strategies and disentangling different mechanisms of the demographic transition would not have been possible. In terms of policy implications, our analyses indicate the potential benefits of an information intervention about the actual infant mortality rate to help some couples in making better-informed fertility decisions. However, it is worth noting that not all expectations are easily modifiable.

Chapter 4 analyzes price dynamics in sequential auctions at the Sydney Fish Market, exploring the factors influencing price trends. Firstly, challenging the theory proposed by Milgrom and Weber (1982), we find that prices for homogeneous products in sequential auctions do not follow a martingale but exhibit a non-monotonic pattern. Secondly, we introduce a unique metric for bidder experience based on transaction numbers. Experience significantly influences price dynamics, with more experienced bidders being better equipped to achieve lower prices in sequential auctions, especially in auctions marked by information asymmetry. Thirdly, to analyze the learning behavior among bidders, we highlight the significance of the first bidder's experience level in shaping subsequent bidding behavior. When led by a more experienced bidder, others tend to place higher bids in the following rounds. In conclusion, this study underscores the profound impact of information asymmetry on auction outcomes. Although we primarily focus on seafood auctions, the insights acquired can resonate more widely, offering a nuanced understanding of auction mechanisms, the significance of information dissemination, and the influence of experience on determining market outcomes.

The remainder of the present chapter discusses future areas for research. Building upon my investigation into the impact of the Child Rights Act in Nigeria in Chapter 2, there is an opportunity for further research to conduct a comparative analysis of legal reforms across diverse regions and their influence on deeply rooted cultural norms. For instance, in 2017, the Malawi government introduced legislation to prohibit marriages under the age of 18, with violators subject to fines. UNICEF (2019) reports indicate that approximately 46 percent of girls in Malawi are married before reaching the age of 18, and 9 percent before the age of 15. While the UN played a significant role in advocating for this law, it was tailored specifically for Malawi and integrated within the Marriage, Divorce, and Family Relations Act. In the future, as more data becomes available, I intend to investigate the impacts of this law, which arguably has a more integrated design developed in cooperation with local leaders. A comparative analysis of treatment effects between Nigeria and Malawi could provide valuable insights into the effectiveness of child marriage bans under distinct legal frameworks.

In Chapter 3 we establish a link between subjective expectations and fertility choices which opens up intriguing avenues for future research. Expanding this question to other regions with high infant mortality rates could provide a broader perspective on the universality of these findings. Assessing the external validity of these findings would contribute to our comprehension of the delayed demographic transition in developing nations. Moreover, exploring the potential of tailored information interventions to modify expectations and influence fertility choices in various contexts could offer valuable insights for policymakers and demographers, and may prevent people from overshooting their target family size. Additionally, with richer data, examining how access to healthcare services and family planning resources interacts with subjective expectations in influencing fertility choices could have significant policy implications.

In Chapter 4, our seafood auction focus provides insights applicable beyond this domain, potentially enriching our comprehension of auction mechanisms, information dissemination's importance, and the influence of experience on market outcomes. Future research can broaden its scope, encompassing diverse goods markets to assess the impact of experience and learning in settings with non-fixed prices. Exploring fresh produce, flower, or security auctions may unveil shared bidding behaviors and price trends. This holds relevance in markets where agents can observe each other, offering a cross-market understanding. Another intriguing avenue is investigating disparities between remote and live bidding, a phenomenon observed here, potentially linked to information acquisition. Delving into underlying factors shaping these behaviors would yield valuable insights.

Appendix I

This appendix corresponds to chapter 2 "*The Failure of International Laws in Local Contexts: the Case of the Child Rights Act in Nigeria*". It includes additional figures and tables that supplement the local context information, empirical evidence, and the discussion.

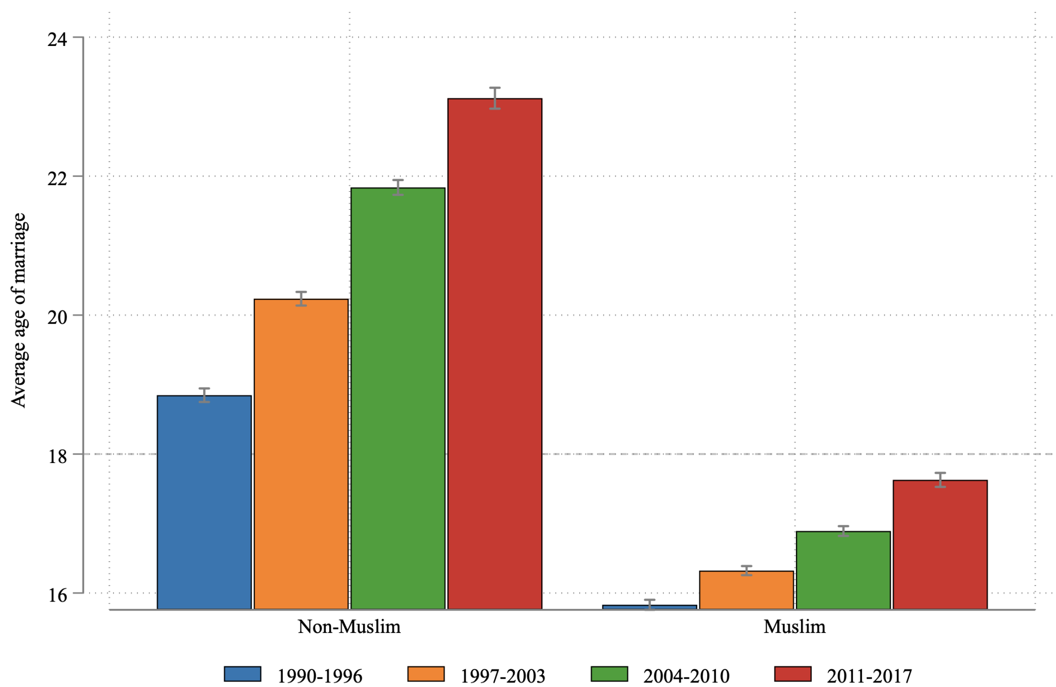


Figure A1.1: Average age at first marriage by religious affiliation

*Notes:*This bar graph displays the average age at first marriage categorized by religious affiliation (Muslim or non-Muslim) across different marriage year groups.

