Incentive structure in telecom supply chain, production diversification, and rural resilience

by

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B.Tech., Punjab Technical University, 2008

M.B.A., North Carolina State University, 2016

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the
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DOCTOR OF PHILOSOPHY

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Abstract

Rural economies worldwide face the problem of technological isolation and environmental instability, which creates both unprecedented challenges and opportunities for the rural communities seeking resilience in a rapidly changing landscape. This dissertation examines two different yet complementary aspects related to rural economic resilience through the open supply chain of telecommunication network infrastructure and agricultural systems.

Rural development has become increasingly central to economic policy as decision-makers recognize its importance to overall economic growth. Although technology offers various solutions to rural resource constraints, telecommunications infrastructure remains disproportionately concentrated in population-dense regions. It creates fundamental disadvantage for rural communities, where businesses and farms need reliable and high-speed connectivity for modern operations. This gap between technological possibilities and rural realities occurs largely from how telecommunications networks are structured. Traditional vertically integrated mobile network supply chains have resulted in high costs, vendor lock-in, and standardized deployment strategies that prioritize dense urban centers while neglecting rural areas. Understanding the incentive structure of mobile telecom network stakeholders is therefore essential for developing viable solutions to bridge digital divide and enable rural regions to participate fully in the economy.

The first essay provides a novel game-theoretic analysis of open radio access networks (ORAN) as an alternative telecommunications supply chain architecture. We assess strategic interactions between telecom supply chain stakeholders—mobile network operators (MNOs), network infrastructure suppliers (NIS), and original equipment manufacturers (OEMs)—across three procurement scenarios: (i) Traditional, (ii) Predatory as monolithic radio access networks (MRAN), and (iii) DirectOEM as ORAN. The second essay investigates how agricultural diversification strategies impact farm resilience in Kansas. Through panel data analysis

spanning 2002-2022, the research documents that production diversification generally enhances farm income stability and improves financial resilience, especially during moderate drought conditions. It also suggests diminishing returns from diversification under extreme drought scenarios, highlighting diversification's limitations to be a sole risk management strategy.

The findings from both studies converge on the importance of strategic adaptation in building rural economic resilience. The telecommunications analysis demonstrates how innovative network architectures and alternate supply chains can improve economic viability even in challenging rural markets, while the agricultural analysis quantifies how production diversification can buffer against unprecedented shocks. Together, these studies offer novel & empirically grounded recommendations for policymakers, network operators, and farmers seeking sustainable rural development pathways in response to technological disruption and environmental change. The research establishes that both technological innovation in telecommunications infrastructure and adaptive agricultural practices represent complementary pathways for strengthening regional economic systems in rural regions in the United States. By evaluating digital connectivity challenges and farm income vulnerabilities in various regions, this dissertation provides a framework to enhance rural regions' adaptive capabilities during shocks.

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Major Professor
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Acknowledgments

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Dedication

To my parents, whose unwavering love, sacrifices, and belief in me made this journey possible.

Chapter 1

Introduction

Rural resilience has emerged as a critical concept in development economics, representing a community's capacity to absorb shocks, adapt to changing conditions, and transform in response to challenges while maintaining essential functions and identity [Folke et al., 2010]. Unlike traditional approaches focused solely on economic growth, resilience theory emphasizes the ability of systems to withstand and recover from disturbances—whether they be economic recessions, natural disasters, technological disrupt, or demographic changes [Wilson, 2010]. The multidimensional nature of rural resilience encompasses economic, social, institutional, and ecological components, requiring analysis that transcends disciplinary boundaries [Darnhofer, 2014]. Regions with high resilience typically demonstrate capacities for learning, innovation, self-organization, and proactive adaptation to changing circumstances rather than merely reactive responses to immediate crises [Berkes, 2008].

From an economic perspective, rural resilience represents a fundamental shift in how we conceptualize and measure rural development success. Traditional economic indicators like GDP growth, employment rates, or sector productivity provide incomplete pictures of rural wellbeing, failing to capture vulnerability to shocks or adaptive capacity [Martin et al., 2016]. Economic resilience in rural contexts involves diversification of income sources, robust supply chains, innovative business models, and the ability to pivot economic activities in response to market disruptions. Several empirical studies demonstrate that economically resilient rural communities experience less severe economic downturns, recover more quickly from shocks, and maintain higher quality of life indicators even during periods of macroeconomic stress. This economic dimension of resilience has gained particular salience in policy discussions following cascading crises of the early twenty-first century—from the 2008 financial collapse to climate-related disruptions and the COVID-19 pandemic—which disproportionately impacted rural communities with limited adaptive capacity [Cutter et al., 2010].

The research landscape on rural resilience has expanded dramatically in recent years, with evolving methodological approaches reflecting its complex, multidimensional nature. Recent studies have increasingly employed advanced computational methods, including bibliometric visualization analysis of large-scale literature databases to identify research hotspots and evolution trends in rural resilience research [Yang, 2022], [Li et al., 2023]. Spatial network analysis has emerged as a prominent methodology, with scholars developing frameworks such as "Rural Network Resilience" to explore mechanisms and pathways of sustainable development [Yu et al., 2024]. Mixed-method approaches combining qualitative case studies with quantitative modeling have gained traction, exemplified by the Rural Resilience Framework developed at North Carolina State University that integrates geospatial analysis, public engagement, and visual narration to help communities adapt to natural hazards and climate change. Despite these methodological advances, significant gaps persist in understanding the complex interplay between technological infrastructure and economic resilience in rural communities—particularly regarding telecommunications systems, which function both as critical infrastructure and as enablers of economic diversification [CORI, 2024].

Game theory offers a particularly valuable methodological framework for analyzing rural telecommunications infrastructure due to the strategic interactions between multiple stakeholders with competing interests [Jiang et al., 2024]. Recent applications have focused on understanding the strategic transformation in the telecommunications industry within competitive and collaborative contexts, particularly as platform technology companies enter markets traditionally dominated by established telecommunications operators. In rural contexts, where market failures are common due to low population density and high deployment costs, game theory helps illuminate the strategic behavior of mobile network operators, infrastructure suppliers, equipment manufacturers, and government entities, providing critical insights for designing effective policy interventions [NTIA, 2024a]. Major government initiatives like the U.S. Broadband Equity, Access, and Deployment (BEAD) Program, which allocates $42.45 billion for expanding high-speed internet infrastructure across all 50 states and U.S. territories, represent significant strategic interventions that reshape stakeholder incentives. The outcomes of such large-scale investments become intertwined with complex strategic decisions by private telecommunications providers regarding where and how to deploy complementary infrastructure, particularly in underserved rural areas. Similar grant programs like Australia's Regional Connectivity Program, which committed $368.4 million toward 297 place-based communications projects across regional, rural, and remote areas, further demonstrate the real-world importance of understanding these strategic interactions [Department of Infrastructure, 2025]. Furthermore, by incorporating spatial dimensions and heterogeneous agent characteristics, game theory can account for the significant geographic and socioeconomic variations across rural regions that influence infrastructure deployment decisions [Guyot et al., 2023].

Therefore, the dissertation is organized as follows: Chapter 2 presents a game-theoretic analysis of alternative telecommunications procurement scenarios and their implications for rural connectivity. Chapter 3 examines the relationship between agricultural diversification and income stability under varying drought conditions in Kansas.

Chapter 2

Incentive Structure in Open Radio Access Network (ORAN)

2.1 Introduction

The rapid advancement of agricultural technologies over recent decades—from high-yield crops and mechanized harvesting to genetically modified organisms (GMOs) and genome editing—has fundamentally transformed food production systems. However, the most significant and accelerating wave of innovation in recent years lies in the integration of Information and Communication Technologies (ICTs) into agriculture (Zhang et al. [2024], Das [2024]). As shown in the timeline Figure 2.1, the 2000s onward marked a shift toward data-driven farming, featuring technologies such as GPS-enabled tractors, drones, digital platforms, and, more recently, artificial intelligence and machine learning. These tools empower producers to monitor, analyze, and optimize agricultural operations with unprecedented precision. Yet, the full potential of these innovations hinges on robust digital infrastructure, open and competitive supply chains, and equitable access across diverse rural geographies. This study aims to contribute to improving the understanding of how open supply chains of ICT mobile network architectures influence deployment decisions and incentive structures across geographical regions, particularly in rural areas.

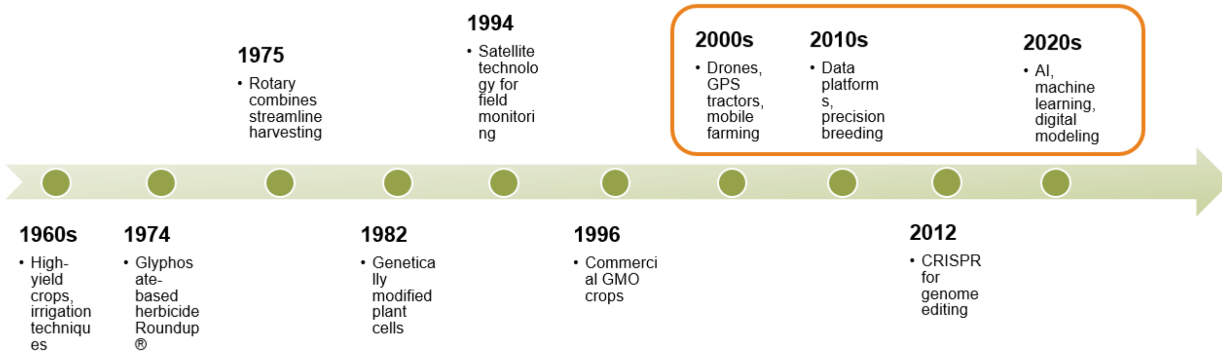


Figure 2.1: Timeline of Major Breakthroughs in Agricultural Technology

The global telecommunications mobile industry, once marked by unprecedented growth in demand, is now witnessing stability. The key stakeholders in the mobile network supply chain shown in Figure 2.2 include Original Equipment Manufacturers (OEM) such as chipmakers and antenna providers, Network Infrastructure Suppliers (NIS) like Nokia and Ericsson, Mobile Network Operators (MNO) such as AT&T and Verizon, and the end Mobile Users. The NIS industry is oligopolistic, with existing NIS infrastructure limiting MNOs' ability to offer innovative solutions for rural regions, thus limiting coverage and speed in these areas. The high costs of maintaining and upgrading infrastructure, due to the capital-intensive nature of the industry, have driven increasing consolidation among MNOs and NIS [NTIA, 2024b, Mazzeo, 2002, Motta and Tarantino, 2021]. As of 2023, 95% of the world's population has close proximity to mobile broadband signals, with 4G networks covering 89% of the global population [ITU, 2023]. However, 2.6 billion people worldwide still remain offline [ITU, 2023]. A recent study estimates that connecting the unconnected globally would require an investment of approximately $418 billion [Oughton et al., 2023]. At the same time, the accelerating adoption of Internet of Things (IoT) technologies is creating new opportunities in wireless connectivity [Ericsson, 2024]. IoT applications, particularly in sectors like logistics, agriculture, and smart cities, are reshaping data requirements and fostering innovation within the telecommunications industry. In the United States, wireless networks supported approximately 78 petabytes of data in 2023, an 89% increase since 2021 by the Cellular Telecommunications and Internet Association [CTIA, 2024]. To meet this demand, U.S. wireless carriers or MNOs have invested a cumulative $705 billion to date, including $30 billion in 2023 alone [CTIA, 2024].

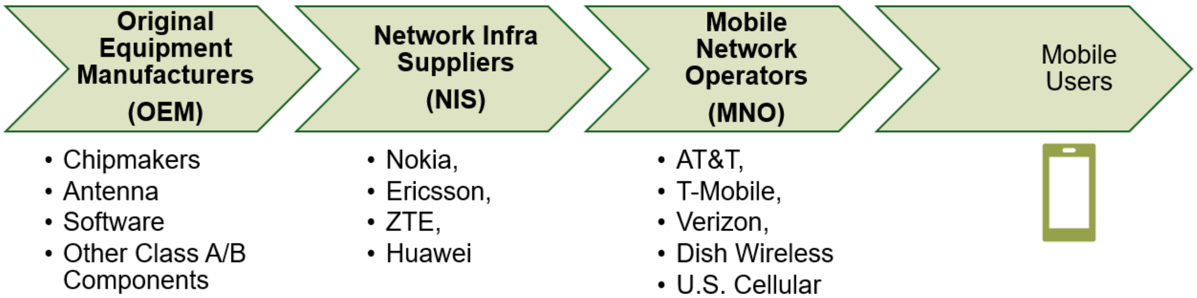


Figure 2.2: Key Stakeholders in Network Supply Chain

Growing demand for data from business-specific network solutions has placed pressure on the network infrastructure industry. To meet the demand for these new use cases and to retain the existing market share, MNOs must provide more innovative and business-specific solutions. This necessitates significant upgrades in network capacity and performance, requiring firms to physically upgrade their networks and rethink their broader network strategies [Rendon Schneir et al., 2019]. Generally, network upgrade costs for MNOs are largely driven by the radio access network (RAN), which accounts for up to 70% of the total network cost [GSMA, 2019].

Traditional RAN infrastructure approaches, commonly known as monolithic radio access networks (MRAN), struggle to meet the growing demand for virtualized, innovative and business specific network solutions. Because MRAN relies on an oligopolistic market structure where a handful of Network Infrastructure Suppliers (NIS), such as Nokia, Ericsson, Huawei, and ZTE, offer custom hardware bundled with proprietary software. The business model of NIS companies, in essence, is to design equipment, buy components, and manufacture final units from Original Equipment Manufacturers (OEMs). This market structure restricts competition and limits mobile network operators' (MNOs' negotiation power for new service deployments and upgrades, often leading to expensive, inflexible generational upgrades with reduced innovation due to vendor lock-in. This is leading to ongoing technical research developments that aim to develop virtualized, software-defined networks with intelligent machine-controlled data traffic management [Yeh et al., 2024]. Traditional MRAN deployments often lack economic justification in less densely populated regions due to high fixed costs and limited revenue potential.

On the policy side, the dominance of a few global suppliers in MRAN exposes MNOs to significant supply chain vulnerabilities. Therefore, the demand for indigenous and open telecom infrastructure supply chains is increasing [Boyens et al., 2021, Department for Science, Innovation and Technology, 2024]. To fulfill such requirements, a growing body of stakeholders are seeking domestic, multi-vendor open ecosystems of suppliers. Its aim is to enhance national security and foster domestic innovation, creating high-skilled jobs and reducing dependency on imported technologies [Kim et al., 2023, NTIA, 2024a,c]. Therefore, many government agencies introduced policies that foster and develop supply chain diversity for RAN upgrades. For example, under the Secure and Trusted Communications Networks Act of 2019, the United States Federal Communications Commission (FCC) promotes open supply chain options [FCC, 2022]. In Japan, the Ministry of Internal Affairs and Communications (MIC) promotes the adoption of ORAN through its Beyond 5G Promotion Strategy [B5G, 2020]. EU policies for 5G and 6G also take a 'technology-specific' approach, focusing on demand-side innovation alongside supply-side efforts [Rossi, 2024].

In response, many industry groups, MNOs, neutral hosts, integrators, businesses, and non-government groups collaboratively designed an open infrastructure RAN supply chain [Oughton et al., 2024]. Various industry alliances, such as the O-RAN Alliance [GSMA, 2020], Meta's Telecom Infra Project (TIP) [Meta, 2016], and the Small Cell Forum [Femto Forum, 2007] have established open interface standards and guidelines for the disaggregation of software from hardware, referred to as Open Radio Access Network (ORAN). Figure 2.3 shows the detailed comparison of architecture and supply chain. Various technical studies suggest that ORAN increases flexibility and fosters innovation, thanks to the ability of ORAN software to be interfaced with commercial off-the-shelf (COTS) hardware, facilitating over-the-air (OTA) virtual updates [Bonati et al., 2020, Polese et al., 2023a].