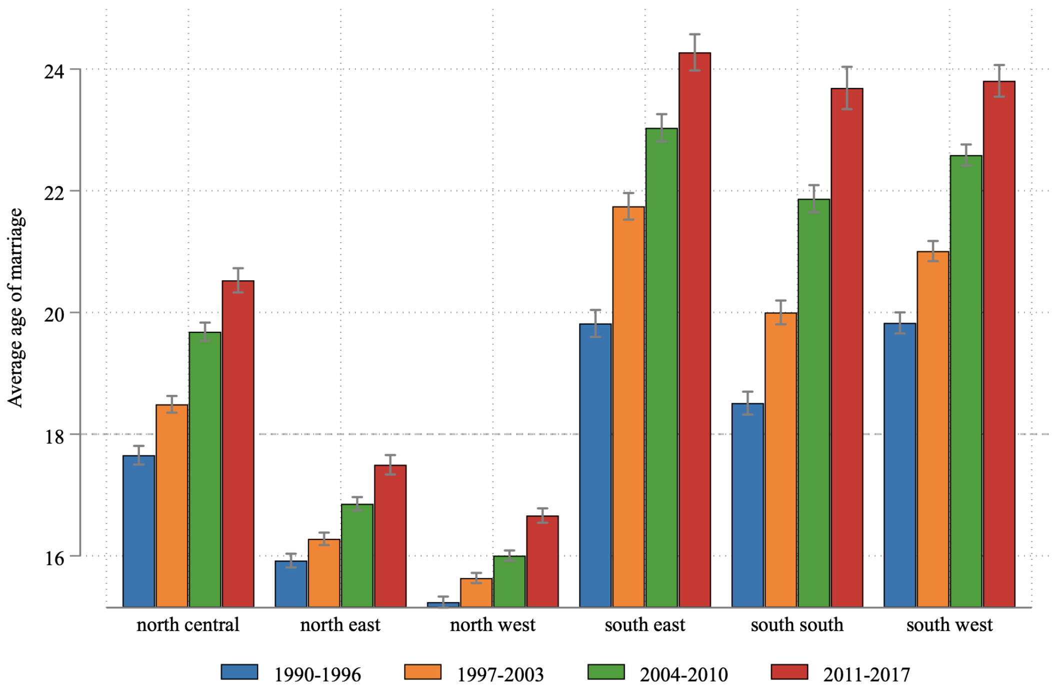


Figure A1.2: Average age at first marriage by regions

*Notes:*This bar graph displays the average age at first marriage categorized by regions across different marriage year groups.

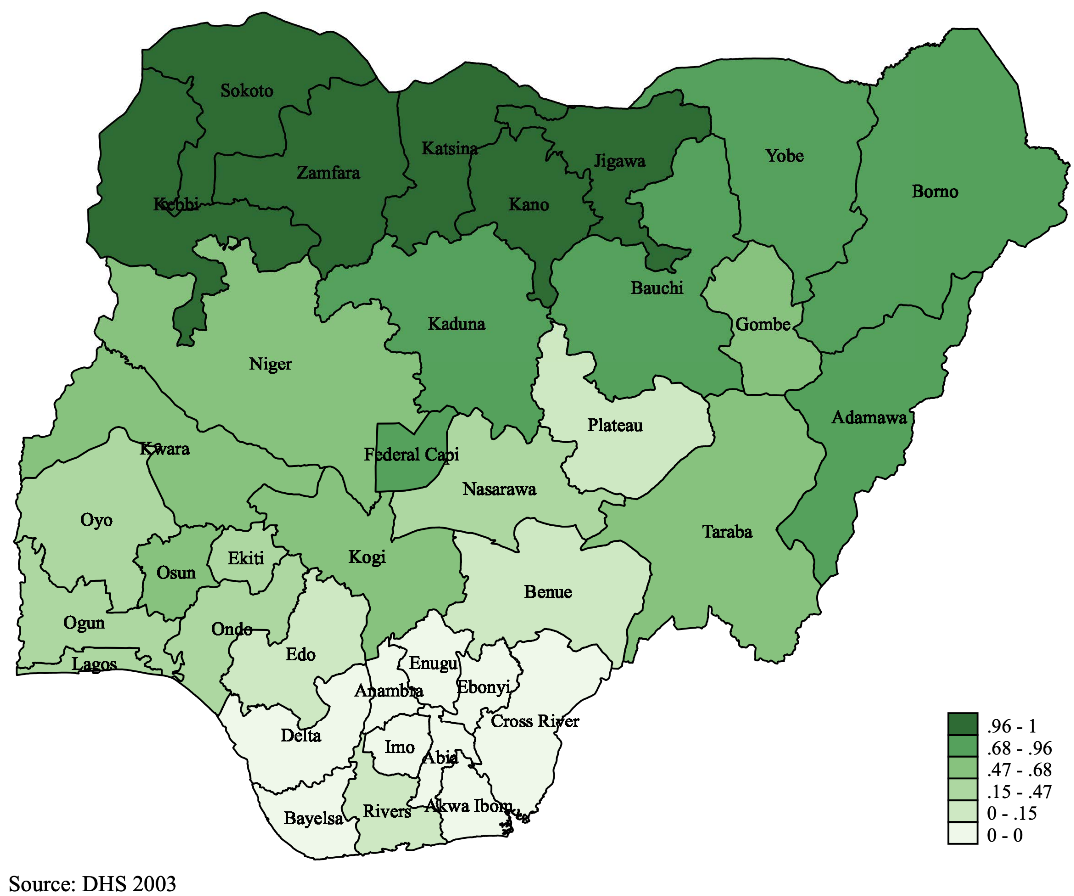


Figure A1.3: Share of Muslim female residents in each state

*Notes:*This cartographic representation displays the proportion of Muslim females within the population of women aged 18 to 25 in the year 2003, utilizing data sourced from the 2003 DHS.

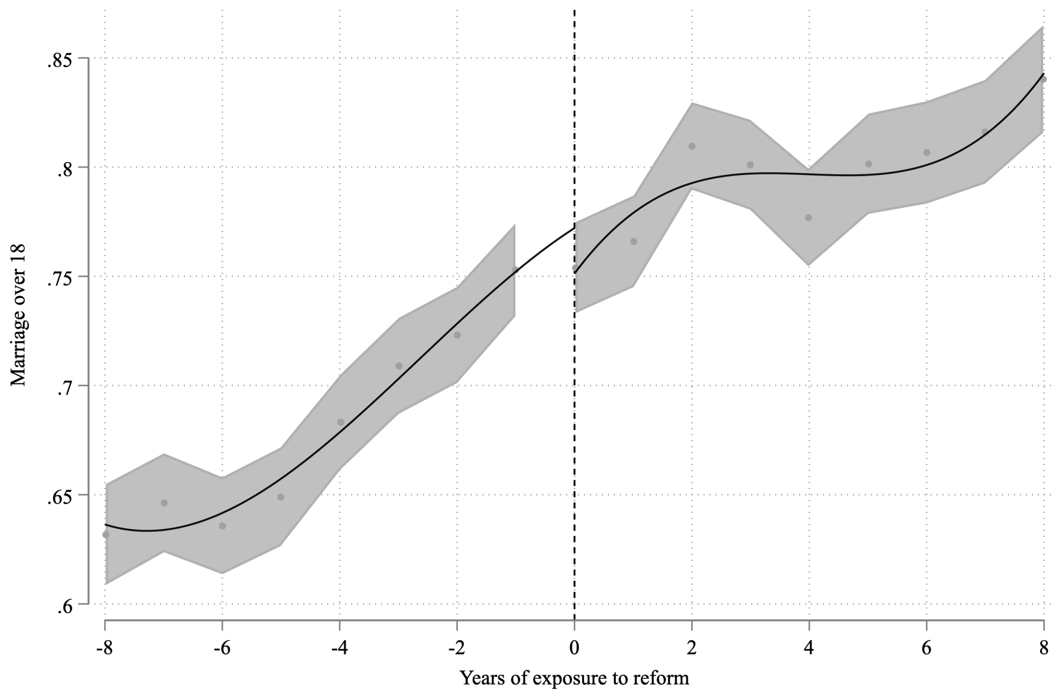
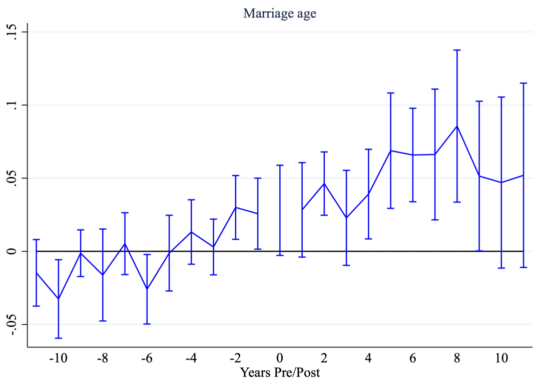
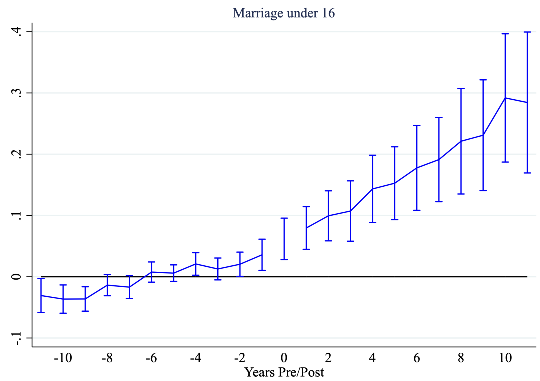


Figure A1.4: Child marriage by age when the CRA was introduced

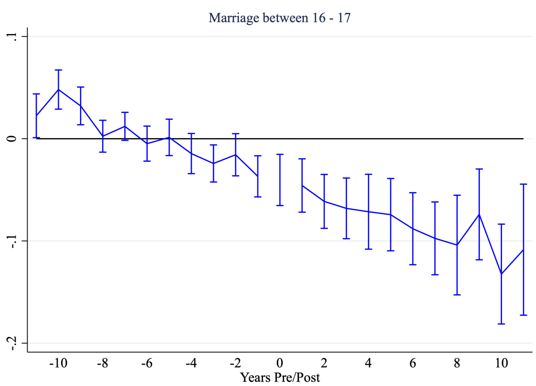
Notes: This figure is based on the Nigeria DHS data and uses a sample of women who were at least 18 years old at the time of the survey. Child marriage, as defined by UNICEF, refers to marriages that occur before the age of 18. The average bin size in this figure comprises 1798 observations.



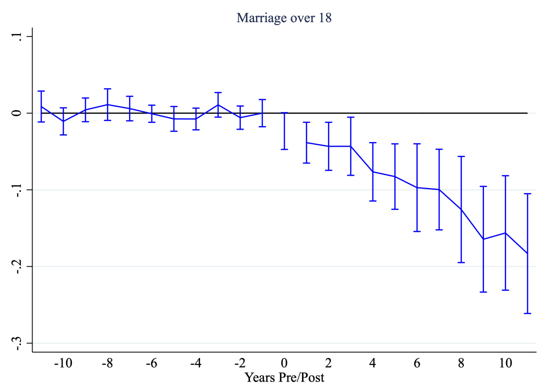
(a) Marriage age



(b) % Under 16



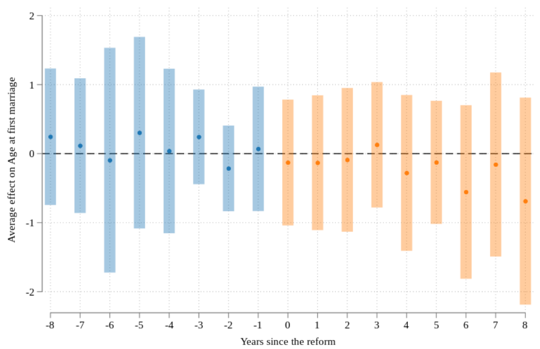
(c) % 16-17



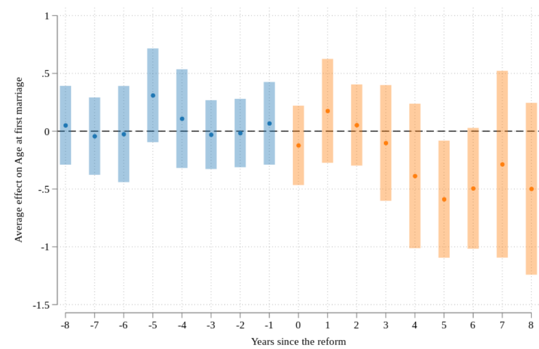
(d) % Over 18

Figure A1.5: Event plots for marriage outcomes using TWFE

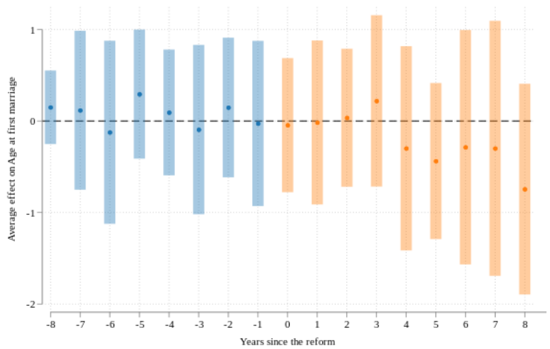
Notes: The figure presents coefficient estimates and their corresponding 95% confidence intervals obtained through the TWFE estimation approach. Standard errors are clustered at the state level. In all regressions, I account for state and marriage year fixed effects, birth year and ethnicity group fixed effects, along with binary variables indicating Muslim affiliation and rural residency. The outcome *Marriage age* represents the age at first marriage, calculated using birth year and month as well as marriage year and month. Additionally, the other outcomes are binary variables that indicate marriage occurring under the age of 16, at ages 16 or 17, or at age 18 or older. Source: Nigeria DHS.