Thus, ORAN represents a paradigm shift towards disaggregated, interoperable, and vendor-

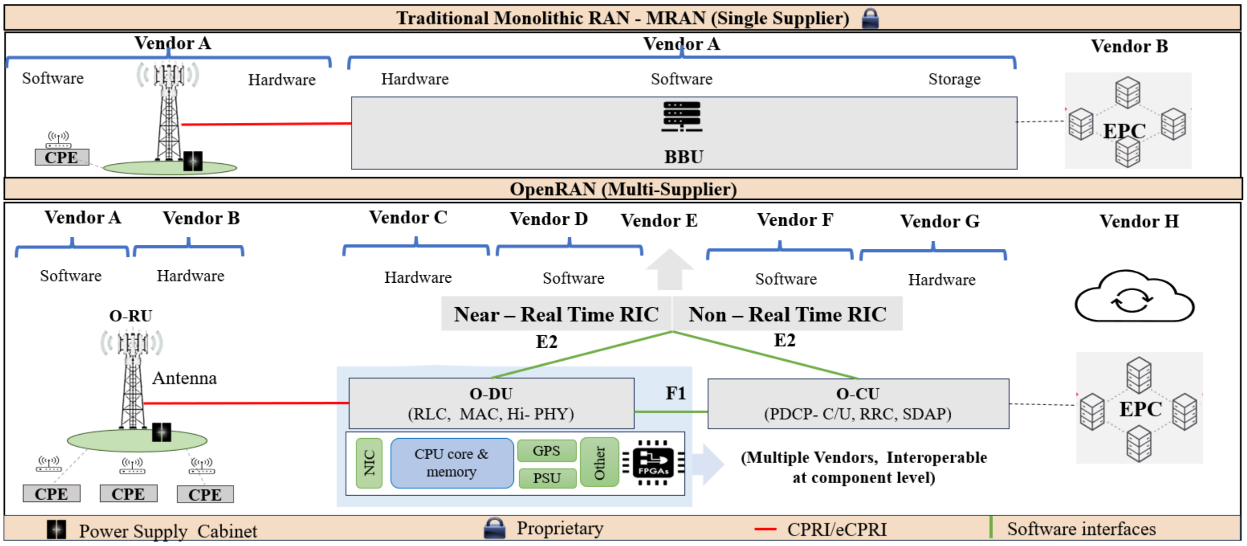


Figure 2.3: MRAN vs ORAN Architecture

neutral RAN architectures. This shift offers both technical and business decentralization. On the technical side, network function virtualization (NFV) and software-defined networking (SDN) enable dynamic allocation of network resources, reducing the need for large upfront investments and allowing more agile responses to fluctuating demand [Hojeij et al., 2023]. In terms of supply chain, ORAN fosters a diverse ecosystem of vendors and solutions, addressing national security concerns and promoting indigenous technological development. Recent innovations further enhance ORAN's potential. HexRAN focuses on fully customizable base station system design [Kak et al., 2023], while multi-vendor, programmable testbeds utilizing NVIDIA ARC and OpenAirInterface facilitate agile network designs and scalable solutions [Villa et al., 2023]. Moreover, deployment of ORAN technologies in rural and underserved regions promises in bridging the digital divide [Slyne et al., 2024]. It allows for targeted bandwidth and latency implementations, making it especially valuable for specialized business operations and connectivity initiatives. These sector-specific drivers highlight ORAN's role not just as a technical evolution, but as an enabler of digital transformation across diverse industries.

However, ORAN do introduce some technical challenges beyond market structure complexities [Cambini and Jiang, 2009]. First, technical issues may arise in multi-vendor environments, leading to conflicts in traffic steering and resource allocation for which conflict management systems are being developed [Wadud et al., 2023]. Second, the multi-sided nature of the Open RAN ecosystem, involving MNOs, vendors, and software suppliers, adds another layer of complexity to identifying and addressing anticompetitive behavior as market dynamics shift, with potential predatory pricing by incumbent suppliers. In any oligopolistic market with few firms, the pricing decision of each firm significantly impacts the market, despite the availability of close substitutes from competitors. Similarly, RAN suppliers as an oligopoly may collude explicitly or implicitly to set prices that maximize their collective profits. This behavior leads to higher prices and lower output than a more competitive market structure. That is why ORAN, which intends to convert the oligopolistic market into a more competitive supplier market, is facing predatory pricing from MRAN suppliers. This dynamic motivates the need for a game theoretic approach to study the strategic interactions between MNOs and suppliers in the ORAN ecosystem. Key area of concern in the adoption of ORAN is the possibility that incumbents may engage in Predatory Pricing or other exclusionary strategies, which could impact the total cost of ownership (TCO).

Therefore, in this capital-intensive and rapidly evolving RAN landscape, MNOs must carefully allocate investments to meet growing data demand while maintaining cost efficiency [Naudts et al., 2016]. Various studies emphasize that equilibrium prices and potential revenue are heavily influenced by suppliers' positions within the network, underscoring the importance of region-specific investment strategies for MNOs to remain competitive [Toka et al., 2021]. However, a significant issue in quantitative decision-making is the lack of available data on costs and prices for each player in the supply chain, often due to closed book contracting terms enforced by non-disclosure agreements (NDAs) in commercial contracts. This lack of transparency exacerbates information asymmetry and moral hazard, reducing incentives for innovation and cost efficiencies across the supply chain.

A significant research gap exists in understanding the strategic incentives required for the adoption of ORAN. Specifically, there is a need for further examination of the dynamics between OEMs that manufacture and supply hardware components, NIS that offer complete network solutions as services, and MNOs. These interactions, particularly in the context of

ORAN, should be compared with MRAN under different procurement scenarios to provide more insights into investment strategies. Understanding incentive structures in ORAN is critical for realizing its promised benefits of increased competition, innovation, and cost reduction in RAN infrastructure, particularly as demand for low-latency, high-bandwidth services grow in underserved regions. While technical specifications and field trials for ORAN mature, the financial incentives driving the adoption by key stakeholders significantly impact regional deployment. Properly aligned stakeholder incentives can help bridge the rural-urban digital divide in coverage, capacity, and latency, while reducing government intervention and making ORAN deployment sustainable. Given this market situation, this research investigates two questions:

1. How can stakeholder incentives, measured as profits, be estimated in single-supplier (MRAN) versus multi-supplier (ORAN) markets, and what strategies are available to each supply chain stakeholder in these markets?
2. What procurement strategies reflect the combinations of these stakeholder actions and how do they impact overall and individual profits?

To address these questions, Section II of this paper reviews the relevant literature on telecom infrastructure optimization strategies, laying the groundwork for the game-theoretic analysis presented in Section III. This is followed by Section IV, which details the United States case used to evaluate the financial and strategic outcomes of different procurement structures in the U.S. telecom industry, comparing MRAN and ORAN incentives. Finally, Section V briefs the conclusion and discussion.

2.2 Literature Review

Many earlier studies on telecom infrastructure investment strategies primarily focused on traditional, vertically integrated network models heavily reliant on proprietary solutions from a limited number of suppliers [Li and Whalley, 2002, Fransman, 2003, Krafft and Krafft, 2003].

This literature review covers a range of topics related to the research questions, providing important background on the current state of knowledge and analysis pertaining to the mobile network equipment market.

There are three ways to enhance a wireless network. First, upgrading the RAN technology to a more spectrally efficient one, such as going from 4G to 5G, results in increased bits per hertz per second. Second, adding additional spectrum bandwidth to sites to increase overall throughput. Third, building more sites to increase the density of assets, which enhances the spectral reuse of spectrum resources. In addition to these three strategies, there are also a range of more minor options to improve the efficiency of wireless networks, ranging from enhanced intercell interference coordination [Lopez-Perez et al., 2011], through cloudification and network slicing [Papageorgiou et al., 2020]. The business model utilized by MNOs can also have a substantial impact on the delivery of ultra-dense wireless networks [Chen et al., 2016], including a range of more basic passive and active infrastructure-sharing options to neutral host models [Cave, 2018], with estimated cost savings of up to USD 940 million in South Korea as an example. The emergence of 5G has represented a paradigm shift in technology and delivery options for MNOs, significantly reshaping the competitive landscape of the telecom industry [Lehr et al., 2021], unlike the incremental improvements of previous generations. One example is the shift towards local private 5G networks, either utilizing locally licensed or shared spectrum bands [Matinmikko-Blue et al., 2018].

The approaches can be utilized to address the specific challenges associated with certain deployment environments, from dense urban to rural and remote areas. E.g. for dense urban areas, research has focused on millimeter-wave frequencies, distributed antenna systems (DAS), the joint deployment of small and macro cells [Araujo et al., 2018], small cells [Cano et al., 2019, Nikam et al., 2020], and massive multiple-input multiple-output (MIMO) [Van Rompaey and Moonen, 2023, Zhao et al., 2024] to increase capacity and reduce per-bit costs. Meanwhile, rural areas see potential in integrating satellite and high-altitude platform systems for wide area coverage [Osoro et al., 2024, Osoro and Oughton, 2021, Yaacoub and Alouini, 2020] and the use of Unmanned Aerial Vehicle (UAV)-based architectures to extend coverage [Chiaraviglio et al., 2017]. NeutRAN architecture is also studied as a way to enhance rural connectivity by enabling spectrum-sharing and elastic resource allocation [Bonati et al., 2023] and low power wide area network (LPWAN) technologies for large-scale IoT deployments for rural distance ranges [Mekki et al., 2019]. However, Oughton et al. [2019] reported that the rural-urban digital divide still exists, finding that rural areas have fewer high-speed fixed and mobile providers but more slower-speed fixed providers than urban areas.

Therefore, alongside network optimization strategies, the demand for modular and customizable network deployments like ORAN gained momentum. Various technical studies demonstrated ORAN's cross-industry potential [Batalla et al., 2022]. dApps have also been proposed as complements to xApps and rApps to enable real-time control for cases like beam management and user scheduling [D'Oro et al., 2022]. Federated deep reinforcement learning techniques emerged as effective solutions for automating RAN slicing in decentralized ORAN architectures [Abouaomar et al., 2023]. Additionally, the combination of digital twin technology with ORAN is seen as a promising direction for resilient 6G RAN deployment [Masaracchia et al., 2023]. Furthermore, the practical applications of ORAN, such as modular traffic steering in open networking, have been demonstrated [Dryjański et al., 2021]. Also, programmable intelligence frameworks for traffic steering further enhance resource allocation within ORAN [Lacava et al., 2023].

Consequently, many researchers have increasingly focused on studying open ecosystems and modular network solutions [Garcia-Saavedra and Costa-Perez, 2021], demonstrating the potential of data-driven optimization in ORAN networks [Bonati et al., 2021]. These innovations have shown the capability to significantly reshape the competitive landscape of the telecom industry [Giannoulakis et al., 2016, Paglierani et al., 2020, Greer et al., 2022, Wypiór et al., 2022]. Moreover, new developments, such as semantic communications in ORAN systems, have demonstrated potential integration with 6G, enabling intelligent, knowledge-driven network infrastructures [Akyildiz et al., 2020, Li and Aijaz, 2023]. Research has further highlighted how adopting open models can reduce dependency on proprietary solutions and foster increased market competition [Oughton and Lehr, 2021]. Expanding on this, a comprehensive review of ORAN systems has added technical depth by covering the complete architecture and design [Rouwet, 2022].

Further studies have delved into the architecture, interfaces, and security challenges of ORAN, demonstrating its potential to reshape market dynamics [Oughton et al., 2024, Polese et al., 2023a]. Machine learning applications in ORAN, particularly at the network edge, have also been investigated [Polese et al., 2021, 2023b]. The deployment of deep reinforcement learning (DRL) models has been proven pivotal in optimizing ORAN's resource allocation, emphasizing the potential of AI-driven approaches [Lotfi et al., 2023]. Additionally, research into multi-agent team learning in disaggregated, virtualized ORAN environments has added to the understanding of the competitive advantages of open models [Rivera et al., 2020]. Moreover, the integration of network digital twins into ORAN environments enhances the ability to simulate and predict network behaviors, improving the overall robustness and adaptability of these systems [Mirzaei et al., 2023]. Advancements like ScalO-RAN optimize AI-based ORAN applications to meet stringent latency requirements [Maxenti et al., 2024]. While benchmarks such as ORAN-Bench-13K highlight the potential of large language models (LLMs) in ORAN for network analytics, anomaly detection, and code generation [Gajjar and Shah, 2024]. Furthermore, adaptive streaming technologies like 360-ADAPT leverage ORAN to enhance quality in streaming 360° opera content by prioritizing audio over video for better use of resources and energy efficiency [Simiscuka et al., 2024]. Additionally, frameworks like PandORA automate DRL agent design for dynamic control in ORAN, achieving significant network performance improvements [Tsampazi et al., 2024]. These studies highlight the growing need for more modular and interoperable alternatives in telecom infrastructure, bringing increased attention to research on open and flexible network architecture. Finally, a comprehensive review of the state-of-the-art in open, programmable, and virtualized 5G networks has outlined the road ahead for further innovations, including AI-driven network orchestration and edge solutions through next-generation open interfaces [Bonati et al., 2020].

In terms of cost-benefit evaluations, several scholars have developed frameworks to assess alternative market and industry structures. These frameworks help evaluate the impact of open ecosystems and technological innovations on traditional market players, providing insights into how market dynamics might evolve under different scenarios [Cano et al., 2019, Paglierani et al., 2020]. For instance, a scenario-based assessment of the future supply and demand for mobile RAN infrastructure enables a comparative understanding of capacity, coverage, and cost [Oughton et al., 2018, Oughton and Frias, 2018]. Additionally, various studies explored policy choices to keep 4G and 5G broadband affordable [Oughton et al., 2022], while other studies examined the techno-economic cost implications of 5G [Koratagere Anantha Kumar and Oughton, 2023, Kumar and Oughton, 2023, Oughton and Frias, 2018].

When analyzing market challenges, various foundational frameworks [Areeda and Turner, 1975, Ordover and Willig, 1981] provide insights into typical Predatory Pricing strategies in such market structures. However, the latest argument on predation in multi-sided markets suggests that market analyses may fail to capture the complexities of multi-sided markets, such as the telecom industry [Jullien and Sand-Zantman, 2021]. Similarly, another study on platform dynamics suggests that incumbents in network effect-driven industries may rationally engage in below-cost pricing for extended periods to prevent the adoption of new platforms [Cabral, 2019]. These studies are directly relevant to the impact of predatory pricing in ORAN. Although helpful, these frameworks may not fully capture the complexities of modern telecom markets, which are characterized by strong network effects and rapid technological changes.

Moreover, beyond pricing strategies, recent research has emphasized a new concept, "predatory innovation", where incumbents deter competition through control over ecosystem design and product innovation rather than direct price manipulation. These non-price strategies—such as market tipping, product collusion, and ecosystem control—allow incumbents to maintain dominance [van Oosten and Onderstal, 2023]. In the context of ORAN, this dominance may be reinforced through long-term exclusive contracts and control over critical network components [Calzolari and Denicolò, 2015]. This multifaceted approach underscores the need for a more nuanced antitrust analysis, as argued by Sidak and Teece [2009]. The market dynamics of the RAN industry provide strong motivation for utilizing a game theoretic approach, as already demonstrated for network sharing strategies in multi-operator cellular networks [Bousia et al., 2016].

Several studies have employed game-theoretic models in the telecommunications sector.

For example, a Bertrand game is used to model spectrum pricing competition among primary service NIS in cognitive radio networks, incorporating quality of service constraints [Niyato and Hossain, 2008]. A Stackelberg game is utilized to optimize data offloading between Long-Term Evolution (LTE) and Wi-Fi networks, and to find economic incentives for balancing traffic load [Anbalagan et al., 2019]. Applied evolutionary game theory and the Hotelling's model are used to analyze collusion and competition strategies among telecom operators [Wen and Fu, 2014]. These studies simulate strategic interactions to enhance decision-making in competitive telecommunications industry environments. In the satellite constellation industry, a game-theoretic framework analyzes competition among satellite constellation operators in low-Earth orbit [Guyot et al., 2023]. This framework employs a two-stage game where operators first choose constellation designs and subsequently compete on price. Such an approach reveals how oligopolistic competition such as RAN industry can lead to suboptimal outcomes in terms of economic welfare and resource allocation.

2.3 Conceptual Framework

This section introduces an economic evaluation framework focusing on the interactions between key RAN supply chain players—MNOs, NIS, and OEMs. Rather than addressing infrastructure sharing between MNOs, the analysis explores the strategic leadership dynamics among these stakeholders. The purpose is to understand the incentive structure of key network industry stakeholders in various supply chain structures and its role in impeding or driving investments and ICT innovations in rural areas.

As the literature suggests, understanding telecom value chain profitability, particularly in the context of ORAN, requires the consideration of both financial and non-financial factors, such as the predatory behavior of existing suppliers or signaling to switch. Also, telecom stakeholders' profits depend on various demographic and technological factors, which vary significantly across different regions, such as urban, suburban, and rural areas. Therefore, it is important to calculate the expected profit function for each stakeholder—MNOs, NIS, and OEMs—to capture individual profits, interdependencies, and strategic interactions within the ecosystem. Each stakeholder plays a critical role in the deployment and success of network infrastructure, with their decisions being closely linked. By calculating the profits for each entity, we aim to understand how one stakeholder's investment incentives in the form of profit impact the outcomes for the others from a game theory perspective.

2.3.1 Game-Theoretic Setup

To analyze the strategic interactions, we employ a three-player sequential game with complete information. We define the game as $\mathcal{G} = \langle \mathcal{N}, (S_i)_{i\in\mathcal{N}}, (u_i)_{i\in\mathcal{N}} \rangle$, where: $\mathcal{N} = \{C, B, A\}$ represents the set of players: Original Equipment Manufacturers (OEMs), Network Infrastructure Suppliers (NISs), and Mobile Network Operators (MNOs), respectively. For each player $i \in \mathcal{N}$, S_i denotes their strategy set, and the specific strategy sets are:

- Player C (OEM): $S_C = \{I_C, R_C\}$ representing the decision to invest in ORAN (I_C) or refrain from ORAN (R_C)
- Player B (NIS): $S_B = \{I_B, R_B\}$ representing the decision to invest in ORAN (I_B) or refrain from ORAN (R_B)
- Player A (MNO): $S_A = \{I_A, R_A\}$ representing the decision to buy ORAN (I_A) or refrain from ORAN (R_A)

The game follows a vertical structure with sequential moves in the order $C \to B \to A$, reflecting the hierarchical nature of the RAN supply chain, where upstream decisions by equipment manufacturers constrain the subsequent choices available to infrastructure suppliers, which in turn influence the adoption decisions of network operators. We apply the solution concept of subgame perfect Nash equilibrium (SPNE), which requires that the strategies constitute a Nash equilibrium in every subgame, and solve for it using backward induction.

Extensive Form Representation

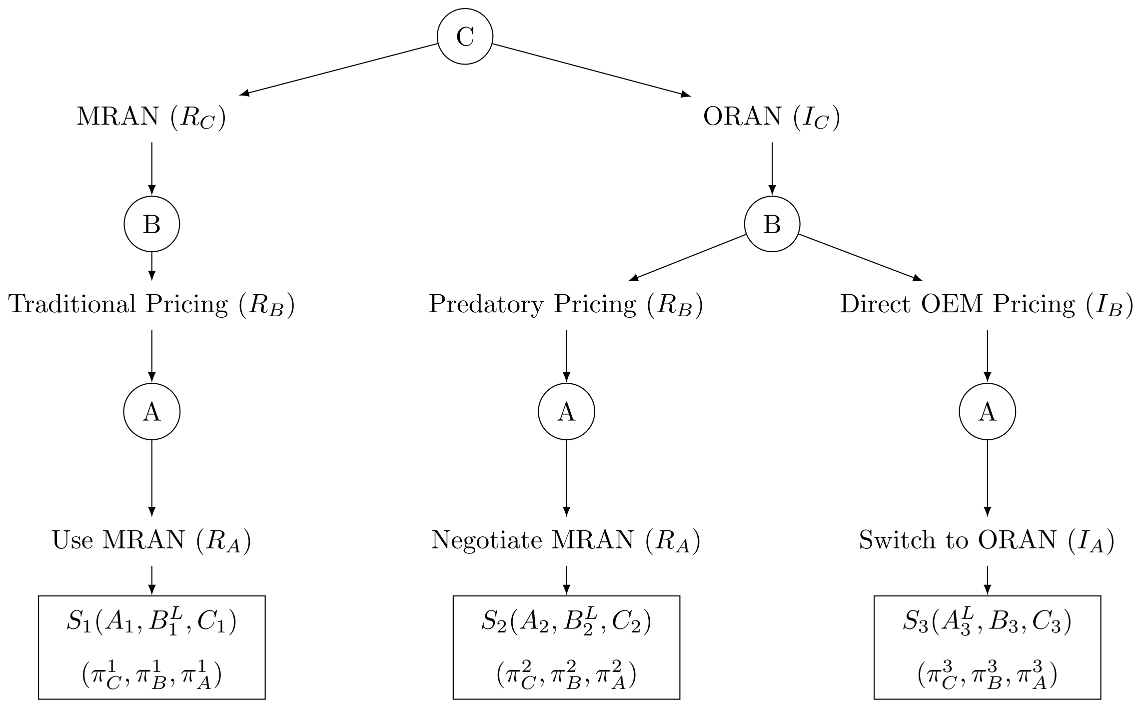


Figure 2.4: Extensive form representation of a three-player sequential game. Players are represented by circles (C=OEM, B=NIS, A=MNO), actions are indicated on branches, and terminal payoffs in rectangles.

Sequential Strategy Space for Players in the RAN Supply Chain

In this sequential three-player game, the strategy space for each player depends on prior moves. The game begins with the OEM, denoted as Player C, who chooses a technology strategy: as they are the manufacturer and have to provide ORAN compliant products . Therefore, strategic options are either *MRAN* or *ORAN*, i.e., $s_C \in \text{MRAN}, \text{ORAN}$.

Conditional on the OEM's choice, the NIS, denoted as Player B, selects a pricing strategy. If the OEM chooses MRAN, the NIS has a single strategy: $s_B \in$ Traditional Pricing. If the OEM chooses ORAN, the NIS can choose between $s_B \in \text{Predatory Pricing}, \text{Direct OEM Pricing}$, depending on its market positioning and competitive intent.

Finally, the MNO, denoted as Player A, responds to the preceding strategic decisions. If the observed path is MRAN with Traditional Pricing, the MNO's strategy is $s_A \in$ Use MRAN.

If the path leads through ORAN with Predatory Pricing, the MNO may choose to $s_A \in$ Negotiate MRAN to avoid switching costs or interoperability issues. Conversely, if the NIS adopts Direct OEM Pricing under ORAN, the MNO has the option to fully transition to the open ecosystem, i.e., $s_A \in$ Switch to ORAN.

Market Scenario	**MNO (A)**	**NIS (B)**	**OEM (C)**	**Total**
Traditional MRAN	π_A^1	π_B^1	π_C^1	$\pi_A^1 + \pi_B^1 + \pi_C^1$
(MRAN + Traditional + Use MRAN)				
Predatory MRAN	π_A^2	π_B^2	π_C^2	$\pi_A^2 + \pi_B^2 + \pi_C^2$
(MRAN + Predatory + Negotiate MRAN)				
Direct OEM ORAN	π_A^1	0	π_C^3	$\pi_A^3 + 0 + \pi_C^3$
(MRAN + DirectOEM + Switch to ORAN)				
Region Type Comparison				
Urban, Suburban vs. Rural Regions	Regional payoff variations based on market size, user density, and infrastructure deployment costs			

Note: π_X^1, π_X^2, π_X^3 represent payoffs for player X under different market scenarios. Total payoffs can be analyzed for welfare implications and supply chain efficiency.

Table 2.1: Payoff Comparison Matrix Across Scenarios

Calculating Profit Functions as Payoffs for Players

We formulate the profit (payoff) for each stakeholder as the net present value (NPV) of their revenue streams minus costs, accounting for discounting over the N-period horizon. For clarity, we present the profit equations for a given region r (different region types such as urban, suburban, rural). All profit calculations incorporate relevant factors such as market size growth and cost structures. Table 2.2 summarizes the notation used in our formulation. The evaluation needs to be done by region types, as solutions to region-specific problems require region-specific understanding of infrastructure economics and stakeholder incentives.

Symbol	**Definition**
$\Pi_{m,r}$, $\Pi_{s,r}$, $\Pi_{o,r}$	Profit (payoff) of MNO, NIS, and OEM in region r over N years.
$R_{m,r,t}$, $C_{m,r,t}$	Revenue and cost for MNO in region r at time t.
P_{rs}, P_{ro}	Price per site by NIS to MNO, and by OEM to NIS in region r.
P_o, P_{cost}	OEM site price and cost of production.
$M_s = P_{rs} - P_{ro}$	NIS margin per unit.
$M_o = P_o - P_{\text{cost}}$	OEM margin per unit.
Sites_{rt}	Number of telecom sites deployed in region r at time t.
$\text{Sites}_{rt,d}$, $\text{Sites}_{rt,a}$	Sites needed by data demand and by coverage area respectively.
D_{rt}	Total data demand in region r at time t (bits/year).
UD_r^{Users}	Annual data usage per user in region r (bytes).
SC_r	Site capacity in region r (bits/year).
A_{total}	Total land area of region r (sq. km).
CA_r	Coverage area per site in region r (sq. km).
R_r, I_r	Site coverage radius and interference factor in region r.
$C_{mr,0}$	Capital expenditure (Capex) for MNO in region r at time 0.
$C_{mr,t>0}$	Operational expenditure (Opex) for MNO after time 0.
$\text{OpexRate}_{r,t}$	Opex as a fraction of Capex in region r and time t.
d, β	Discount rate and discount factor ($\beta = 1/(1+d)$).
$U_{r,t}$	Number of active users in region r at time t.
$\text{ARPU}_{r,t}$	Average revenue per user in region r at time t.
$\text{ARPU}_t^{\text{national}}$	National average ARPU at time t.
$\text{MHI}_{r,t}$, NHI_t	Median and national household income.
g_r	Population growth rate in region r.
P_{r0}	Initial population in region r.
S_r, A_r	Smartphone penetration and active user rate in region r.
B_r, SE_r, NS_r	Bandwidth, spectral efficiency, and number of sectors per site in r.

Table 2.2: Notation list of variables and parameters used in payoff calculations.

MNO Payoffs (Π_{mr})

The first stakeholder is the consumer of this infrastructure MNO, denoted as m. They earn revenue via active user subscriptions, adjusted ARPU. The profit model incorporates capital and operating expenditures, which are subjected to discounting over time. The subsequent equations delineate the calculation of MNO revenue as well as net present value (NPV) profit across various market structures.

Variable	Equation	Description
Revenue (R_{mrt}) =	$\text{ARPU}_{rt} \times U_{rt}$	Revenue from mobile users in region r at time t, based on adjusted ARPU and active users.
ARPU Adjustment (ARPU_{rt}) =	$\text{ARPU}_t^{\text{national}} \left(\frac{\text{MHI}_{rt}}{\text{NHI}_t} \right)$	ARPU scaled to local income levels using median household income Elliott et al. [2023].
Active Users (U_{rt}) =	$P_{r0}(1 + g_r)^{t-1} \times S_r \times A_r$	Estimated smartphone users in year t considering population, adoption, and activity.
Total Profit (NPV) (Π_{mr}) =	$R_{mr,0} - C_{mr,0} + \sum_{t=1}^{N-1} \frac{R_{mrt} - C_{mrt}}{(1+d)^t}$	Net present value of profits over N years after subtracting Capex and Opex.
Capex ($C_{mr,0}$) =	$\text{Sites}_{rt} \times P_s$	Initial infrastructure investment cost in year 0 based on unit site price.
Opex ($C_{mr,t>0}$) =	$\text{Sites}_{rt} \times P_s \times \text{OpexRate}_{rt}$	Annual operational and maintenance costs as a share of Capex.
Total Sites (Sites_{rt}) =	$\max(\text{Sites}_{rt,d}, \text{Sites}_{rt,a})$	Number of sites required, determined by both data demand and coverage needs.
Sites from Demand ($\text{Sites}_{rt,d}$) =	$\frac{D_{rt}}{\text{SC}_{rt}}$	Sites required to satisfy data throughput based on demand and site capacity.
Sites from Area ($\text{Sites}_{rt,a}$) =	$\frac{A_{\text{total}}}{CA_r}$	Sites required to ensure geographic coverage across the region.
Coverage Area per Site (CA_r) =	$\pi R_r^2(1 - I_r)$	Effective coverage area of a single site after accounting for interference.
Data Demand (D_{rt}) =	$U_{rt} \times UD_r^{\text{Users}} \times 8$	Total annual regional data demand in bits.
Site Capacity (SC_r) =	$B_r \times SE_r \times NS_r \times 2592000 \times 12 \times 10^6$	Annual site throughput capacity based on technical configuration.

Table 2.3: Mathematical expressions for MNO revenue, profit, and cost components.

These formulations allow for the estimation of infrastructure requirements and cost trajectories under different deployment scenarios and regional characteristics.

NIS Payoffs(B)

The second important stakeholder in the RAN supply chain is NIS, denoted as s, which provides the necessary hardware and software solutions to MNOs. Their expected profit over the N-year period is influenced by the contracts they secure with MNOs, the pricing of their products, and the costs associated with design customization and R&D, as they are not directly producing the products. In an oligopolistic market, each region is typically supplied by one exclusive NIS. Assuming the same margin is applied to both capex and opex, the expected profit for a supplier in region r can be expressed as follows.

Variable	**Equation**	**Description**
NIS Margin per Unit (M_s) =	$P_{rs} - P_{ro}$	Unit profit margin for NIS, defined as the difference between NIS sale price to MNO and purchase price from OEM.
NIS Profit (NPV) (Π_{sr}) =	$\text{Sites}_t \cdot M_s + \sum_{t=1}^{N-1} \frac{\text{Sites}_t \cdot M_s \cdot \text{OpexRate}_{rt}}{(1+d)^t}$	Net present value of NIS profit over N years, from initial capex margins and discounted opex margins.

Table 2.4: Mathematical expressions for NIS profit in region r over time horizon N.

OEM Payoffs(C)

The third stakeholder category is OEMs, denoted as o, responsible for providing the key components and equipment used in RAN infrastructure along with baseline software interfaces. Multiple OEMs collaborate with contract manufacturers to supply finished equipment to NIS in the MRAN structure, and provide white-box hardware in the ORAN structure.Since OEM revenue occurs as a one-time capex in year 0, expected profit in region r can be expressed as:

Variable	Equation	Description
OEM Margin per Unit (M_o) =	$P_o - P_{\text{cost}}$	Unit margin for OEM, calculated as the difference between the sale price and the production cost per equipment unit.
OEM Profit (Capex Only) (Π_{or}) =	$\text{Sites}_t \cdot M_o$	Total OEM profit in region r, derived from equipment sales in year 0, assuming a one-time capex-based transaction.

Table 2.5: Mathematical expressions for OEM margins and profit in region r.

Solving for Subgame Perfect Nash Equilibrium

To identify the subgame perfect Nash equilibrium (SPNE) of our sequential game, we employ backward induction—solving the game from the final decision node and working backward to the initial node. This approach ensures that each player's strategy is optimal given all possible future moves. Starting with Player A (MNO), we determine their best response at each decision node by comparing profit outcomes across available options. For each of Player A's decision nodes, we calculate:

$$BR_A(s_B, s_C) = \arg\max_{s_A \in S_A} \Pi_A(s_A, s_B, s_C) \tag{2.1}$$

Moving to Player B (NIS), we incorporate Player A's optimal responses into B's decision calculus. For each of Player B's decision nodes, we solve:

$$BR_B(s_C) = \arg\max_{s_B \in S_B} \Pi_B(s_B, BR_A(s_B, s_C), s_C) \tag{2.2}$$

Finally, Player C (OEM) makes the initial strategic choice by anticipating the optimal responses of both subsequent players:

$$BR_C = \arg\max_{s_C \in S_C} \Pi_C(s_C, BR_B(s_C), BR_A(BR_B(s_C), s_C)) \tag{2.3}$$

The resulting strategy profile $(BR_C, BR_B(BR_C), BR_A(BR_B(BR_C), BR_C))$ constitutes the SPNE. This equilibrium is computed separately for each region type (urban, suburban, rural) to capture the distinct economic conditions that influence stakeholder incentives across different deployment environments.

Leadership Based Equilibrium Method

While backward induction provides a structured approach to finding the SPNE in our sequential game, we further employ a method to verify our results and gain additional insights into the strategic dynamics. This approach directly compares the payoff values at each terminal node to identify equilibrium paths through domination analysis. For each region type r (urban, suburban, rural), we calculate the complete set of payoff vectors $(\pi_A^i, \pi_B^i, \pi_C^i)$ for all possible strategy profiles $i \in \{1, 2, 3\}$ while evaluating the leadership in each scenario. A key aspect of this game is to shift price dominance from NIS to MNOs under a competitive industry structure. Since MNOs are the customers, they should be able to bid—or not bid—during the procurement process.

The first scenario is a Traditional Pricing scenario (s_1). It involves a standard procurement process where suppliers and OEMs offer existing market-rate prices. This approach maintains stable cost structures and margins, fostering long-term supplier relationships [Cambini and Jiang, 2009]. Second is the Predatory Pricing scenario (s_2). It occurs when MNOs signal their intent to switch suppliers, prompting NIS to adopt aggressive pricing tactics to retain contracts. Although this strategy may result in lower unit prices and reduced supplier margins in the short term, it may negatively impact RAN's long-term performance, potentially leading to decreased research and development (R&D) investments and operational efficiency. Last is the Direct OEM Pricing scenario (s_3). In this scenario, MNOs bypass NIS altogether and directly procure equipment from OEMs, which is called the ORAN ecosystem. This requires upfront investment and time to get the necessary hardware and software, with added maintenance responsibility.

The objective of this method is to evaluate and compare supply chain profits as incentives by region type under each scenario. For MRAN ($s_1, s_2,$), objective function can be expressed as a sequential profit maximization under traditional and predatory supply chain:

Player B - NIS (leader)

$$m_{sr}^{*} = \arg \max_{m_{sr} \in [m_{sr}^{\min}, m_{sr}^{\max}]} \sum_{t=1}^{N} \beta^{t} \Pi_{sr}(m_{sr}) \tag{2.4}$$

Player C - OEM (follower)

$$m_{or}^{*}(m_{sr}) = \arg \max_{m_{or} \in [m_{or}^{\min}, m_{or}^{\max}]} \sum_{t=1}^{N} \beta^{t} \Pi_{mr}(m_{or}, m_{sr}^{*}) \tag{2.5}$$

Player A - MNO (passive)

$$\Pi_{mr} = Q_{mr}(P_{mr} - C_{nr} - m_{nr} - C_{or} - m_{or}) \tag{2.6}$$

Whereas the objective function changed for the ORAN scenario, specifically the OEMDirect S3 scenario, to a joint profit maximization due to the competitive nature of the market, The MNO now bypasses the NIS and directly procures infrastructure components from the OEM. The best response functions for both the MNO and OEM are as follows. These best response functions can be characterized by the prices and site quantities that maximize joint industry profits.

ORAN(s_3),

$$\max \sum_{t=1}^{N} \beta^{t} [\Pi_{mr} + \Pi_{or}] \tag{2.7}$$

where:

- s_1 is a Traditional Pricing scenario.
- s_2 is the Predatory Pricing scenario.
- s_3 is the Direct OEM Pricing scenario.
- Π_{mr} represents the profits of the MNOs in region r.
- Π_{sr} represents the profits of the NIS in region r.
- Π_{or} represents the profits of the OEMs (Original Equipment Manufacturers) region r.
- t denotes each period or stage of the market dynamics being considered, up to N periods.

- β^t is the discount factor with $0 < \beta < 1$.
- m^*_{nr}, m^*_{or}: Margins set by Player NIS and Player OEM

2.4 Simulation : United States

The simulation in this study utilizes data across U.S. counties to evaluate the strategic incentives within a game-theoretic framework under MRAN (Traditional, Predatory) and ORAN (DirectOEM) scenarios. Key input datasets include demographic and economic indicators sourced from the U.S. Census Bureau, which provides granular county-level information such as population density and business activity through the County Business Patterns (CBP) program. These demographic variables are integrated to represent regional demand potential alongside population-driven variations in the marginal cost structures of deployment. Median household income data from the 2020 census is incorporated to estimate average revenue per user (ARPU) as a function of local household conditions.