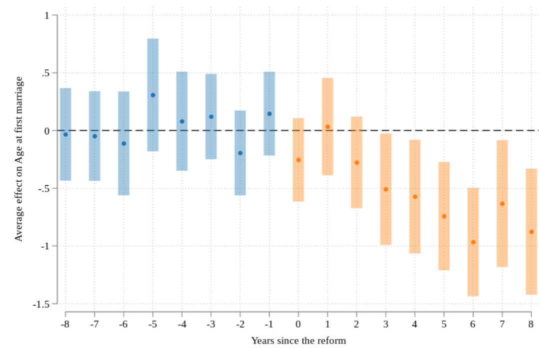
(a) no radio



(b) owns radio



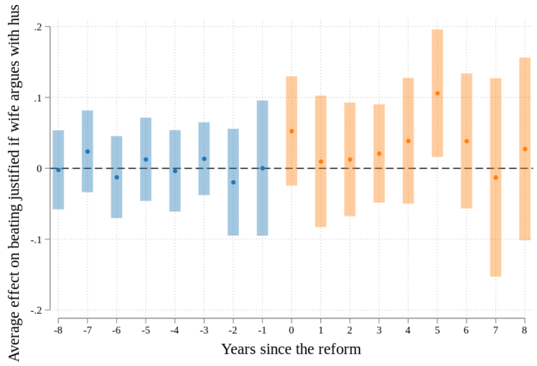
(c) no TV



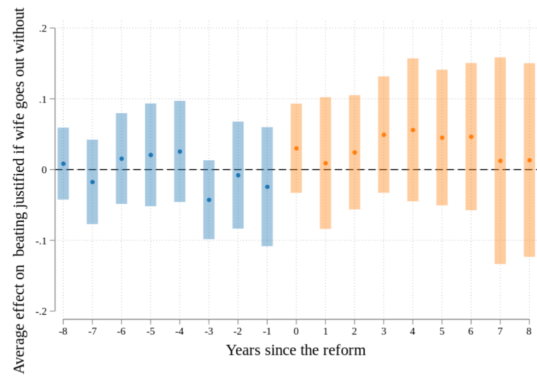
(d) owns TV

Figure A1.6: Effect of the CRA on marriage age in TV/Radio ownership subsamples

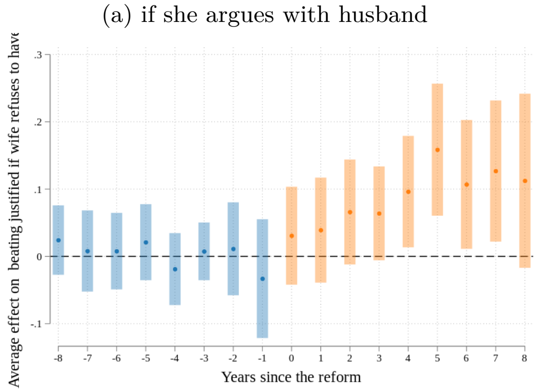
Notes: The figure presents coefficient estimates and their corresponding 95% confidence intervals obtained through the Callaway and Sant'Anna (2021) estimation approach. State-level clustered standard errors are computed using a doubly robust difference-in-differences estimator, employing stabilized inverse probability weighting. In all regressions, I account for state and marriage year fixed effects, birth year and ethnicity group fixed effects, along with binary variables indicating Muslim affiliation and rural residency. Each plot illustrates the effect of the CRA on marriage age separately for respondents who own or do not own a TV/radio. Source: Nigeria DHS.



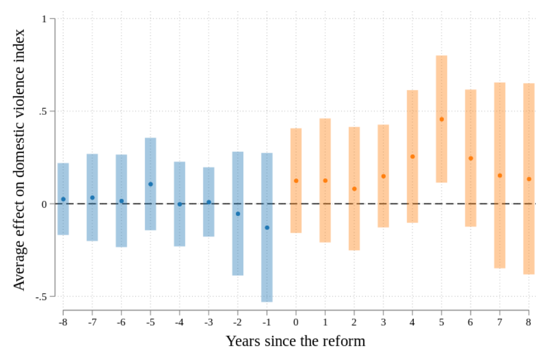
(a) if she argues with husband



(b) if she goes out without asking



(c) if she refuses to have sex



(d) domestic violence index

Figure A1.7: Effect of the CRA on domestic violence indices

Notes: The figure presents coefficient estimates and their corresponding 95% confidence intervals obtained through the Callaway and Sant'Anna (2021) estimation approach. State-level clustered standard errors are computed using a doubly robust difference-in-differences estimator, employing stabilized inverse probability weighting. In all regressions, I account for state and marriage year fixed effects, birth year and ethnicity group fixed effects, along with binary variables indicating Muslim affiliation and rural residency. The outcome variables represents the attitudes of respondents towards domestic violence under different scenarios. Source: Nigeria DHS.

Table A1.1: Summary Statistics by treatment - Females, Nigeria DHS Sample

	Treated		Never-treated		Difference
	mean	sd	mean	sd	b
Region					
North	0.38	0.48	1.00	0.00	-0.62***
South	0.62	0.48	0.00	0.00	0.62***
Rural	0.55	0.50	0.75	0.43	-0.20***
Religion					
Muslim	0.25	0.43	0.92	0.28	-0.67***
Christian	0.73	0.44	0.07	0.26	0.66***
Traditionalist	0.01	0.10	0.01	0.09	0.00***
Ethnicity groups					
Yoruba	0.21	0.41	0.00	0.05	0.21***
Igbo	0.23	0.42	0.00	0.05	0.23***
Hausa-Fulani	0.08	0.27	0.79	0.41	-0.71***
Others	0.48	0.50	0.21	0.40	0.27***
Outcome variables					
Age at first marriage	19.55	5.06	15.57	3.21	3.98***
Marriage under 16	0.15	0.36	0.55	0.50	-0.40***
Marriage from 16 to 17	0.12	0.33	0.18	0.39	-0.06***
Marriage over 18	0.72	0.45	0.25	0.43	0.46***
Education - Employment					
Education in years	8.18	5.02	2.48	4.70	5.69***
No education	0.18	0.38	0.72	0.45	-0.54***
Primary level	0.21	0.41	0.11	0.31	0.10***
Secondary level	0.49	0.50	0.14	0.35	0.34***
Higher	0.12	0.33	0.03	0.17	0.10***
Employed	0.67	0.47	0.52	0.50	0.15***
Other characteristics					
Majority Muslim cluster	0.24	0.43	0.88	0.33	-0.64***
Under Sharia	0.09	0.29	0.92	0.27	-0.83***
Ever Married	0.65	0.48	0.87	0.33	-0.22***
Age	29.00	9.68	28.58	9.56	0.42***
Age gap with husband	9.50	7.78	12.23	8.05	-2.73***
Marriage to first birth	17.99	22.78	29.92	30.27	-11.93***
Number of children	2.29	2.33	3.05	2.62	-0.77***
Domestic violence index	0.96	1.62	1.67	2.02	-0.71***
Decision-making index	-0.10	1.90	-1.39	1.38	1.29***
Can ask to use condom	0.50	0.50	0.27	0.45	0.23***
Can refuse sex	0.73	0.44	0.43	0.49	0.30***
Observations	79379		42395		121774

Notes: Summary statistics are derived for all women aged 15-49 from Nigeria DHS, spanning waves 2003, 2008, 2013, and 2018, and are separated for women residing in eventually-treated and never-treated states. The last column reports the difference in means between these two samples. The domestic violence index is computed by adding together the binary variables related to questions about whether beating is justified in cases where the wife neglects children, argues with her husband, goes out without informing her husband, or burns the food. The decision-making index sums variables for healthcare, purchases, family visits, and personal earnings. Negative values indicate no decision-making power.

Table A1.2: TWFE results with majority religion interaction

	Marriage age	% Under 16	% at 16/17	% Over 18
Post reform	0.144***	0.305***	-0.211***	-0.103***
	(0.0419)	(0.0456)	(0.0231)	(0.0271)
Post*Majority-Muslim	-0.323***	-0.137***	0.0690**	0.0721***
	(0.0852)	(0.0431)	(0.0266)	(0.0262)
Observations	86745	86019	85251	84018
baseline	18.02	0.367	0.184	0.454

Notes: The table displays TWFE aggregated treatment effect coefficients relying on the conditional parallel-trends assumption, with standard errors clustered at the state level. The first row presents treatment effects for marriage age outcomes of respondents residing in majority Muslim clusters, while the second row reports treatment effects for respondents in majority non-Muslim clusters.