On the supply side, we use broadband availability, speed, and usage data from the Federal Communications Commission (FCC) to understand regional infrastructure differences. The FCC's Measuring Broadband America reports offer detailed mobile broadband performance metrics, which help us compare network quality and how users in different regions respond to service changes. Infrastructure deployment cost estimates are derived from the FCC's catalog, which outlines costs specific to different technology deployments (e.g., RAN upgrades) and regional geographies. These cost parameters are crucial for capturing the varying operational expenditures in densely populated urban centers compared to sparsely populated rural areas. This diverse array of data sources, spanning demographic, economic, and telecom-specific indicators, enables a multifaceted analysis of the potential for ORAN adoption across various region types in the United States (see Supplementary Material for data source and capacity calculations), illustrating how solutions vary across different geographies based on cost structures and regional characteristics for United States.

This diverse array of data sources, spanning demographic, economic, and telecom-specific indicators, enables a multifaceted analysis of the potential for Open RAN adoption across various region types in the United States.

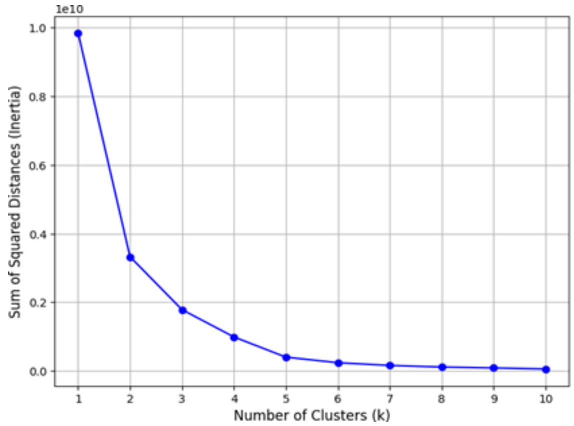
Category	Variables	Sources
Demographics & Household	Population, Growth Rate	U.S. Census Bureau, 2020 Census Population [U.S. Census Bureau, 2020a]
	Land Area	U.S. Census Bureau, 2023 Gazetteer Files [U.S. Census Bureau, 2023]
	Businesses, Growth Rate	U.S. Census Bureau, County Business Patterns (CBP) Survey [U.S. Census Bureau, 2020b]
	Median Household Income (MHI)	USDA ERS [U.S. Department of Agriculture Economic Research Service, 2020]
Network	Existing Telecom Sites	Unwired labs OpenCellID [Unwiredlabs, 2020]
	Data Demand & Speed Demand	FCC [Federal Communications Commission, 2020]
Cost	FCC final catalog	FCC [Federal Communications Commission, 2021]

Table 2.6: Datasets used for the analysis, including variables and sources

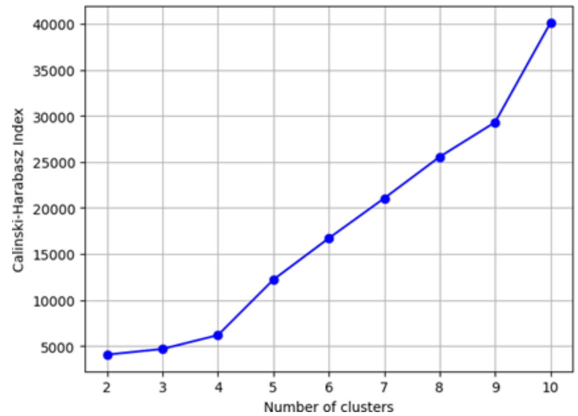
County Clustering into Region Types

We employ an unsupervised learning approach to classify U.S. counties into eight distinct region types (e.g., urban, suburban, rural) using k-means clustering. The clustering uses two key features for each county: population density (people per square km) and cellular site density (sites per square km). These features capture the intensity of demand and the extent of existing network infrastructure, respectively. By clustering on these metrics, we obtain groups of counties that range from highly urbanized (high population and cell densities) to extremely rural (low densities). We label the clusters for interpretability, with one cluster designated as *Urban*, two as *Suburban* (medium-high density), and five as *Rural* (varying lower densities).

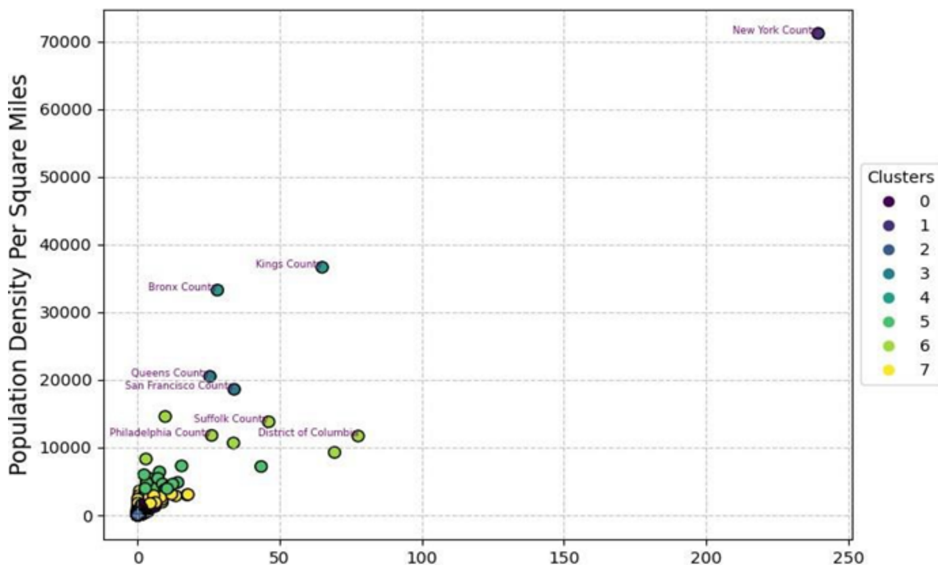
The choice of $k = 8$ clusters is guided by standard validation methods. We applied the *Elbow method* to the clustering results, examining how the within-cluster sum of squared distances (inertia) declines as k increases. The inertia showed a noticeable “elbow” (diminishing returns) around $k = 8$. We also calculated the *Calinski-Harabasz Index* for different k, which peaked near $k = 8$, indicating that the clustering structure is most pronounced at this number of clusters. Figure 2.5 illustrates these trends: the elbow plot flattens at eight clusters, and the Calinski-Harabasz score is high at $k = 8$. Based on these metrics, we selected eight clusters as an appropriate balance between detail and generalization.



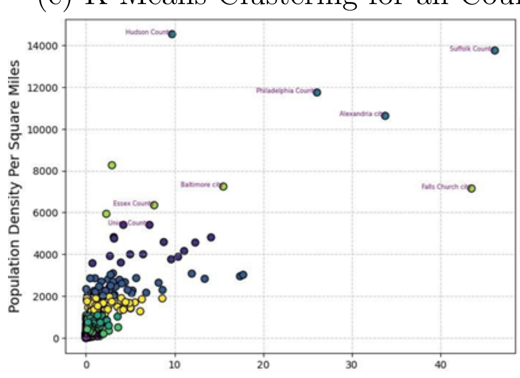
(a) Elbow Method Results



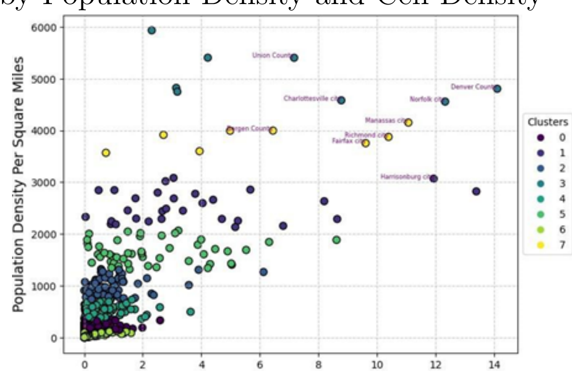
(b) Calinski-Harabasz Method Results



(c) K-Means Clustering for all Counties by Population Density and Cell Density



(d) K-Means Clustering (8SD, Z score)



(e) K-Means Clustering (7SD, Z score)

Figure 2.5: Comparison of Clustering Methods for K-means Clusters with Results

The results from cluster analysis demonstrate distinct clusters among counties based on cell density and population density, with notable high-density outliers, such as New York County and Kings County, clearly labeled for reference. Also, the scatter plot Figure 2.6 visually presents these classifications, highlighting the differences in population density and existing telecom cell densities across regions. The urban areas show high density, while the gradual decline into suburban and rural regions illustrates the varying infrastructure needs. Furthermore, it indicates that population density is the primary driver of infrastructure requirements.

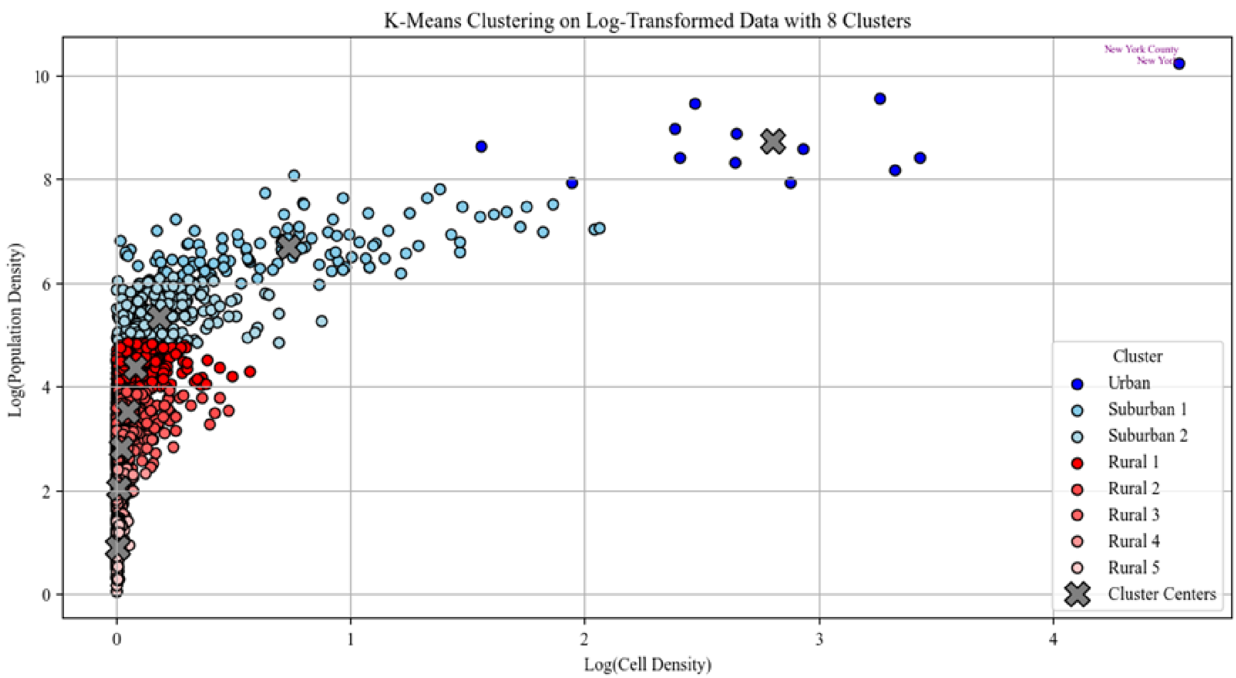


Figure 2.6: Region Types Based on Population Thresholds

The resulting classification system comprises eight categories based on cell and population density. Table 2.7 presents the centroid values of the eight clusters in terms of population and site density, highlighting the clear differences among region types. For example, the *Urban* cluster has a population density over an order of magnitude higher than the most rural clusters, and likewise a far greater site density. In contrast, the *Rural 5* cluster (the sparsest rural category) has very low population density and correspondingly sparse infrastructure. By design, more clusters are allocated to rural types to capture gradations in sparsity.

Region Type	Population Density	Cell Site Density
Urban	1,200 km^{-2}	0.15 km^{-2}
Suburban 1	450 km^{-2}	0.06 km^{-2}
Suburban 2	150 km^{-2}	0.02 km^{-2}
Rural 1	50 km^{-2}	0.01 km^{-2}
Rural 2	20 km^{-2}	0.005 km^{-2}
Rural 3	10 km^{-2}	0.003 km^{-2}
Rural 4	5 km^{-2}	0.0015 km^{-2}
Rural 5	2 km^{-2}	0.0005 km^{-2}

Table 2.7: Cluster centroids for the 8 region types, characterized by population density and site density

Urban areas are categorized into Urban (e.g., metropolitan cities like New York), with very high population and cell density, and Suburban 1, which has high population and moderate cell density, both requiring advanced RAN technologies like massive MIMO. Suburban 2 represents transition zones with moderate population and cell density. The rural gradient includes Rural 1 (semi-rural edges with mixed use), Rural 2 (small towns with light agriculture), Rural 3 (low-density farming areas), Rural 4 (vast farmlands), and Rural 5 (remote wilderness), each reflecting decreasing population and cell densities. These classifications guide tailored telecom infrastructure strategies. This detailed categorization allows for a nuanced approach to understanding and addressing infrastructure needs from densely populated urban areas to sparsely populated rural zones. The significant variations in cell and population densities across these clusters highlight the diverse challenges in implementing adequate wireless network coverage across different regions.

Supply Configuration Selection and Capacity Specifications

The configurations used in this study are selected to meet the distinct capacity and coverage requirements of Urban/Suburban1 and Suburban2, as well as rural regions in USA counties. For urban and suburban areas, both the Traditional/Predatory and Direct OEM Pricing model provides MRAN and utilize high-capacity configurations setups i.e., the Traditional/Predatory models rely on multi-band LTE antennas with 10T10R to 20T20R configurations, enhanced by mMIMO eNodeB (64T64R) with 60 MHz bandwidth for advanced mobility features, ensuring

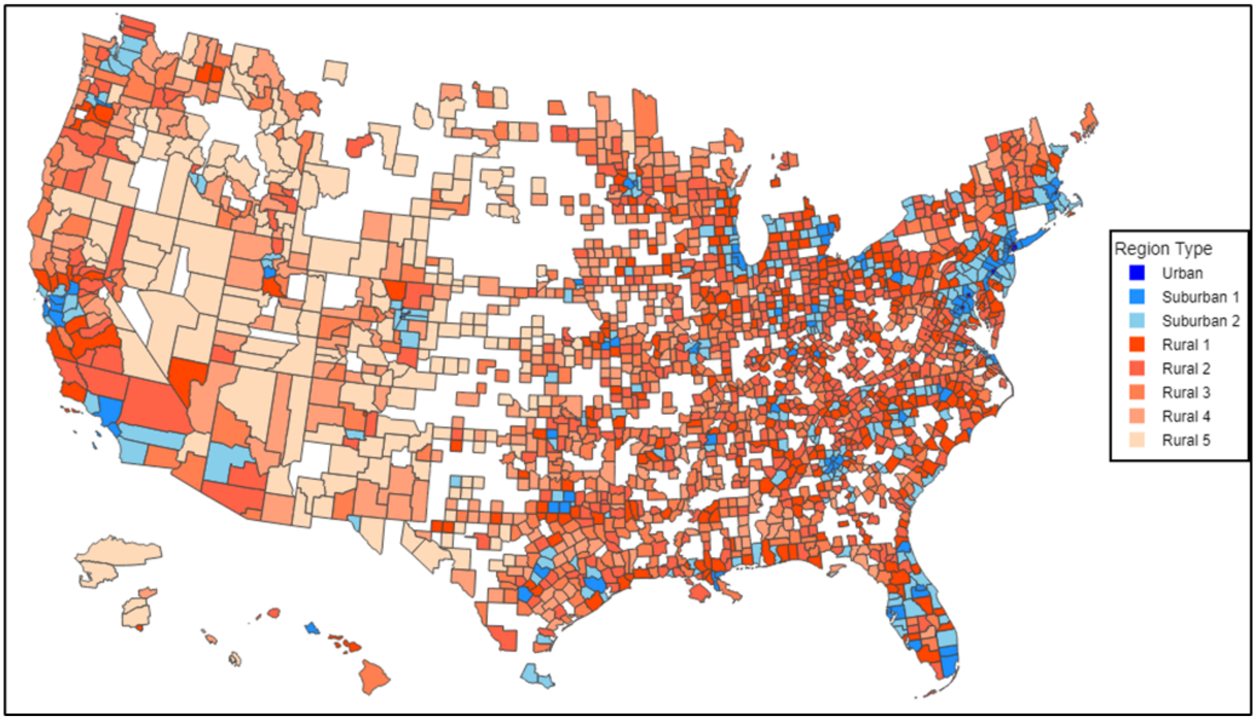


Figure 2.7: Map of U.S. Counties Categorized by Region Type (by population and cell density)

high throughput in densely populated areas. The Direct OEM provides ORAN configuration and enhances this further with 5G Sub6 (100 MHz) carriers, providing low-latency, high-speed connectivity and supporting large user bases in urban settings.

In rural regions, the focus shifts toward coverage and cost efficiency. The Traditional/Predatory models utilize non-MIMO eNodeB with 20 MHz/sector and Fixed Wireless Access (FWA) features, ensuring wide-area coverage with fewer sites. The Direct OEM model also employs a Macrocell with a 4G 20 MHz carrier, providing sufficient capacity for low-density areas. Both configurations offer power flexibility (20W to 320W) to adapt to various terrain conditions. They are well-suited for the sparse population and large geographical areas typical of rural regions. These configurations balance cost, coverage, and capacity, ensuring optimal service across diverse county types.

Configuration-based Coverage

Table 2.8 summarizes the capacity and coverage that each configuration type provides. The selected configuration determines the bandwidth, spectral efficiency, and number of sectors, where higher bandwidths and spectral efficiencies allow for greater capacity. In urban/suburban regions, the use of mMIMO technology with configurations such as 64T64R improves capacity and spectral efficiency, but it can lead to a reduction in coverage area due to signal interference and obstacles in dense environments. This is why the coverage area in these regions remains at 7.07 sq km, despite high spectral efficiency. In contrast, rural areas rely on non-MIMO configurations, which cover larger areas (up to 176.71 sq km), although with lower spectral efficiency in traditional models.

Direct OEM configurations further enhance capacity, especially in urban regions, with 100 MHz bandwidth and 50 bps/Hz spectral efficiency. In comparison, rural regions benefit from improved spectral efficiency (20 bps/Hz) compared to traditional setups. However, rural configurations prioritize wide coverage over maximum data throughput, making them more cost-effective for low-density regions where fewer users need high-speed data access.

Site Parameter	Urban/Suburban 1-type Site	Suburban 2/Rural-type Site
Bandwidth	60 MHz	20 MHz
Spectral efficiency	40 bit/s/Hz	10 bit/s/Hz
Number of sectors	3	1
Coverage radius	≈1.5 km	≈7.5 km
Coverage area	$\sim$7 km^2	$\sim$177 km^2

Table 2.8: Assumed network capacity and coverage parameters per cell site (representative values for urban vs. rural regions).

Using these inputs, the simulation is run for each region type to compute the payoffs $\Pi_{mr}, \Pi_{sr}, \Pi_{or}$. The clustering-based approach enables us to observe how profitability varies from urban to rural settings, thereby shedding light on which areas are attractive or challenging for new RAN deployments.

2.4.1 Assumptions and Key Parameters

Due to the lack of data on invoice, bill of materials expenditure on infrastructure per county, the analysis relies on the FCC catalog, which provides the closest available estimates for costs, allowing for standardized cost assumptions across regions. We assume a 10-year investment horizon, as the typical lifespan of RAN infrastructure is 10 years, after which significant upgrades or replacements are required. All costs and revenues are projected over this period to reflect the infrastructure's operational lifecycle. In addition, a 5% discount rate is applied to calculate the NPV of future cash flows. For this study, inference is assumed to be 0 for all scenarios and region types.

In the Traditional scenario, MNOs engage with both NIS and OEMs for service delivery. The predatory scenario reflects a pricing strategy where MNOs bid for Open RAN. This prompts network suppliers to offer predatory pricing to counter the competition and maintain market dominance. The DirectOEM scenario bypasses the role of network suppliers, enabling MNOs to directly procure equipment and services from OEMs.

MNO cost assumptions are derived from the FCC catalog Table A.1. The base costs are assumed to differ by region type, with urban and Suburban 1 regions incurring significantly higher deployment costs compared to Suburban 2 and all Rural 1-5 areas. For the Traditional scenario, the initial setup cost of deploying telecom infrastructure is \$232,823 per site in Urban and Suburban 1 regions as per the FCC MIMO catalog for MIMO technologies that suit the population densities, and \$63,237 for Suburban 2 and Rural 1-5 regions. In contrast, for the predatory and DirectOEM scenarios, i.e., ORAN, MNO costs are significantly reduced to \$108,000 and \$42,500 per site for Urban/Suburban 1 and Suburban 2 and all Rural 1-5 regions, respectively, based on the ORAN configurations chosen.

Operating expenses (Opex) are assumed to be a fixed percentage of Capex, varying across scenarios. In the Traditional and predatory scenarios, Opex is set at 12%, whereas the DirectOEM scenario incurs slightly higher Opex, at 13%. These Opex rates account for the ongoing operational and maintenance costs associated with telecom infrastructure deployment and service provision.

The summary statistics for each region type in Table 2.9 provide insights into key variables such as population, MHI, data consumption, and existing infrastructure density. We have a dataset with a total of N=2074 U.S. counties.

Region Type	Counties (N)	Population (k)	Median Household Income ($k)	Monthly Data Demand (GB)	Avg. Cell Density (sites/km^2)	Population Density Range (mean) (people/km^2)
Urban	13	762	85	168	21.191	2,760–27,469 (7,899)
Suburban 1	117	637	78	96	1.361	391–3,190 (893)
Suburban 2	240	258	76	36	0.215	126–445 (222)
Rural 1	334	91	65	10	0.091	51–128 (80)
Rural 2	466	44	59	6	0.052	23–50 (34)
Rural 3	441	23	55	3	0.025	10–23 (16)
Rural 4	279	15	55	2	0.014	3–10 (7)
Rural 5	184	8	57	1	0.005	0–3 (2)

Note: Population is reported in thousands. Cell density refers to the average number of sites per square kilometer. Population density is shown as minimum–maximum (mean).

Table 2.9: Descriptive statistics by region type.

The descriptive summaries of variables shown in Table 2.9 and Figure 2.8 demonstrate significant urban-rural disparities. The data shows that urban areas generate high revenues from small land areas. In contrast, rural regions produce lower revenues across larger territories, highlighting the varying market dynamics across the U.S. This pattern reflects broader economic disparities between urban and rural areas. The considerable variability within each region type indicates that MNOs should tailor their strategies to specific regional conditions rather than applying a one-size-fits-all approach. This provides a foundation for developing targeted Open RAN investment strategies that consider the diverse economic landscapes across different U.S. region types.

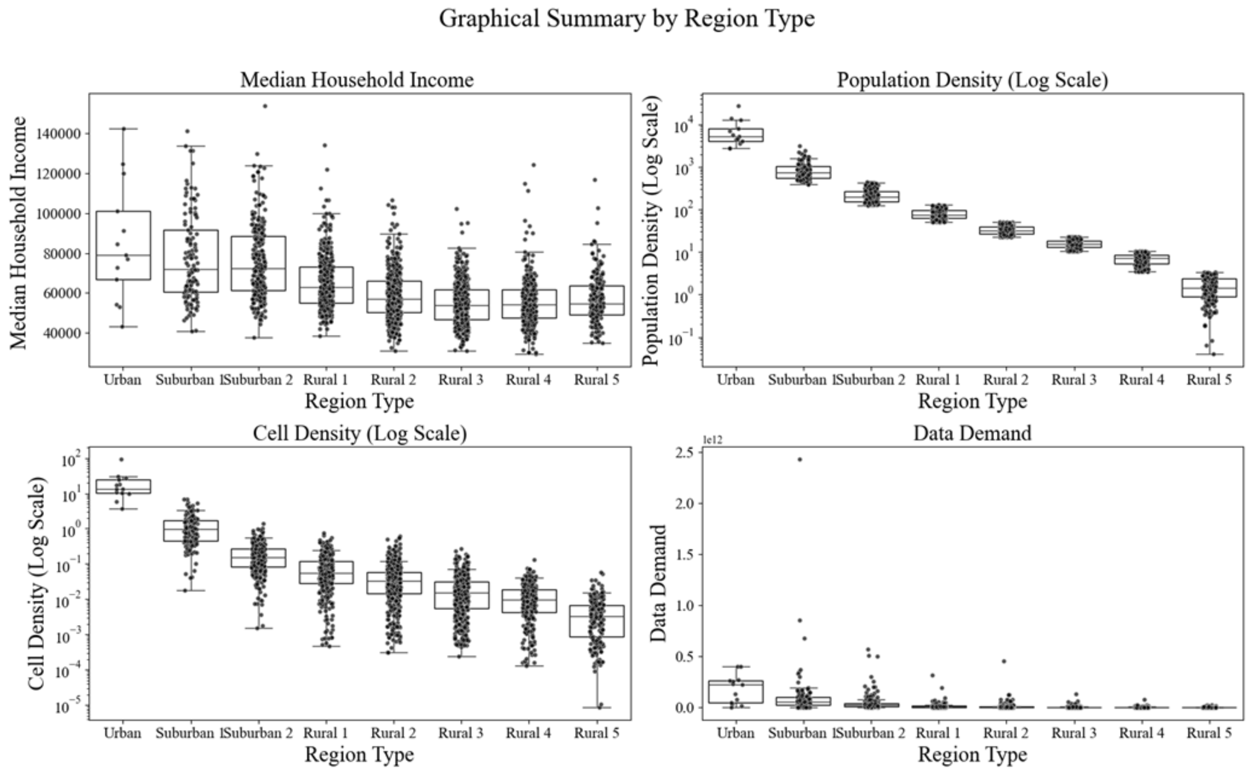


Figure 2.8: Graphical descriptive summary of key variables

To estimate the revenue for MNOs in each region type, we consider two primary factors: the total number of active smartphone users and the ARPU specific to that region type. Our approach utilizes population data from the 2020 U.S. Census, providing accurate county-level demographics. For user adoption, we reference the GSMA North America 2020 report, which indicates an overall smartphone penetration rate of 83% for North America. ARPU data is derived from the CTIA annual wireless industry survey report, which finds an average ARPU of $35.74 for the United States in 2021.

To account for regional economic disparities, we weighed this national ARPU using the MHI of each county. This normalization process allows for a more accurate representation of revenue potential across diverse regions. This results in adjusted ARPU values for each of our defined region types: Urban, Suburban 1, Suburban 2, and Rural 1 through 5. These adjusted ARPU values reflect the varying economic conditions and potential revenue generation across different region types, providing a more nuanced basis for our revenue estimations in the Open RAN investment analysis. All other uncertainties and assumptions taken in the model are highlighted in section 4.3 Assumptions and Key Parameters and listed in supplementary Table 2.10 - List of Parameters Used in Model as the model inputs.

General Parameters		
Parameter	**Value**	**Description**
Investment Horizon	10	Typical for Telecom Capex
Discount Rate	5%	Industry Standard
Players	MNO, NIS, OEM	Key Players in RAN Deployment
Procurement Scenarios	Traditional, Predatory, DirectOEM	Traditional and Predatory gives MRAN and DirectOEM gives ORAN
Smartphone User Percentage	89%	Smartphone Users by GSMA NA 2020
Active User Percentage	83%	Active Users on the Network (GSMA NA 2020)
ARPU (average)	$40	Average Revenue Per User (CSIA Survey 2020)
Price Parameters		
Parameter Region	**Traditional**	**Predatory / DirectOEM**
MNO Cost/NIS Price Urban/-Suburban	232,823	108,000
Rural	63,237	42,500
Opex Rate	12%	12% / 13%

Table 2.10: List of Parameters Used in the Model

2.4.2 Simulation Results

This analysis delves into the transition from MRAN to ORAN, assessing its alignment with the study's objectives of improving cost efficiency, addressing infrastructure disparities, and enhancing profitability across a diverse set of regions. By overcoming the limitations of traditional MRAN models, such as higher costs and vendor lock-in, ORAN offers a scalable, flexible, and cost-effective solution. The results validate ORAN's potential to create a more competitive ecosystem, particularly in addressing the unique challenges posed by varying regional demand and infrastructure requirements.

The quantitative results highlight a consistent improvement in MNO payoffs across all region types when transitioning from MRAN to ORAN. In urban areas, the Net Present Value (NPV) of MNO payoffs increased by 10%, rising from $30 million under MRAN to $33 million under ORAN, driven by higher demand density and advanced network optimization. Similarly, in Suburban 1 regions, payoffs rose from \$24 million to \$26.4 million, also reflecting a 10% gain, emphasizing the impact of ORAN in regions with moderate infrastructure investments. Even in rural areas, which typically face significant cost and demand challenges, ORAN adoption delivered comparable efficiency gains. For instance, Rural 1 payoffs increased by 10%, from \$12 million under MRAN to \$13.2 million under ORAN, showcasing ORAN's ability to bridge the profitability gap in low-demand regions.

enThese findings underscore ORAN's transformative role in modernizing RAN infrastructure. By reducing infrastructure costs and fostering scalability, ORAN enables MNOs to align regional investment strategies with profitability goals effectively. The results further highlight ORAN's ability to create a balanced and competitive landscape, benefiting not only high-demand urban centers but also underserved rural areas, making it a critical driver for equitable and efficient network deployment.

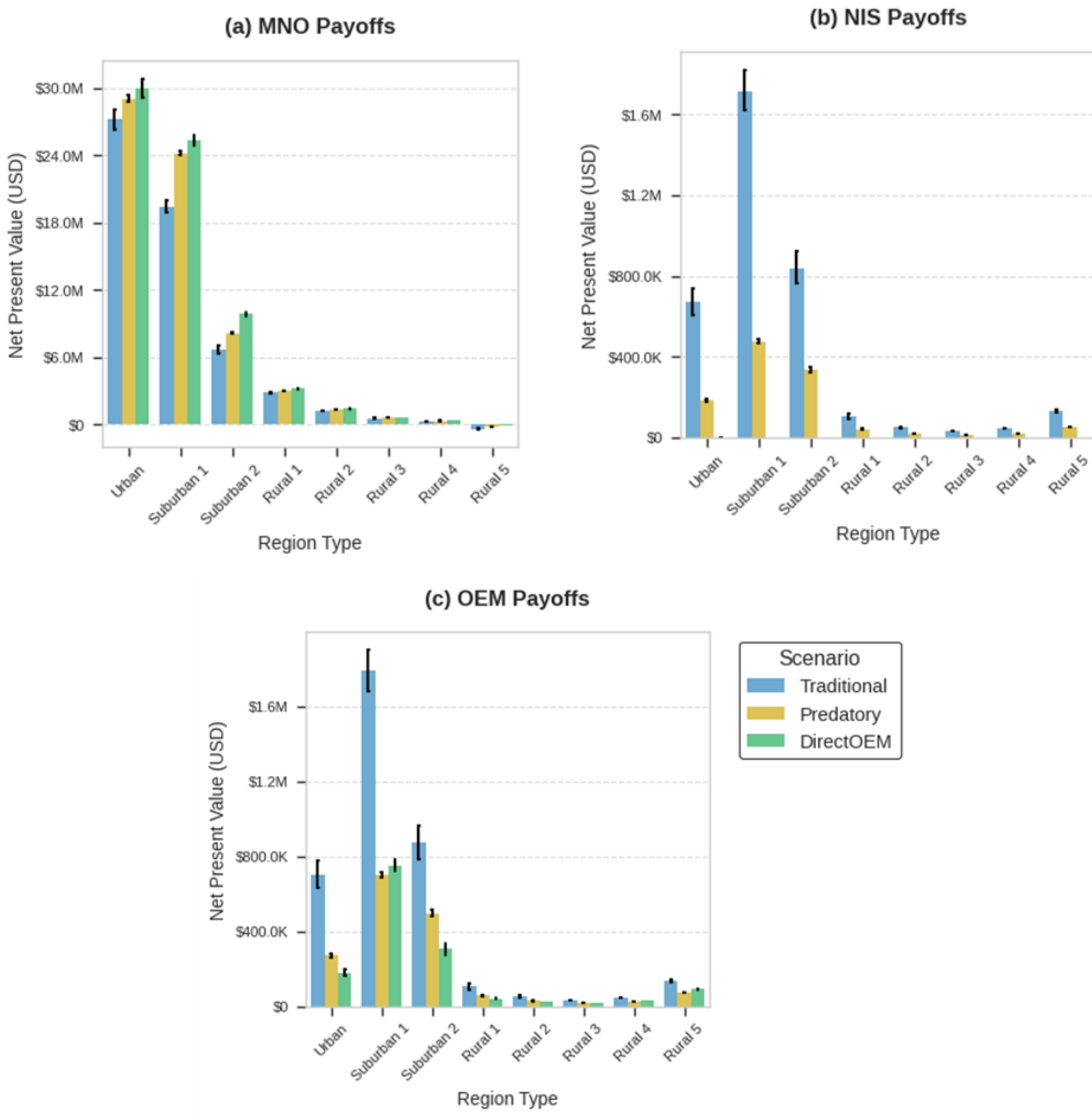


Figure 2.9: Comparison of MRAN (Traditional and Predatory) with ORAN payoffs as Net Profit

Identifying a global equilibrium involves finding optimal margins for different stakeholders (e.g., MNOs, NIS, and OEM) such that total profits are maximized across all scenarios. We employed a Random Forest Regressor to identify the optimal margins for NIS and OEM that maximize the total profit across different scenarios and regions. The input features include the scenario, region type, year, NIS margin, and OEM margin. The Random Forest model was trained using 100 decision trees. After training, a Gaussian process optimization to identify the NIS and OEM margin values that maximized predicted profits. The objective function minimized the negative predicted profit, effectively searching for the margins that would yield the highest cumulative profit across the different stakeholders. The results from the Random Forest model optimization highlight significant insights into profit distribution across stakeholders in the telecom supply chain.

The optimization process, conducted over 50 iterations, identified the optimal NIS and OEM margins. The analysis determined the optimal NIS margin to be approximately 41.86% and the OEM margin to be around 17.34%. These optimal margins correspond to the highest predicted total profit across all stakeholders, suggesting important strategic implications. This model provides a robust method for determining optimal pricing strategies across multiple deployment scenarios and regions, contributing to more informed decision-making in telecom network planning and investment with key insights.