Table A1.3: Callaway and Sant'Anna (2021) assumptions

Assumption	Requirement	Discussion
Conditional parallel trends based on "not-yet-treated" groups	Starting from period g, cohort g - consisting of states that passed the CRA in year g - must follow the same trend as the not-yet treated groups if they had not implemented the CRA.	Figure 2.5 illustrates that state groups treated at various times display similar marriage age trends before the reform.
Limited treatment anticipation	I assume no anticipation.	In Nigeria, with diverse regions and communities, it often takes time for awareness of new laws and their implications to spread uniformly. Figure 2.5 provides assurance that there is no anticipation effect, as there is no abrupt jump or decline observed around the reform cutoff.
Irreversibility of treatment	Once a unit becomes treated, that unit will remain treated in the next period.	No state repealed the law after its enactment.
Random sampling	Each unit i is randomly drawn from a large population of interest.	DHS sampling frame follows random sampling for representability.
Overlap	For each treated unit with covariates X_i, there are at least some untreated units in the population with the same value of X_i.	The large sample size ensures that individuals with the same birth year, ethnicity, rural/urban residence, and religion reside in different states, which were exposed to varying treatment years and statuses.

Table A1.4: Aggregated Treatment Effects for subsamples based on radio/TV ownership and residence

	Marriage Age	% Under 16	% at 16-17	% Over 18
Panel A: Radio ownership				
ATT - no radio	-0.387	0.107**	-0.0218	-0.0707
s.e.	(0.455)	(0.0452)	(0.0487)	(0.0533)
Observations	28231	27935	27615	27069
ATT - with radio	-0.389*	0.0684***	0.0159	-0.0740***
	(0.219)	(0.0181)	(0.0179)	(0.0223)
Observations	59407	58969	58506	57815
Panel B: TV ownership				
ATT - no TV	-0.341	0.109**	-0.00338	-0.0923**
s.e.	(0.412)	(0.0430)	(0.0381)	(0.0436)
Observations	52427	51757	51067	50011
ATT - with TV	-0.685***	0.0582***	0.0484**	-0.0869***
s.e.	(0.183)	(0.0166)	(0.0205)	(0.0231)
Observations	35160	35096	35003	34826
Panel C: Rural/Urban residence				
ATT - rural	-0.138	0.108***	0.00888	-0.0911***
s.e.	(0.319)	(0.0308)	(0.0234)	(0.0321)
Observations				
ATT - urban	-0.768***	0.0701***	0.0205	-0.0862***
s.e.	(0.225)	(0.0188)	(0.0209)	(0.0257)
Observations	29839	29780	29694	29529

Notes: The table presents aggregated treatment effect parameters based on the conditional parallel-trends assumption, and the results are clustered at the state level. Panel A reports the weighted average of all available group-time average treatment effects based on radio ownership. Panel B reports the same for TV ownership. Panel C reports results for subsamples based on rural/urban residence.

Appendix II

This appendix corresponds to chapter 3 "*Infant Mortality Expectation and Fertility Choice in Rural Malawi*". It includes additional figures and tables that supplement the local context information, empirical evidence, and the discussion.

The Imperfect IV method

Their assumptions in the context of this paper are given by:

A1 $\rho_{m_{iv},\epsilon_{iv}}\rho_{\bar{h}_{iv},\epsilon_{iv}} \geq 0$;

A2 $|\rho_{m_{iv},\epsilon_{iv}}| \leq |\rho_{\bar{h}_{iv},\epsilon_{iv}}|$.

A1 implies that the instrument has (weakly) the same direction of correlation with the omitted error term as the endogenous variable, infant mortality expectation. The correlation between the spatially-weighted average health ratings for children and the error term must have the same sign as the correlation between the infant mortality expectation and the error term. This assumption is credible as average health ratings (measured such that a higher score means poorer health) and infant mortality expectation are likely to be affected in the same direction by the shocks that determine fertility. For example, a time-varying positive local shock in health (such as a new health facility in the village) would decrease both infant mortality expectation and average child health. The first stage regression results also indicate that they are positively correlated (Table 3.3, col. 3, 4), which indirectly implies that any shocks that determine fertility would plausibly have an impact in the same direction for both.

A2 requires that the instrument *past spatially-weighted average child health* must be less correlated with the random term, ϵ_{iv}, compared to *past infant mortality expectation*. This assumption is not necessary for bounding; however, it helps to tighten the bound more in most cases. We discuss that it is likely to hold in our case as local health shocks are controlled via village fixed effects, and individual shocks are more likely to determine subjective infant mortality expectation than average child health due to the way the instrument is constructed. While the respondent reports her own subjective infant mortality expectation, average child health is constructed using other respondents' reports about other children who live within 5 km to the respondent. Thus, the instrument is less likely to be affected by an individual's unobserved characteristics.

Table A2.1 provides a summary of the bound analysis of Nevo and Rosen, 2012 where x is the endogenous variable, z is the instrumental variable, and $v(1)(= \sigma_x Z - 1\sigma_z X)$ is the constructed instrument that is cleared out from the spurious correlation under the assumption of the imperfect instrument and endogenous variable are equally endogenous.

Table A2.1: Summary of Nevo and Rosen (2012) bounding process

	Assumption 2		No Assumption 2	
	$\sigma_{xz} < 0$	$\sigma_{xz} > 0$	$\sigma_{xz} < 0$	$\sigma_{xz} > 0$
$\rho_{x\epsilon} > 0$	$\beta_z^{iv} \leq \beta \leq \beta_{v(1)}^{iv}$	$\beta \leq min\{\beta_{v(1)}^{iv}, \beta_z^{iv},\}$	$\beta_z^{iv} \leq \beta \leq \beta^{ols}$	$\beta \leq min\{\beta^{ols}, \beta_z^{iv},\}$
$\rho_{x\epsilon} < 0$	$\beta_{v(1)}^{iv} \leq \beta \leq \beta_z^{iv}$	$\beta \geq max\{\beta_{v(1)}^{iv}, \beta_z^{iv},\}$	$\beta^{ols} \leq \beta \leq \beta_z^{iv}$	$\beta \geq max\{\beta^{ols}, \beta_z^{iv},\}$

Notes: More details on this procedure are available in Nevo and Rosen, 2012. In our context; x is infant mortality expectation, and z is the average child health.

For the bounding analysis, Nevo and Rosen, 2012 construct the ratio of correlations of the instrument and the endogenous variable X with the error term, $\lambda^* = \frac{\rho_{zu}}{\rho_{xu}}$. They also create a function $V(\lambda) = \sigma_x Z - \lambda\sigma_z X$. By definition, $V(\lambda^*)$ is a valid instrument as it is the weighted average of Z and X such that the spurious effect is cleared, hence it is uncorrelated with the error term. However, we do not know the value λ^*, but given A1 and A2, we know that $0 \leq \lambda^* \leq 1$. Hence $\beta_{v(1)}^{IV}$ is used in the bounding process, replacing β^{OLS}.

The probability limits of the standard OLS and IV estimators can be useful to understand the procedure:

$$\beta^{OLS} = \beta + \frac{\sigma_{x\epsilon}}{\sigma_x^2},$$
$$\beta_z^{IV} = \beta + \frac{\sigma_{z\epsilon}}{\sigma_{xz}},$$
$$\beta_{v(1)}^{IV} = \frac{\sigma_x\sigma_{zy} - \sigma_z\sigma_{xy}}{\sigma_x(\sigma_{xz} - \sigma_z\sigma_x)}.$$

Even though A2 is not necessary for the bounding, it allows us to use $V(1)$ as an instrument and help tighten the bound. The idea is that the higher the correlation between X and Z, the tighter the bounds achieved by using $\beta^{IV}_{v(1)}$. Even if the IV is invalid, given that λ^* is small, it will correct the OLS estimate in the right direction. Their confidence interval is constructed by calculating the confidence bands for the estimated bound.