First, the lower margin for OEMs reflects increasing cost pressures in equipment manufacturing as the market shifts towards more decentralized and open network systems like ORAN. This may prompt OEMs to adjust their pricing models or seek alternative revenue streams to maintain profitability amidst evolving industry dynamics. Finally, these insights reinforce the importance of strategic margin balancing in contract negotiations and partnerships. Telecom firms can enhance profitability by securing cost-effective OEM contracts while allowing network integrators to maintain higher margins. This approach aligns with the emerging trend of decentralization and could drive better financial performance in both traditional and DirectOEM deployment scenarios.

While our model focuses primarily on deployment and operational costs, it is important to note that security considerations in ORAN implementations can impact both performance and costs. Recent research has shown that encryption on critical ORAN interfaces can add latency and limit throughput. While not explicitly factored into our current cost model, these security-related performance impacts should be considered in future, more detailed analyses of ORAN deployments [Groen et al., 2023].

2.5 Conclusion and Discussion

Our analysis reveals that ORAN deployment consistently demonstrates higher net present value (NPV) of profits in urban and suburban regions, outperforming traditional procurement strategies. However, rural areas present lower NPVs across all scenarios, with significant county-level variability. This regional disparity underscores the need for tailored deployment strategies based on local population density, infrastructure requirements, and economic conditions.

The strategic interactions between MNOs, NIS, and OEMs, as analyzed through our game-theoretic framework, highlight the complex dynamics of telecom supply chains. In the traditional and predatory scenarios, NIS firms maintain significant market power, while the DirectOEM (ORAN) scenario redistributes this leverage, creating a more balanced ecosystem. The optimal margin analysis suggests that NIS providers operate with substantially higher margins (around 42%) compared to OEMs (approximately 17%), revealing important structural inefficiencies in the current market.

These findings have significant implications for both industry stakeholders and policymakers. For MNOs, the results suggest that ORAN adoption represents a viable path to improved financial performance, particularly in densely populated areas. For policymakers, our research provides empirical support for initiatives promoting open ecosystems, especially in underserved regions where traditional deployment models may not be economically sustainable.

Future research should explore additional factors that may influence ORAN adoption, such as security considerations, implementation costs, and regulatory frameworks. A more granular analysis incorporating real-world deployment data would further enhance our understanding of the economic implications of ORAN adoption across diverse regional contexts.

Chapter 3

Effects of Production Diversification On Net Farm Income: Evidence from Kansas

3.1 Introduction

Agricultural producers face significant revenue risks due to external factors such as adverse weather, crop pests or diseases, and market volatility. While conventional risk management techniques can manage specific risks, they often lack the capacity to mitigate the impacts of unpredictable events. This limitation has led to the emergence of a system resilience approach as a potential complement to traditional risk management options. Considering farms as socio-ecological systems, system resilience methods can help farmers to prepare for unexpected shocks [Lin, 2011] and has started to find applications in production agriculture Hammond et al. [2013]. Recognizing this alternative, production diversification has emerged as an effective strategy for stabilizing expected returns in volatile agricultural environments McNamara and Weiss [2005], Mugera et al. [2016], Lindbloom et al. [2022]. This approach aligns with portfolio theory, where farmers, as risk-averse agents, seek to optimize their expected utility by balancing returns and risk across multiple crops or enterprises.

The literature on the benefits of diversification is studied well, particularly in stabilizing crop yield and supporting food security under stressors such as extreme weather, abiotic stress, and market fluctuations. Various studies Lin [2011], Harvey et al. [2014], Hendricks et al. [2014], Gaudin et al. [2015], Renard et al. [2023], Degani et al. [2019], Dardonville et al. [2020], Bowles et al. [2020], Harkness et al. [2021], Pates and Hendricks [2021], Ebel et al. [2022] indicate that strategies like crop diversity and rotation play a crucial role in long-term yield and supply stability. Theories such as the biodiversity insurance hypothesis Yachi and Loreau [1999] and the agricultural insurance hypothesis further suggest that crop diversification acts as a natural insurance against crop loss by stabilizing productivity Tilman et al. [2006], Proulx et al. [2010]. Notably, a recent study highlighted the role of farm diversification in aiding small farmers during COVID-19 lockdowns Benedek et al. [2021].

Literature Review

Literature on production diversification decisions indicates that multiple factors shape farmers' choices. Agronomic aspects—such as soil quality, climate suitability, crop rotation benefits—and environmental considerations like water availability and pest pressures significantly influence these decisions. Beyond these factors, diversification is increasingly recognized as a vital risk management tool. For instance, reviews examining risk management aspects in detail Tack and Yu [2021] emphasize that production diversification decisions are driven by two key elements: the farmer's risk preference and the inherent unpredictability of farming outcomes, which is represented by the stochastic joint distribution of output prices and production shocks. Further research Di Falco and Chavas [2009], Baumgärtner and Quaas [2010], Chavas and Di Falco [2012], Bezabih and Sarr [2012], Kandulu et al. [2012], Rao [2019], Ouattara et al. [2019] demonstrates that anticipated risks (ex-ante risk) and farmers' attitudes towards these risks are significant drivers of crop diversification. Moreover, diversification can enhance overall farm productivity by leveraging economies of agronomic scope, such as biological interactions, input synergies, and market risk balancing. Diversification also serves as a potential strategy to mitigate risks in the face of incomplete markets for insurance and credit, particularly in agricultural contexts where such market failures are common.

While the body of research provides valuable insights into the benefits of diversification, the literature on its direct effects on farm financial resilience remains limited, underscoring the need for empirical evidence that quantifies the relationship between diversification and farm-level financial outcomes. To address this gap, Lindbloom et al. [2022] used data from the Kansas Farm Management Association (KFMA) to assess the impact of diversification on farm resilience, employing a resilience triangle methodology. This study employed a resilience triangle methodology - a graphical analysis technique that focuses on the extent and duration of a system's disruption over time - to assess the impact of diversification on farm resilience. The study found that diversifying crop acreage influences resilience non-linearly, effective only up to a certain diversification threshold. These limitations in capturing the multifaceted aspects of resilience under complex and stochastic agricultural risks highlight the need for more sophisticated analytical approaches that can account for the endogeneity of diversification decisions and heterogeneity across farms.

To address this, we frame our analysis within a profit maximization model, extending traditional portfolio theory to the agricultural context. We examine net farm income generated from a diversified portfolio of crops and mixed (crop, livestock) income as production choice. Therefore, this study seeks to answer the following research questions: (1) How does production diversification affect the distribution of net farm income in Kansas agricultural operations? (2) What is the optimal level of diversification for maximizing financial resilience against environmental shocks? (3) How do different types of diversification compare in their ability to stabilize farm income during periods of stress? Through rigorous empirical analysis of the KFMA panel data, we aim to provide evidence-based recommendations for farm management strategies that enhance long-term financial sustainability.

We are using two-way fixed effects method to analyse the impact of drought interaction with diversification and its impact on farm income. This approach addresses limitations in previous studies by accounting for the entire distribution of farm income, providing a more comprehensive measure of financial resilience. This concept is moving beyond the area of the triangle method to more accurately identify and aggregate farm-level resilience.

Our objective, therefore, is to empirically estimate the impact of production diversification on net farm income in Kansas using a panel dataset from the Kansas Farm Management Association (KFMA), a state with significant agricultural output and variability, as an empirical setting. Our panel data approach allows us to control for unobserved farm-level heterogeneity and time-invariant factors that may influence diversification decisions. Hence, our analysis seeks to understand how multiple types of on-farm income & acreage choices for crops can compensate for financial losses stemming from sudden loss of income during shock. Therefore, the objective is to quantify the contributors to diversification choices. These findings will not only inform individual farm management decisions but could also guide policymakers in designing more effective agricultural support programs that incentivize optimal diversification practices, potentially shifting focus from reactive disaster assistance to proactive resilience-building measures that better protect farm livelihoods and promote sustainable agricultural systems in Kansas and beyond.

Agricultural Policy Pathway and Diversification Incentives

Farm production in Kansas became more concentrated between 2002 and 2022, as shown in Figure 3.1, likely reflecting producer responses to enduring policy incentives that have consistently favored specialization in a narrow set of major commodities. As the chronology of policies shown in Figure 3.2, U.S. agricultural policy has progressed through a series of phases that have reinforced production concentration over diversification.

The Agricultural Adjustment Act of 1933 marked the onset of commodity-specific support mechanisms that shaped subsequent production decisions. This path-dependent structure was amplified during the 1960s and 1970s through legislation such as the Emergency Feed Grains Act (1961) and the "Fencerow to Fencerow" planting initiative, both of which increased the risk-adjusted profitability of corn, soybean, and wheat, thereby reducing the relative returns to diversified cropping systems.

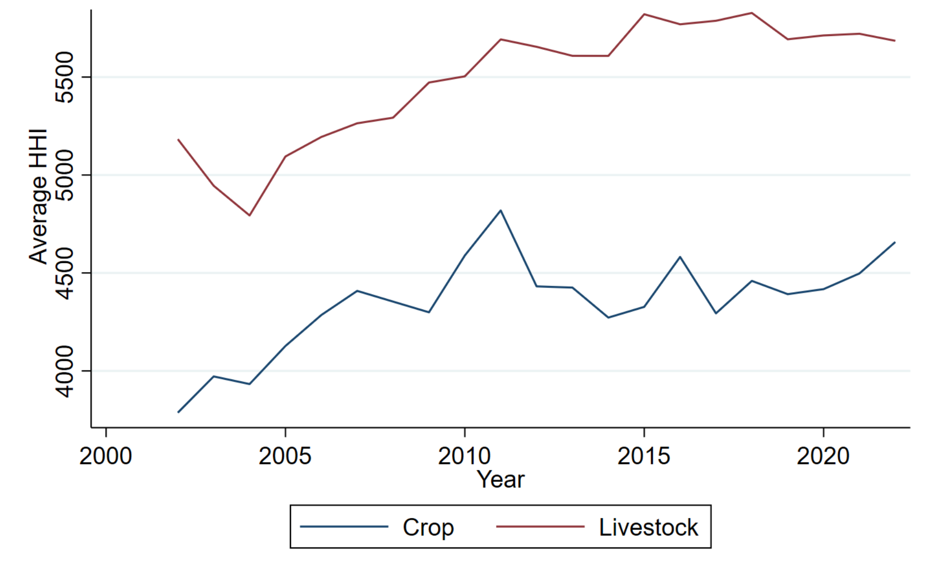


Figure 3.1: Overall Trends in Crop and Livestock HHI: 2002–2022

Policy developments in subsequent decades continued to reinforce this trend. The 1985 Food Security Act introduced conservation programs such as the Conservation Reserve Program (CRP) and the Acreage Limitation Program (ALP), but retained commodity-oriented risk protection that implicitly devalued the benefits of diversified production. Similarly, the 1996 "Freedom to Farm" Act nominally expanded planting flexibility, yet imposed restrictions on fruit and vegetable production on contract acreage—effectively discouraging diversification on program farms. The 2018 Farm Bill offered marginal improvements through increased flexibility between Price Loss Coverage (PLC) and Agriculture Risk Coverage (ARC) programs and greater support for specialty and organic crops, but these changes have not substantially shifted the core incentive structure away from specialization.

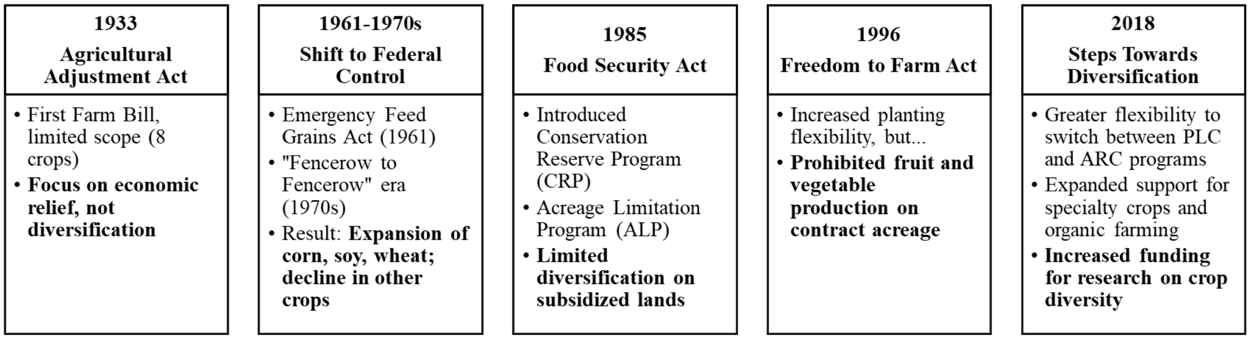


Figure 3.2: Chronological Timeline of Major U.S. Agricultural Policies Influencing Farm Diversification

These policy dynamics help contextualize the empirical results presented in this study. While the returns to specialization are directly captured by producers, the positive externalities associated with diversification—particularly system-level resilience to shocks such as drought—remain largely uncompensated. Our analysis of diversification and income resilience during drought conditions reveals significant positive externalities that are not priced by markets nor fully addressed through current agricultural practices.

3.2 Data and Variable Descriptions

Analyzing the impact of production diversification on farm financial performance requires long-term farm-level data. However, datasets like the U.S. Census of Agriculture do not provide the required farm-level details to understand the dynamic adjustments of farm operations. This study leverages a unique dataset from the Kansas Farm Management Association (KFMA) survey [1] to analyze agricultural trends, wherein farmers explicitly provide detailed data on farm production and finances for research purposes. The panel data spans 2002-2022 (21 years) and includes 232 Kansas farms, offering a rich longitudinal perspective on diversification strategies and financial performance. As shown in Figure 3.1, mean inflation-adjusted farm income varies spatially and temporally due to localized growing conditions, market conditions, and production technology.

[1]2KFMA is one of the largest farm management programs in the U.S., which consists of six regional associations that maintain historical Kansas farm-level operational and financial information.

Table 3.1: Descriptive Statistics by Farm Type and Year (2002 vs 2022)

Variable	**Crop-only (2002)**	**Mixed (2002)**	**Crop-only (2022)**	**Mixed (2022)**
Age and Education				
Age	48.93 (10.57)	49.55 (9.04)	68.98 (9.13)	66.74 (8.91)
Education	242.29 (583.40)	348.97 (1078.37)	193.33 (1411.46)	237.79 (1967.47)
Farm Characteristics				
Crop Acres	1433.78 (904.51)	1189.31 (857.91)	1424.40 (1034.33)	1502.71 (1291.58)
Debt-Asset, YearEnd	0.42 (0.47)	0.38 (0.28)	0.09 (0.14)	0.16 (0.14)
Adjusted Financials ($)				
Value of Farm Prod. (k)	327.77 (269.55)	389.83 (365.64)	737.85 (652.89)	941.04 (899.31)
Net Farm Income (k)	49.39 (72.76)	49.29 (109.43)	176.80 (225.87)	184.42 (223.97)
Gov Payments (k)	22.86 (19.64)	27.08 (19.68)	13.81 (27.16)	14.81 (33.24)
Crop Insurance Inc. (k)	27.46 (40.35)	24.82 (41.36)	98.88 (135.26)	102.19 (227.32)
Crop Insurance Exp. (k)	9.84 (12.79)	5.49 (7.55)	26.08 (26.79)	23.92 (26.43)
Farm Inc./ Acre	33.02 (53.58)	49.68 (155.41)	111.98 (114.17)	141.95 (202.28)
Farm Inc. no supp./Acre	4.20 (60.91)	0.65 (148.62)	51.94 (150.77)	94.13 (219.08)
Diversi. Characteristics				
Crop Count $\succ$ acres	3.73 (1.67)	5.38 (2.11)	3.11 (1.28)	5.50 (2.51)
CropCount $\geq$ 10% $	2.71 (0.87)	3.05 (0.96)	2.37 (0.76)	2.62 (0.84)
CropCount $\geq$ 10% Acr.	2.84 (1.00)	2.94 (0.86)	2.46 (0.74)	2.94 (0.90)

The sample comprises 231 crop-only or mixed (crop and livestock) farms and one livestock-only farm, captured in the farm type categorical variable. In 2002, there were 45 crop-only and 186 mixed farms, while in 2022, the numbers shifted to 90 crop-only and 141 mixed farms, indicating a trend towards more crop-only operations over time. The average crop acreage remained relatively stable, with crop-only farms having slightly higher acreage than mixed farms in both years. The debt-asset ratio decreased from 2002 to 2022, with crop-only farms exhibiting a lower ratio than mixed farms in both years, indicating improved financial positions. Due to the lack of data on livestock-only farms, the analysis focuses primarily on crop diversification and its impact on farm financial resilience.

Figure 3.3 depicts Kansas farm income from 1973-2022, revealing significant disruptions during three major drought events (1980, 1999, and 2012). Despite these shocks, median farm income increased over five decades, with substantially wider income variability after 2000.

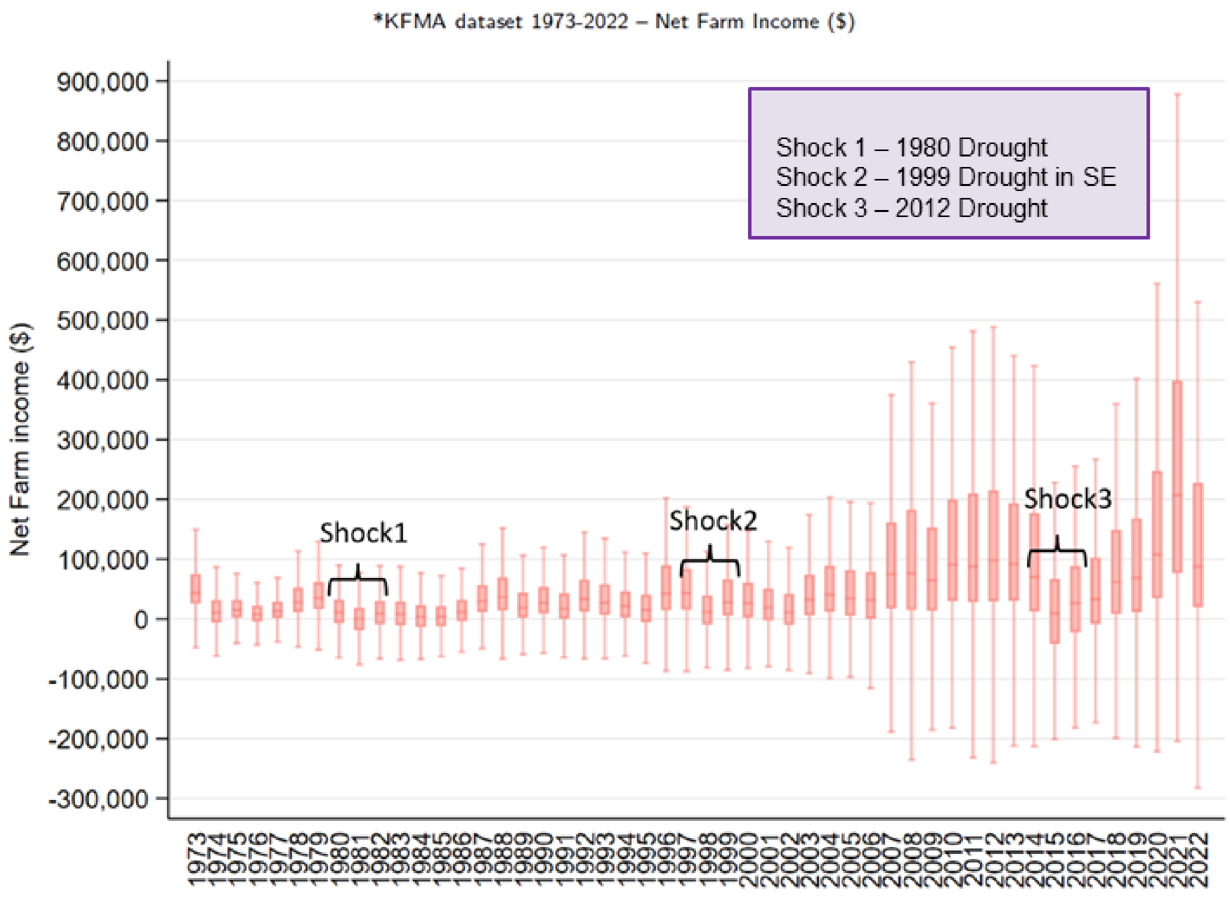


Figure 3.3: Historical Trends in Kansas Net Farm Income

The inverse hyperbolic sine transformation is employed to net farm income and other financial metrics in order to effectively manage negative and zero values. Additionally, the Consumer Price Index (CPI) adjusts all financial measures for inflation in Equation B.1. The interpretation of the coefficients would be similar to using a log of the dependent [Bellemare and Wichman, 2020]. The density plots in Figure 3.4 provide insights into the distribution of adjusted mean farm income before and after 2012, a severe drought year taken to understand the pre and post-shock variation in mean farm income.

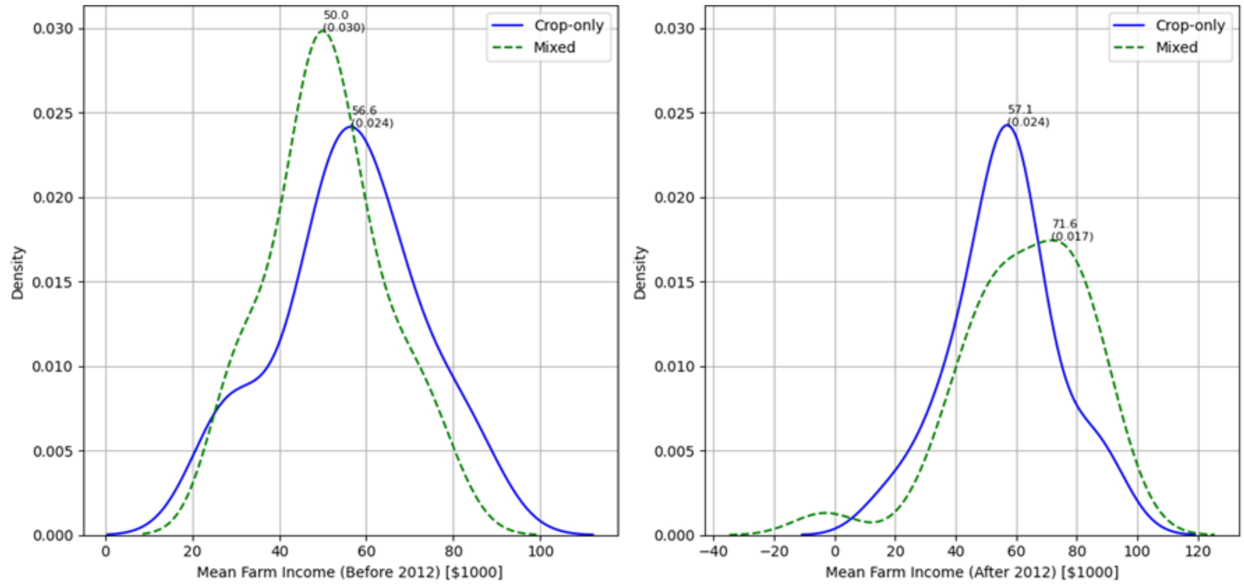


Figure 3.4: Density Distribution of Adjusted Net Farm Income Farm Type

Similarly, the density plot categorized by the number of crops grown in figure 3.5 shows a clear pattern: farms with a greater number of crops tend to have higher inflation-adjusted mean farm income without government support or insurance. The peak of the distribution shifts progressively to the right as the number of crops increases, with farms growing six or more crops exhibiting the highest income levels. The distributions of mean farm income without government payments, insurance premiums, and claims exhibit a rightward shift even after 2012. Also, the figures B.2, and B.3 in appendix on HHI for crop diversification vary significantly across farms in income and acreage.

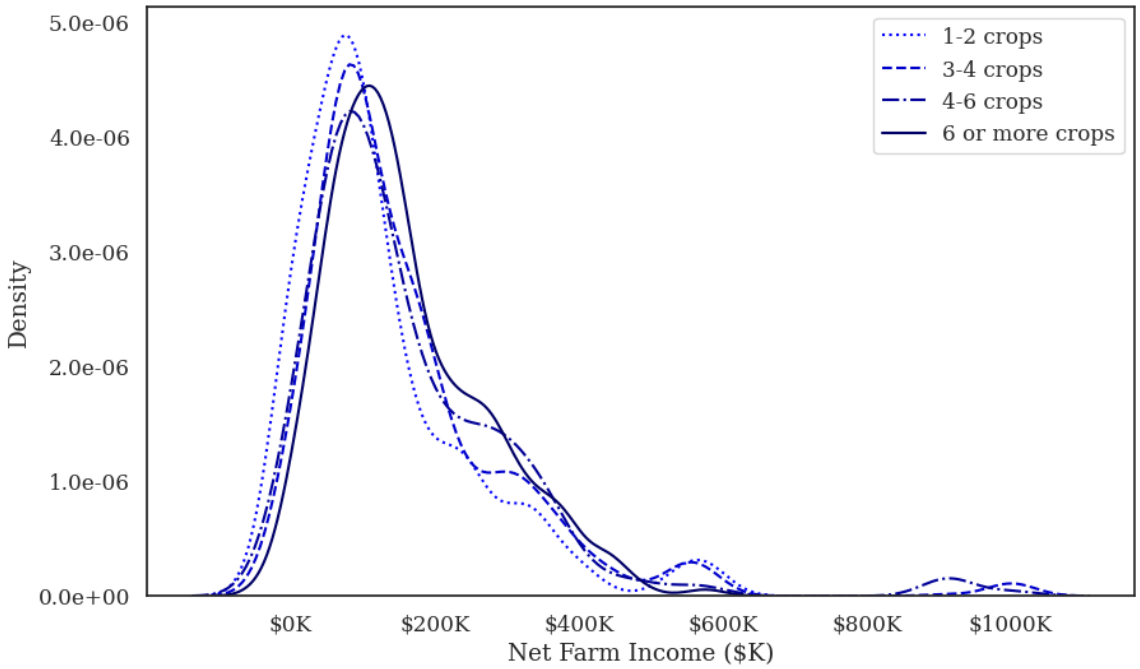


Figure 3.5: Density Distribution of Adjusted Net Farm Income Across Farm Type

Variable	**1-2 crops**	**3-4 crops**	**4-6 crops**	**6 or more crops**
Observations	671	1761	1382	1058
Crop Acres	1226.0 (945.4)	1451.5 (1161.0)	1457.9 (1044.3)	1479.2 (1005.9)
Debt-Asset Ratio	0.244 (0.260)	0.228 (0.247)	0.244 (0.233)	0.262 (0.225)
Farm Production ($k)	578.0 (549.0)	708.0 (684.0)	687.0 (643.0)	738.0 (606.0)
Net Farm Income ($k)	128.0 (207.0)	164.0 (230.0)	157.0 (228.0)	166.0 (200.0)
Government Payments ($k)	33.4 (41.5)	42.2 (51.9)	40.2 (43.9)	44.2 (48.6)
Insurance Income ($k)	27.1 (71.6)	32.9 (89.4)	32.2 (96.8)	30.1 (72.3)
Insurance Expense ($k)	16.7 (22.9)	19.2 (23.4)	17.2 (21.7)	16.8 (19.0)
Net Farm Income (No Support) ($k)	83.8 (210.0)	108.0 (223.0)	102.0 (218.0)	108.0 (199.0)
Total Livestock Income ($k)	103.0 (291.0)	97.5 (251.0)	190.0 (483.0)	286.0 (502.0)
Farm Income Per Acre ($)	112.4 (298.9)	123.7 (170.7)	112.8 (153.6)	124.1 (143.0)
F.I. (No Support) Per Acre ($)	71.3 (301.6)	84.3 (176.2)	74.6 (152.1)	85.8 (144.5)

Table 3.2: Descriptive Statistics by Crop Count Categories

We also used the Drought Severity and Coverage Index (DSCI), [2]. an experimental metric

[2]The Drought Severity and Coverage Index (DSCI) integrates various meteorological and hydrological

used by the U.S. Drought Monitor to quantify the overall drought conditions within a given area. It combines information about the severity and spatial extent of drought into a single numerical value. The DSCI ranges from 0 to 500, with 0 indicating that none of the area is abnormally dry or in drought conditions and 500 representing an exceptional drought (D4 level) across the entire area. The Index is calculated by assigning numerical values to the different drought categories (D0-D4) and then weighting them by the proportion of the area each category affects : available at drought monitor website.

Measuring Farm Production Diversification (S)

Quantifying farm diversification requires measures that capture both the number of crops grown and their relative distribution across the farm operation in each year t. We employ three complementary metrics to comprehensively assess diversification strategies and their relationship to farm resilience.

First, we compute two versions of the Herfindahl-Hirschman Index (HHI) to capture both the physical and economic dimensions of diversification. Originally developed for assessing market concentration, the HHI is calculated for each year t as follows:

$$HHI_{\text{acreage},t} = \sum_{i=1}^{n} \left(\text{share}_{i,\text{acreage},t}\right)^2, \tag{3.1}$$

$$HHI_{\text{income},t} = \sum_{i=1}^{n} \left(\text{share}_{i,\text{income},t}\right)^2. \tag{3.2}$$

Here, $\text{share}_{i,\text{acreage},t}$ and $\text{share}_{i,\text{income},t}$ denote the proportion of total farm acreage and total farm income, respectively, allocated to crop i in year t. The HHI ranges from $\frac{1}{n}$ (equal shares across all crops) to 1 (a single crop dominating production), with higher values indicating greater concentration (i.e., less diversification).

In addition, we assess diversification using the Shannon Diversity Index (SDI), which is more sensitive to the presence of crops with small shares. For each year t, the SDI for acreage

indicators—such as precipitation deficits, soil moisture anomalies, and temperature variations—to provide a comprehensive assessment of drought severity. The index facilitates comparisons across different regions and time periods, thereby supporting effective water resource management and policy decision-making.

allocation is defined as:

$$SDI_{\text{acreage},t} = -\sum_{i=1}^{n} \left(\text{share}_{i,\text{acreage},t} \times \ln\left(\text{share}_{i,\text{acreage},t}\right)\right). \tag{3.3}$$

Higher SDI values indicate greater diversification, with the index equaling zero when only one crop is grown and increasing as both the number of crops and the evenness of their distribution increase.

Finally, to provide a more intuitive measure of meaningful diversification, we compute Crop Share Threshold Counts. These counts tally the number of crops that exceed a 10% threshold of either total acreage or income in each year t:

$$Count_{\text{acreage},t} = \sum_{i=1}^{n} \mathbf{1}\left(\text{share}_{i,\text{acreage},t} > 0.10\right), \tag{3.4}$$

$$Count_{\text{income},t} = \sum_{i=1}^{n} \mathbf{1}\left(\text{share}_{i,\text{income},t} > 0.10\right), \tag{3.5}$$

where $\mathbf{1}(\cdot)$ is an indicator function that equals 1 when the condition inside is true and 0 otherwise. This approach distinguishes between farms with multiple significant crops and those with one dominant crop accompanied by several minor crops, providing a practical measure of diversification that is easily interpretable by farmers and policymakers :contentReference[oaicite:0]index=0.

Temporal Trends in Diversification

Table 3.3 presents descriptive statistics for these diversification measures in 2002 and 2022, revealing important temporal trends in Kansas agricultural practices.

The data reveal a clear trend toward greater crop concentration over the two-decade period. HHI measures increased for both acreage (from 0.368 to 0.399) and income (from 0.369 to 0.448), indicating reduced diversification. This trend is corroborated by concurrent decreases in Shannon Diversity Index values for both acreage (from 1.203 to 1.110) and income (from 1.232 to 0.989). Similarly, the average number of crops contributing at least

	2002			2022		
Variable	Mean (SD)	Min	Max	Mean (SD)	Min	Max
HHI (Acreage)	.3675 (.1437)	0	1	.3986 (.1768)	0	1
HHI (Income)	.3689 (.1544)	0	1	.4477 (.1872)	0	1
SDI (Acreage)	1.2027 (.3809)	0	2.0936	1.1095 (.4443)	0	2.2224
SDI (Income)	1.2318 (.3810)	0	2.0394	.9893 (.4141)	0	1.9553
Crop Share Count (Income)	2.9 (.9711)	0	6	2.5 (.8322)	0	5
Crop Share Count (Acreage)	2.9 (.9067)	0	6	2.7 (.8899)	0	5

Table 3.3: Descriptive statistics for diversification indices in 2002 and 2022

10% to farm income declined from 2.9 to 2.5, while the acreage-based threshold count showed a smaller decrease from 2.9 to 2.7.

These patterns suggest a structural shift in Kansas agriculture toward more specialized production systems. This specialization trend may reflect technological advancements enabling greater economies of scale, market consolidation pressures favoring specialized production, or changes in agricultural policy incentives. However, as our subsequent analysis demonstrates, this concentration trend may have significant implications for farms' financial resilience during environmental stress periods like drought.

Spatial Variation in Diversification

Diversification patterns exhibit substantial spatial variation across Kansas, as shown in Figure 3.6. Western Kansas counties generally show higher HHI values (less diversification) compared to central and eastern counties, particularly for acreage-based measures. This geographic pattern reflects differences in climate, soil types, irrigation infrastructure, and historical cropping patterns. The semi-arid conditions in western Kansas traditionally favor wheat monoculture or wheat-fallow rotations, while the more abundant rainfall in eastern counties enables greater crop diversity.