Figures

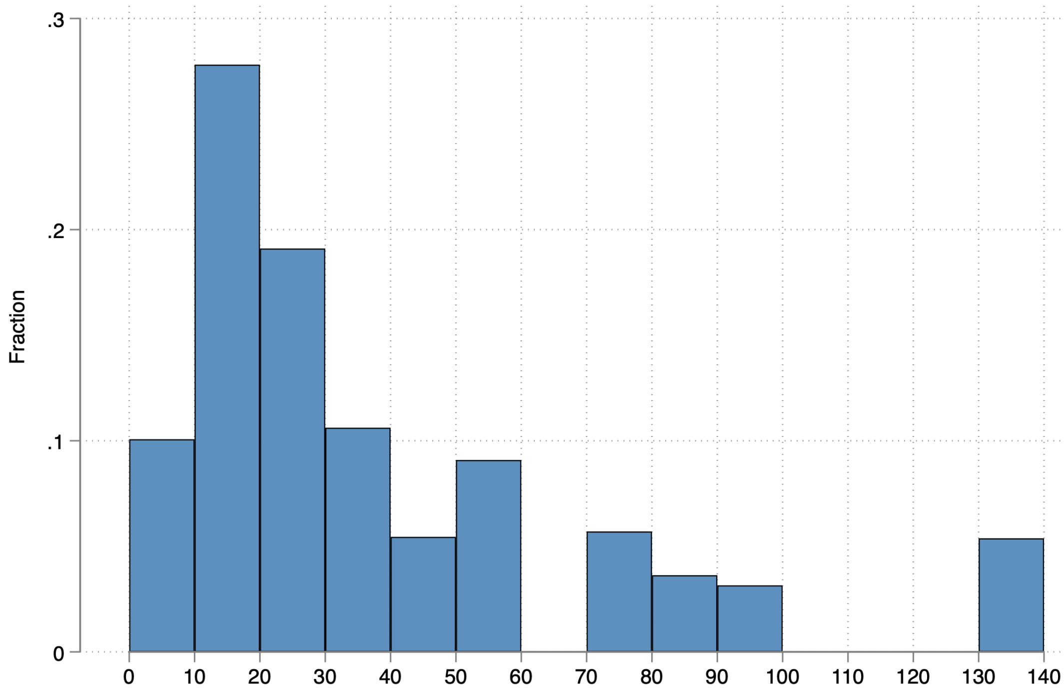


Figure A2.1: Distribution of number of respondents in 115 villages

Tables

Table A2.2: Characteristics of the all sample and analytical sample

	All sample			Analytical sample		
	mean	sd	count	mean	sd	count
Female	0.55	0.50	5701	0.59	0.49	2707
Age group						
less than 19	0.04	0.20	5701	0.02	0.15	2707
20-29	0.37	0.48	5701	0.32	0.47	2707
30-39	0.27	0.45	5701	0.29	0.45	2707
40-49	0.24	0.43	5701	0.28	0.45	2707
50-59	0.08	0.27	5701	0.09	0.29	2707
Education						
No schooling	0.17	0.38	5701	0.18	0.39	2707
Primary level	0.66	0.47	5695	0.66	0.47	2707
Secondary level	0.17	0.37	5695	0.15	0.36	2707
Higher level	0.00	0.06	5695	0.00	0.05	2707
Family						
Married	0.86	0.35	5701	0.86	0.35	2707
Number of children	3.81	2.95	5656	4.18	3.14	2707
Religion						
Catholic	0.17	0.38	5701	0.17	0.37	2707
Muslim	0.25	0.43	5701	0.25	0.43	2707
Indigenous Christian	0.14	0.35	5701	0.15	0.36	2707
Other Christian	0.36	0.48	5701	0.35	0.48	2707
Other religion	0.08	0.27	5701	0.07	0.26	2707
No religion	0.01	0.10	5701	0.01	0.09	2707
Region						
Central	0.33	0.47	5701	0.28	0.45	2707
Southern	0.34	0.47	5701	0.35	0.48	2707
Northern	0.33	0.47	5701	0.37	0.48	2707
Key variables						
Any child in the last 2 years (%)	0.42	0.49	4034	0.39	0.49	2486
Any birth in the last 2 years (%)	0.53	0.50	5415	0.50	0.50	2707
Past infant mortality expectation	2.43	2.05	4161	2.45	2.06	2707
Current infant mortality expectation	2.46	1.93	5701	2.49	1.93	2699
Past average kid health	1.91	0.26	3363	1.91	0.26	2707

Infant mortality expectation variables are measured between 0-10. Spatially-weighted average parental rating of child health (past average kid health) is measured between 1-5.

Table A2.3: IV probit results

	Any child	**Any birth**
Past infant mortality expectation (0-10)	0.323***	0.368***
	(0.109)	(0.093)
Number of children	0.201***	0.136***
	(0.051)	(0.041)
Female	-0.220***	-0.122*
	(0.079)	(0.068)
Married	0.564***	0.564***
	(0.153)	(0.193)
Age group		
20-29	-0.011	0.410***
	(0.158)	(0.134)
30-39	-0.583**	-0.0204
	(0.249)	(0.160)
40-49	-1.182***	-0.538**
	(0.399)	(0.271)
Education		
Primary level	0.197***	0.062
	(0.069)	(0.069)
Secondary level +	0.339***	0.064
	(0.108)	(0.122)
Year		
2008	0.041	0.075
	(0.056)	(0.060)
Observations	2451	2680

Notes: Standard errors clustered in village level are in parentheses. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$. Results presented above are from IV probit regressions where the outcomes are fertility measures. All regressions include number of children, gender, marital status variables and age group, education, village, religion and wealth level fixed effects. The key variable is *past infant mortality expectation*, instrumented by *past average health perception*.

Table A2.4: Main Results - missing instrument replaced with village average

Outcome		**Any child**			**Any birth**	
	OLS	First-stage	IV	OLS	First-stage	IV
Past infant mortality expectation (0-10)	0.002 (0.004)		0.262*** (0.081)	-0.001 (0.004)		0.248*** (0.092)
Past average child health (0-5)		0.713*** (0.161)			0.607*** (0.153)	
Number of children	0.049*** (0.016)	-0.007 (0.016)	0.051*** (0.014)	0.038*** (0.011)	-0.012 (0.014)	0.041*** (0.010)
Female	-0.076*** (0.014)	0.030 (0.082)	-0.082*** (0.025)	-0.055*** (0.015)	0.027 (0.078)	-0.061** (0.025)
Married	0.248*** (0.026)	0.026 (0.105)	0.241*** (0.038)	0.320*** (0.028)	0.066 (0.111)	0.303*** (0.041)
Age group						
20-29	-0.082* (0.046)	-0.385* (0.220)	0.029 (0.073)	0.015 (0.045)	-0.426* (0.220)	0.129* (0.073)
30-39	-0.241*** (0.067)	-0.329 (0.263)	-0.145 (0.089)	-0.108* (0.059)	-0.361 (0.260)	-0.010 (0.087)
40-49	-0.439*** (0.078)	-0.292 (0.261)	-0.351*** (0.099)	-0.348*** (0.068)	-0.299 (0.253)	-0.263*** (0.090)
Education						
Primary level	0.015 (0.021)	-0.184* (0.100)	0.067* (0.035)	-0.009 (0.019)	-0.134 (0.095)	0.028 (0.032)
Secondary level +	0.030 (0.035)	-0.251 (0.167)	0.100 (0.061)	-0.043 (0.032)	-0.185 (0.157)	0.006 (0.057)
Year						
2008	0.016 (0.021)	-0.054 (0.077)	0.012 (0.027)	0.037* (0.019)	-0.050 (0.079)	0.033 (0.025)
F statistic			19.538			15.715
Observations	3725	3725	3725	4014	4014	4014

Notes: The column names *OLS*, *F-S*, and *IV* correspond to the results obtained from Ordinary Least Squares (OLS), first-stage, and Instrumental Variable (IV) regressions, respectively. Within the age and education groups, the reference categories are individuals younger than 20 years and those with no education, respectively. The base year for all analyses is 2010. Additionally, all regression models incorporate fixed effects for village, religion, and wealth level. The outcome variables under consideration are *any child in the next two years* and *any birth in the next two years*. The primary explanatory variable of interest is *past infant mortality expectation*, which is instrumented using *past average child health* as the instrumental variable. Standard errors clustered in village level are in parentheses. ***: p <0.01, **: p <0.05, *: p <0.1.

Table A2.5: Main Results - missing instrument replaced with current wave's data

Outcome	**Any child**			**Any birth**		
	OLS	F-S	IV	OLS	F-S	IV
Past infant mortality expectation (0-10)	0.002		0.304***	0.000		0.319*
	(0.004)		(0.097)	(0.003)		(0.164)
Past average child health (0-5)		0.621***			0.330**	
		(0.148)			(0.145)	
Number of children	0.050***	-0.004	0.051***	0.037***	-0.013	0.041***
	(0.015)	(0.016)	(0.013)	(0.009)	(0.012)	(0.008)
Female	-0.074***	-0.013	-0.068**	-0.046***	0.046	-0.060**
	(0.014)	(0.083)	(0.029)	(0.013)	(0.076)	(0.026)
Married	0.239***	-0.018	0.244***	0.306***	0.004	0.303***
	(0.026)	(0.107)	(0.042)	(0.025)	(0.103)	(0.042)
Age group						
20-29	-0.085*	-0.396*	0.045	-0.042	-0.277	0.051
	(0.047)	(0.217)	(0.079)	(0.038)	(0.183)	(0.077)
30-29	-0.246***	-0.339	-0.133	-0.195***	-0.282	-0.101
	(0.067)	(0.255)	(0.093)	(0.047)	(0.203)	(0.087)
40-49	-0.443***	-0.324	-0.333***	-0.418***	-0.216	-0.343***
	(0.078)	(0.256)	(0.102)	(0.055)	(0.207)	(0.089)
Education						
Primary level	0.011	-0.187*	0.072*	-0.011	-0.087	0.018
	(0.023)	(0.105)	(0.042)	(0.019)	(0.091)	(0.036)
Secondary level +	0.024	-0.270	0.108	-0.019	-0.136	0.025
	(0.034)	(0.172)	(0.069)	(0.030)	(0.134)	(0.059)
Year						
2008	0.027	-0.021	0.015	0.024	-0.071	0.036
	(0.021)	(0.072)	(0.029)	(0.018)	(0.062)	(0.024)
F statistic			17.487			5.226
Observations	3934	3934	3934	5260	5260	5260

Notes: The column names *OLS*, *F-S*, and *IV* correspond to the results obtained from Ordinary Least Squares (OLS), first-stage, and Instrumental Variable (IV) regressions, respectively. Within the age and education groups, the reference categories are individuals younger than 20 years and those with no education, respectively. The base year for all analyses is 2010. Additionally, all regression models incorporate fixed effects for village, religion, and wealth level. The outcome variables under consideration are *any child in the next two years* and *any birth in the next two years.* The primary explanatory variable of interest is *past infant mortality expectation*, which is instrumented using *past average child health* as the instrumental variable. Standard errors clustered at the village level are in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Table A2.6: Main Results - under different decay functions and bandwidths

	Exponential		Inverse		Quartic	
Variables	5 km	10 km	5 km	10 km	5 km	10 km
Past infant mortality	0.138**	0.140**	0.090	0.098*	0.122*	0.088
expectation (0-10)	(0.070)	(0.070)	(0.064)	(0.056)	(0.067)	(0.054)
Number of children	0.044***	0.044***	0.044***	0.044***	0.044***	0.044***
	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)
Female	-0.066***	-0.065***	-0.070***	-0.068***	-0.067***	-0.069***
	(0.022)	(0.022)	(0.020)	(0.020)	(0.022)	(0.020)
Married	0.250***	0.250***	0.249***	0.249***	0.250***	0.249***
	(0.038)	(0.038)	(0.035)	(0.035)	(0.037)	(0.035)
Age group						
20-29	0.033	0.035	0.016	0.019	0.028	0.016
	(0.063)	(0.063)	(0.056)	(0.056)	(0.059)	(0.054)
30-39	-0.126	-0.126	-0.137*	-0.136*	-0.129*	-0.138*
	(0.081)	(0.081)	(0.076)	(0.076)	(0.078)	(0.075)
40-49	-0.320***	-0.320***	-0.333***	-0.332***	-0.324***	-0.335***
	(0.093)	(0.093)	(0.089)	(0.088)	(0.090)	(0.087)
Education						
Primary level	0.057*	0.058*	0.043	0.045	0.053	0.042
	(0.034)	(0.034)	(0.030)	(0.030)	(0.033)	(0.029)
Secondary level +	0.092*	0.092*	0.072	0.074	0.085*	0.070
	(0.053)	(0.053)	(0.048)	(0.047)	(0.051)	(0.046)
Year						
2008	0.016	0.016	0.016	0.016	0.016	0.016
	(0.023)	(0.023)	(0.021)	(0.022)	(0.022)	(0.021)
F statistic	15.88	15.85	14.60	15.41	14.21	15.70
Wooldridge's (1995)	3.53	3.79	1.80	2.87	2.79	2.50
robust score test	(p=0.063)	(p=0.054)	(p=0.182)	(p=0.093)	(p=0.097)	(p=0.117)
Observations	2,500	2,502	2,500	2,502	2,500	2,502

Standard errors are clustered at the village level. All regressions include village, religion and wealth level fixed effects. In age groups, the base group is respondents younger than 20; in education, the base group is no education ; and the base year is 2010.

Appendix III

This appendix corresponds to chapter 4 "*Expertise, Signaling, and Learning in Fish Auctions*". It includes additional figures and tables that supplement the local context information, empirical evidence, and the discussion.

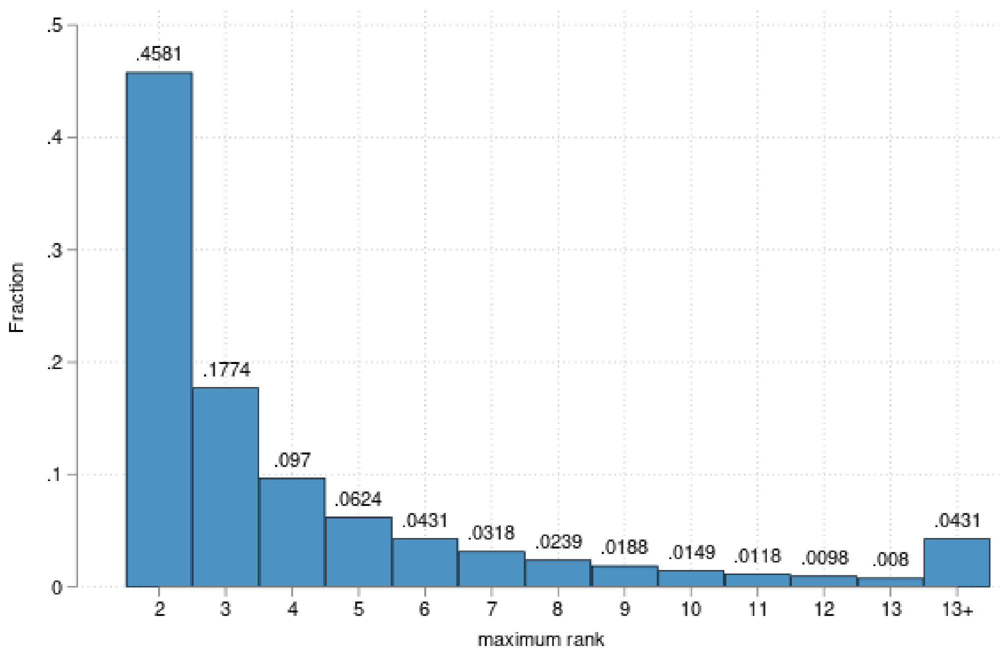


Figure A3.1: Distribution of maximum rank

Notes: This figure illustrates the distribution of the total number of rounds for all multi-unit auctions.

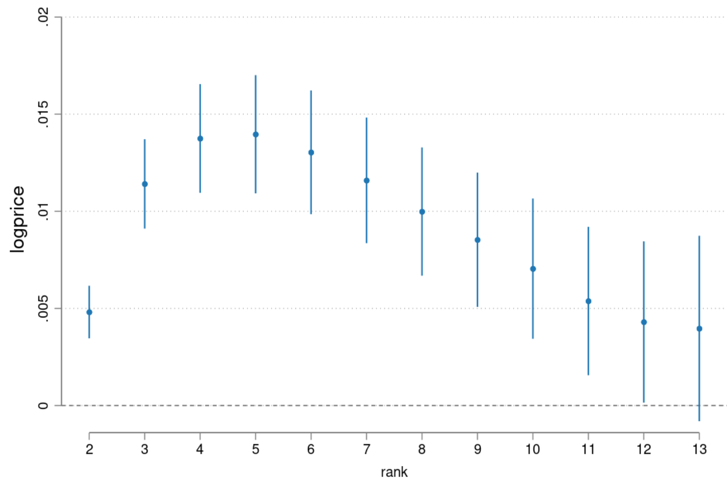


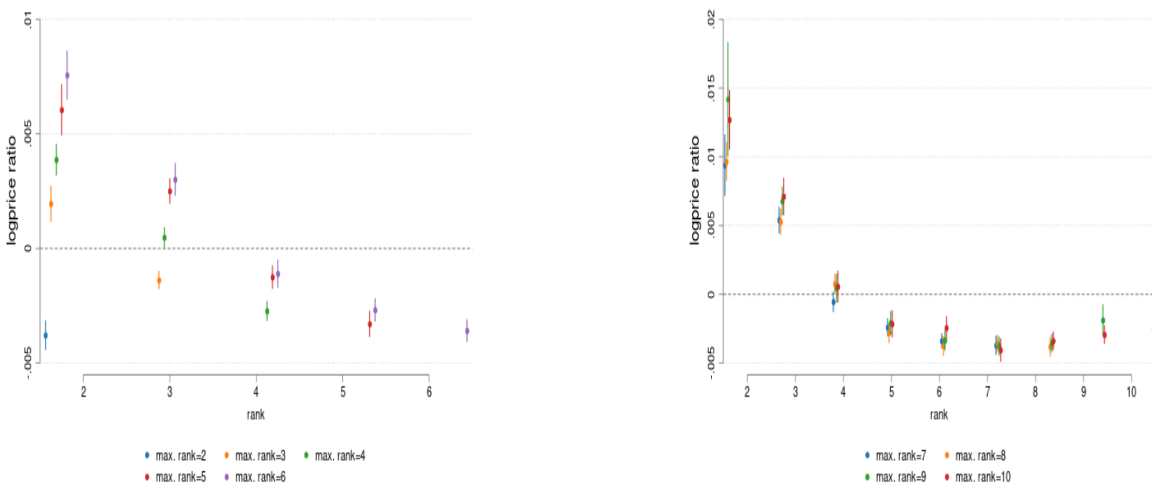
Figure A3.2: Effect of Rank on Price Dynamics - following equation 4.1

Notes: This figure visually depicts the price dynamics in sequential auctions relative to the first round (rank number=1). Each point corresponds to the coefficient on the rank number r_{ij} in equation 4.1, denoted as β_j, and is presented with 95% confidence intervals. These coefficients compare the log prices of each rank with the log price of rank number 1.

Table A3.1: Effect of Experience on Price Dynamics by Uncertainty

PANEL A: High Uncertainty Species					
Rank numbers	1→2	2→3	3→4	4→5	5→6
Intercept	-0.0027***	-0.0011***	-0.0036***	-0.0046***	-0.0061***
	(0.00046)	(0.00028)	(0.00031)	(0.00035)	(0.00037)
Difference in Experience	-0.0111***	-0.0076***	-0.0060***	-0.0057***	-0.0042***
	(0.00056)	(0.00050)	(0.00054)	(0.00057)	(0.00053)
Difference in Remote bidding	0.0098***	0.0091***	0.0069***	0.0054***	0.0070***
	(0.00122)	(0.00116)	(0.00109)	(0.00109)	(0.00117)
Observations	297,000	164,176	109,223	78,669	59,011
R^2	0.027	0.016	0.015	0.014	0.021
PANEL B: Low Uncertainty Species					
Rank numbers	**1→2**	**2→3**	**3→4**	**4→5**	**5→6**
Intercept	0.0014**	0.0065***	0.0026***	0.0007***	-0.0001
	(0.00049)	(0.00014)	(0.00013)	(0.00016)	(0.00014)
Difference in Experience	-0.0066***	-0.0021***	-0.0015***	-0.0018***	-0.0017***
	(0.00042)	(0.00018)	(0.00024)	(0.00019)	(0.00022)
Difference in Remote bidding	0.0052***	0.0019***	0.0023***	0.0022***	0.0016***
	(0.00078)	(0.00029)	(0.00029)	(0.00032)	(0.00034)
Observations	346,621	153,640	97,579	69,661	52,914
R^2	0.013	0.016	0.014	0.009	0.015

Notes: This table provides a comprehensive analysis of log price changes for ranks 2 to 6, with separate evaluations for species characterized by high and low price variance. The coefficients displayed in Panel A pertain to species in the highest price variance quartile, while those in Panel B pertain to species within the lowest price variance quartile. These coefficients reveal the influence of the rank number on price changes for each subsample. Heteroskedasticity-robust standard errors, clustered by species, are presented within parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.



(a) max. rank 2 to 6

(b) max. rank 7 to 10

Figure A3.3: Rank effects by maximum rank

Notes: This figure illustrates the price dynamics in sequential auctions, categorizing them into groups based on different maximum ranks, ranging from 2 to 10. Each coefficient point is accompanied by its corresponding 95% confidence intervals.

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