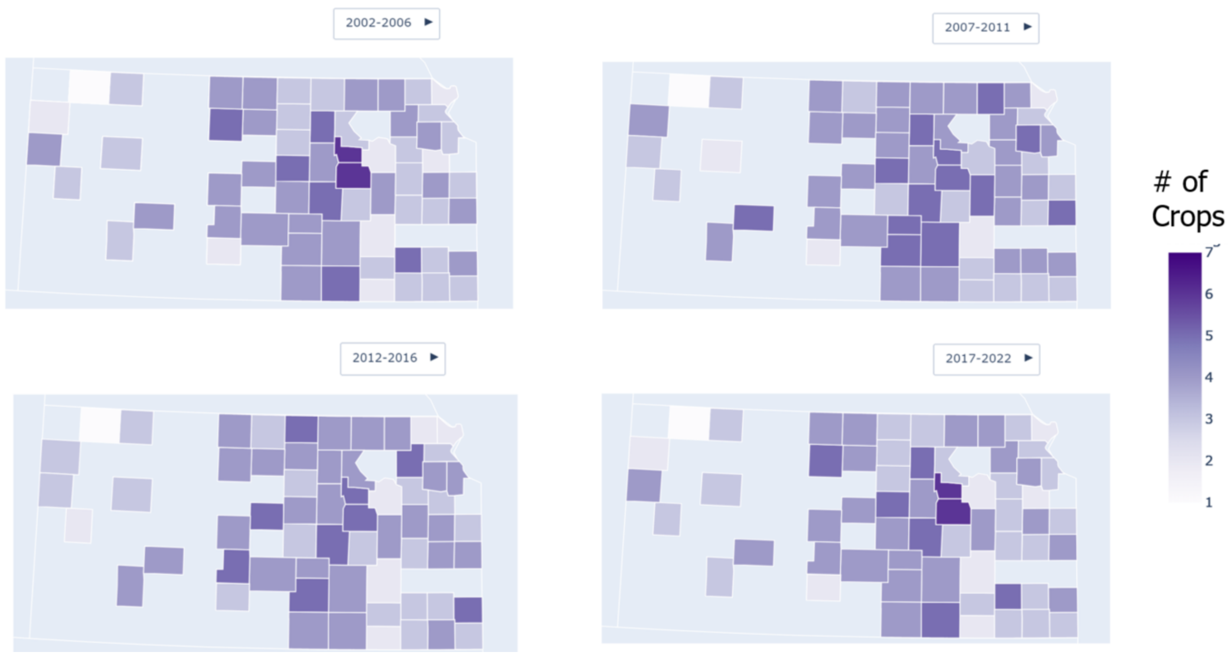


Figure 3.6: Historical Trends in Crop Counts Across Kansas

The income-based diversification measures Figure **??** exhibit distinct spatial patterns compared to acreage-based measures, emphasizing the difference between physical and economic diversification. Certain counties that demonstrate moderate acreage diversification still display high income concentration, particularly in instances where a dominant high-value crop significantly contributes to farm revenue, despite the presence of secondary crops by acreage.The considerable variation in diversification strategies across the state, alongside the fluctuating exposure to drought conditions over time, provides the necessary variation to assess the impacts of diversification on farm financial performance amidst environmental stress.

3.3 Methodology

3.3.1 Model Selection and Theoretical Background

Our methodological approach uses econometric panel two way fixed effect methods to comprehensively analyze the relationship between crop diversification, drought conditions, and farm income. This dual approach allows us to capture both linear and non-linear patterns.

The econometric approach is grounded in the literature on the relationship between crop diversification, drought as environmental stressor, and farm income. We employ a two-way fixed effects panel data model, a choice informed by recent developments in the field and the nature of our research question. The use of panel data models in agricultural economics has become increasingly prevalent due to their ability to control for unobserved heterogeneity and capture dynamic relationships. As highlighted by Hendricks et al. [2014] research on crop supply dynamics, panel data techniques allow for more robust inference by controlling for time-invariant farm characteristics. Our choice of a two-way fixed effects model aligns with this approach, enabling us to account for both farm-specific and year-specific unobserved factors.

The inclusion of interaction terms between diversification measures and drought indices in our model is inspired by the work of Tack et al. [2018], who employed a similar approach to study on climate change impacts on crop insurance. This interaction allows us to examine how the effect of diversification on farm income varies with drought severity, providing insights into the potential of diversification as a risk management strategy. Our focus on drought as a key environmental stressor is motivated by the growing body of literature emphasizing the importance of climate risk in agriculture. For instance, Ortiz-Bobea et al. By incorporating detailed drought measures, we extend this line of inquiry to examine how farm-level diversification strategies interact with such environmental risks.

To complement the econometric approach and capture complex non-linear relationships, we integrate machine learning methods, specifically LASSO feature selection, Random Forest, and XGBoost algorithms. The application of machine learning at the farm level dataset is a novel method, demonstrating its potential for identifying complex patterns in farm data. Our machine learning approach is built to identify important determinants of farm income and quantify the relative importance of diversification measures compared to other factors.

3.3.2 Econometric Model

Two-Way Fixed Effects Specification

Our baseline model is specified as follows:

$$y_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 S_{it} + \beta_3 (D_{it} \times S_{it}) + \boldsymbol{\gamma} \mathbf{X}_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{3.6}$$

In this equation, y_{it} represents the inverse hyperbolic sine (IHS) transformed adjusted net farm income for farm i in year t. We use the IHS transformation to address potential non-linearity and to accommodate zero or negative values in the dependent variable. D_{it} denotes the drought measure, which is operationalized in two ways: as the Drought Severity and Coverage Index (DSCI) and as individual drought levels (D0-D4). S_{it} represents the crop diversity measure, for which we use either the Shannon Index or the Herfindahl-Hirschman Index (HHI). The interaction term $(D_{it} \times S_{it})$ allows us to examine how the effect of diversification changes with drought severity. $\mathbf{X}_{it}$ is a vector of control variables including crop acres, debt-to-asset ratio, lagged government payments, and lagged insurance income and expenses. Farm-specific fixed effects are captured by α_i, while λ_t represents year fixed effects. Finally, ε_{it} is the error term.

We estimate two variations of this model to provide a comprehensive analysis: (1) Shannon Index by income with DSCI, (2) Shannon Index with individual drought levels (D0-D4), (3) Shannon Index by acreage with DSCI, and (4) Shannon Index by acreage with individual drought levels (D0-D4). For the models using individual drought levels, we expand the equation to:

$$y_{it} = \beta_0 + \beta_1 S_{it} + \sum_{k=0}^{4} (\delta_k D_{k,it} + \theta_k (S_{it} \times D_{k,it})) + \boldsymbol{\gamma} \mathbf{X}_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{3.7}$$

Here, $D_{k,it}$ represents the kth level of drought (D0 to D4), allowing for a more nuanced analysis of how different drought intensities interact with diversification strategies. We apply the inverse hyperbolic sine (IHS) transformation to our dependent variable (adjusted net farm income) and to certain independent variables (government payments, insurance income, and insurance expense) and IHS defined as:

$$\text{IHS}(x) = \ln(x + \sqrt{x^2 + 1}) \tag{3.8}$$

This transformation behaves similarly to a logarithmic transformation for positive values but is defined for zero and negative values. It allows us to interpret the coefficients approximately as percentage changes for small values, similar to a log-log model.

To interpret the interaction terms and understand how the impact of diversification changes with drought severity, we calculate marginal effects. For the DSCI models, the marginal effect of diversification is given by:

$$\frac{\partial y_{it}}{\partial S_{it}} = \beta_1 + \beta_3 D_{it} \tag{3.9}$$

For models with individual drought levels, we compute:

$$\frac{\partial y_{it}}{\partial S_{it}} = \beta_1 + \sum_{k=0}^{4} \theta_k D_{k,it} \tag{3.10}$$

We estimate our model using the fixed effects estimator, which accounts for time-invariant unobserved heterogeneity across farms. The two-way fixed effects approach also controls for year-specific shocks that affect all farms, such as macroeconomic conditions or widespread weather events. To account for potential heteroskedasticity and within-farm correlation over time, we use cluster-robust standard errors at the farm level.

3.4 Estimation Results

Table 3.4 presents the results of our fixed-effects panel data models examining the impact of crop diversity and drought on farm income. We estimate four models: two using the Shannon Index as a measure of crop diversity by acreage (columns 1 and 3) and crop diversity by income (columns 2 and 4). For each diversity measure, we estimate one model using the

Drought Severity and Coverage Index (DSCI) and another using individual drought levels (D0-D4). The results reveal several key findings. Crop diversity, as measured by the Shannon Index, has a positive and marginally significant effect on farm income in the DSCI model, while the HHI shows a negative and marginally significant effect, consistent with the Shannon Index results as it measures concentration rather than diversity. Drought severity (DSCI) has a significant negative impact on farm income in both DSCI models. When considering individual drought levels, severe (D2) and exceptional (D4) drought have significant negative impacts on farm income. Notably, the interaction between the Shannon Index and exceptional drought (D4) is negative and significant, suggesting that the benefits of diversity diminish under extreme drought conditions. Among the control variables, crop acres consistently show a positive and significant effect on farm income across all models, while the debt-to-asset ratio shows a significant negative effect. Interestingly, government payments and insurance variables do not show significant effects, which may warrant further investigation. These results suggest that while crop diversity generally has a positive impact on farm income, its effectiveness as a risk management strategy may be limited under extreme drought conditions. The models explain about 6.8% of the within-farm variation in income, indicating that there are other important factors influencing farm income variability that are not captured in our current specification.

Table 3.4: Impact of Crop Diversity and Drought on Farm Income

	(1)	(2)	(3)	(4)
Shannon CA	1.472 (0.942)		1.525 (1.198)	
ShannonCI		0.985 (0.993)		0.929 (1.225)
DSCI	-0.013*** (0.003)	-0.014*** (0.003)		
D0			-0.028 (0.017)	-0.021 (0.018)
D1			0.037 (0.023)	0.024 (0.023)
D2			-0.109*** (0.026)	-0.100*** (0.027)
D3			-0.014 (0.030)	-0.022 (0.033)
D4			-0.087** (0.043)	-0.072 (0.051)
ShannonCA × DSCI	-0.002 (0.005)			
ShannonCI × DSCI		-0.003 (0.006)		
ShannonCA × D0			-0.047 (0.038)	
ShannonCA × D1			0.110** (0.049)	
ShannonCA × D2			-0.107* (0.061)	
ShannonCA × D3			0.053 (0.067)	
ShannonCA × D4			-0.093 (0.075)	
ShannonCI × D0				-0.028 (0.037)
ShannonCI × D1				0.075 (0.047)
ShannonCI × D2				-0.077 (0.059)
ShannonCI × D3				0.030 (0.066)
ShannonCI × D4				-0.055 (0.086)
Crop Acres	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Debt-to-Asset Ratio	-2.983*** (0.383)	-3.001*** (0.383)	-2.988*** (0.386)	-3.003*** (0.387)
Govt Payments (lag)	0.005 (0.058)	0.008 (0.058)	0.004 (0.058)	0.009 (0.058)
Insurance Income (lag)	-0.021 (0.020)	-0.021 (0.020)	-0.021 (0.020)	-0.020 (0.020)
Insurance Expense (lag)	-0.009 (0.044)	-0.005 (0.044)	-0.010 (0.044)	-0.007 (0.044)
Constant	8.678*** (0.762)	8.448*** (0.770)	8.615*** (0.848)	8.318*** (0.850)
Observations	9,140	9,140	9,140	9,140
R-sq Within	0.051	0.050	0.053	0.052
Fixed Effects	Farm, Year			

Note: Financial variables: IHS-transformed inflation adjusted. Standard errors clustered at farm level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

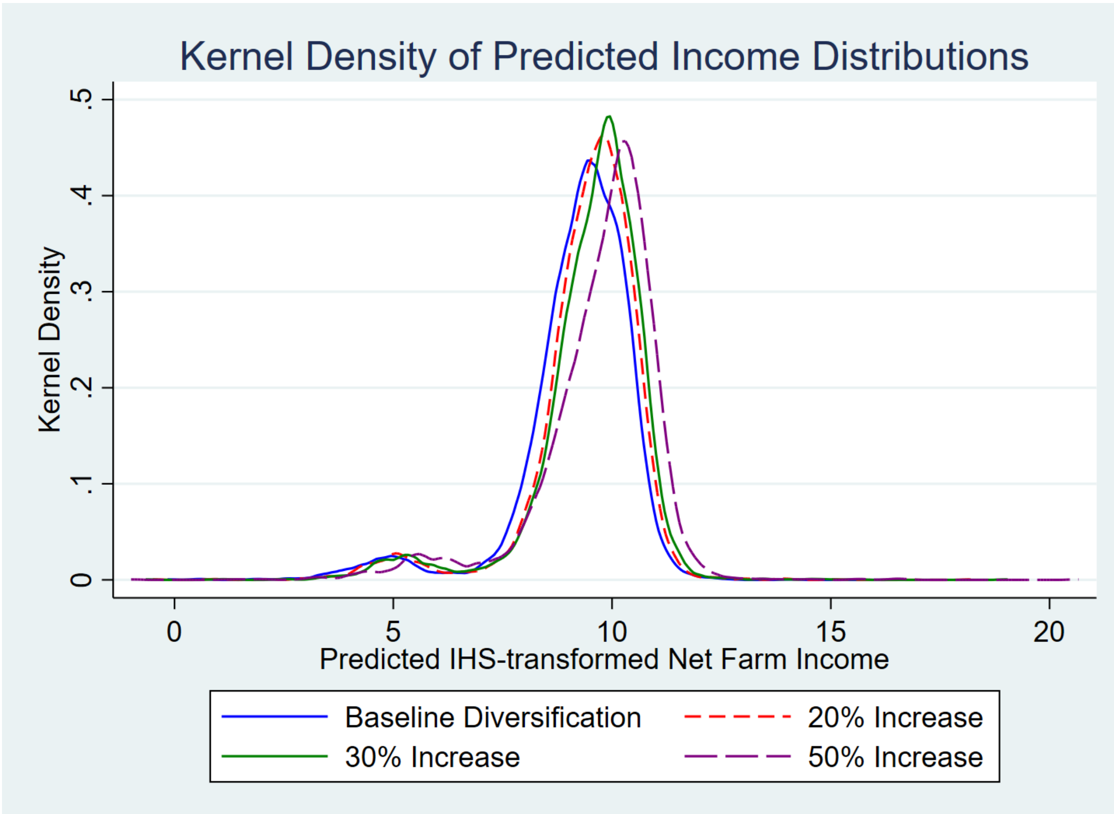


Figure 3.7: Kernel Density of Predicted Income Distributions.

The baseline diversification is represented by the solid blue line, while the 20%, 30%, and 50% increases in diversification are depicted by the red dashed, green dashed-dotted, and purple long-dashed lines, respectively.

The kernel density plot shown in Figure 3.7 illustrates the distribution of predicted IHS-transformed net farm income under varying levels of diversification. The baseline diversification is represented by the solid blue line, while the 20%, 30%, and 50% increases in diversification are depicted by the red dashed, green dashed-dotted, and purple long-dashed lines, respectively. As diversification increases, the peak of the income distribution shifts slightly to the right, indicating a higher predicted net farm income. This suggests that greater diversification may lead to improved financial outcomes for farms. Additionally, the distributions remain relatively narrow, implying that the variation in predicted incomes does not significantly increase with higher diversification levels. This stability could indicate that increased diversification provides consistent benefits across different farm scenarios.

3.5 Conclusion

This chapter examines the relationship between production diversification and net farm income, particularly focusing on financial resilience during environmental shocks, using detailed farm-level data from the Kansas Farm Management Association spanning 2002–2022. The empirical findings confirm that production diversification generally enhances farm income stability and improves financial resilience, especially during moderate drought conditions. However, the results also suggest diminishing returns from diversification under extreme drought scenarios, highlighting diversification's limitations as a sole risk management strategy.

The analysis indicates significant structural shifts toward greater specialization in Kansas agriculture, driven by historical policy incentives that have consistently favored commodity-specific production systems. Despite increased specialization, our results suggest meaningful economic benefits from diversification strategies, as evidenced by higher predicted net farm incomes with increased diversification.

From a policy perspective, these findings underscore the importance of recalibrating agricultural support programs to explicitly value and incentivize diversification practices. Policies that internalize diversification's positive externalities, particularly its role in mitigating financial losses during drought events, could lead to substantial gains in farm-level and systemic resilience. Encouraging diversification not only aligns with resilience-enhancing policy goals but also supports the long-term financial sustainability and stability of agricultural systems in Kansas and beyond.

This study has several limitations that should be considered when interpreting the results. First, the analysis primarily focused on crop diversification and did not extensively examine the role of livestock integration due to data constraints. Second, the study relied on historical data from Kansas, which may limit generalizability to other agricultural regions with different climatic and economic conditions. Third, the study's methodological approach, while controlling for observed heterogeneity, may not fully capture all unobservable farm-specific factors, off-farm income factors influencing diversification decisions, and outcomes.

Future research should aim to address these limitations by incorporating comprehensive data on livestock integration to examine its potential complementary role in diversification strategies. Additionally, expanding the geographical scope to include diverse agricultural regions would enhance the robustness and generalizability of the findings. Methodologically, future studies could benefit from employing advanced econometric techniques or experimental designs to better control for unobserved heterogeneity and causal inference, providing deeper insights into the mechanisms linking diversification and farm resilience.

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Appendix A

Supplementary Material for Chapter 2

Description	Low ($)	High ($)	Average ($)*
Urban and Suburban Deployment			
Antenna - LTE (Long-Term Evolution) Multi-band, >16dBi, 10 port - 10T10R through 20 port - 20T20R	1,479	10,995	6,237
mMIMO eNodeB 3 Sector Per Band (64T64R 20 MHz 1 Band FWA - 64T64R 60 MHz 1 Band with Advanced Mobility Features)	85,000	368,172	226,586
Total for Urban and Suburban	**86,479**	**379,167**	**232,823**
Rural Deployment			
Antenna - LTE (Long-Term Evolution) Multi-band, >16dBi, 10 port - 10T10R through 20 port - 20T20R	1,479	10,995	6,237
non-MIMO eNodeB with 3 sectors, single spectrum band of up to 20 MHz/sector. Fixed Wireless features. Range due to Low Power radio (20W) vs High Power radio (up to 320W). Price includes RRHs, BBU, Ancillaries, Software Features, and Capacity Licensing. Price excludes antennas, tower cabling, tower ancillaries and over voltage protection (OVP)	45,000	69,000	57,000
Total for Rural	**46,479**	**79,995**	**63,237**

* Averages are used in the simulation model

Table A.1: FCC Catalog - Traditional Monolithic RAN (MRAN) Technology Specifications and Pricing

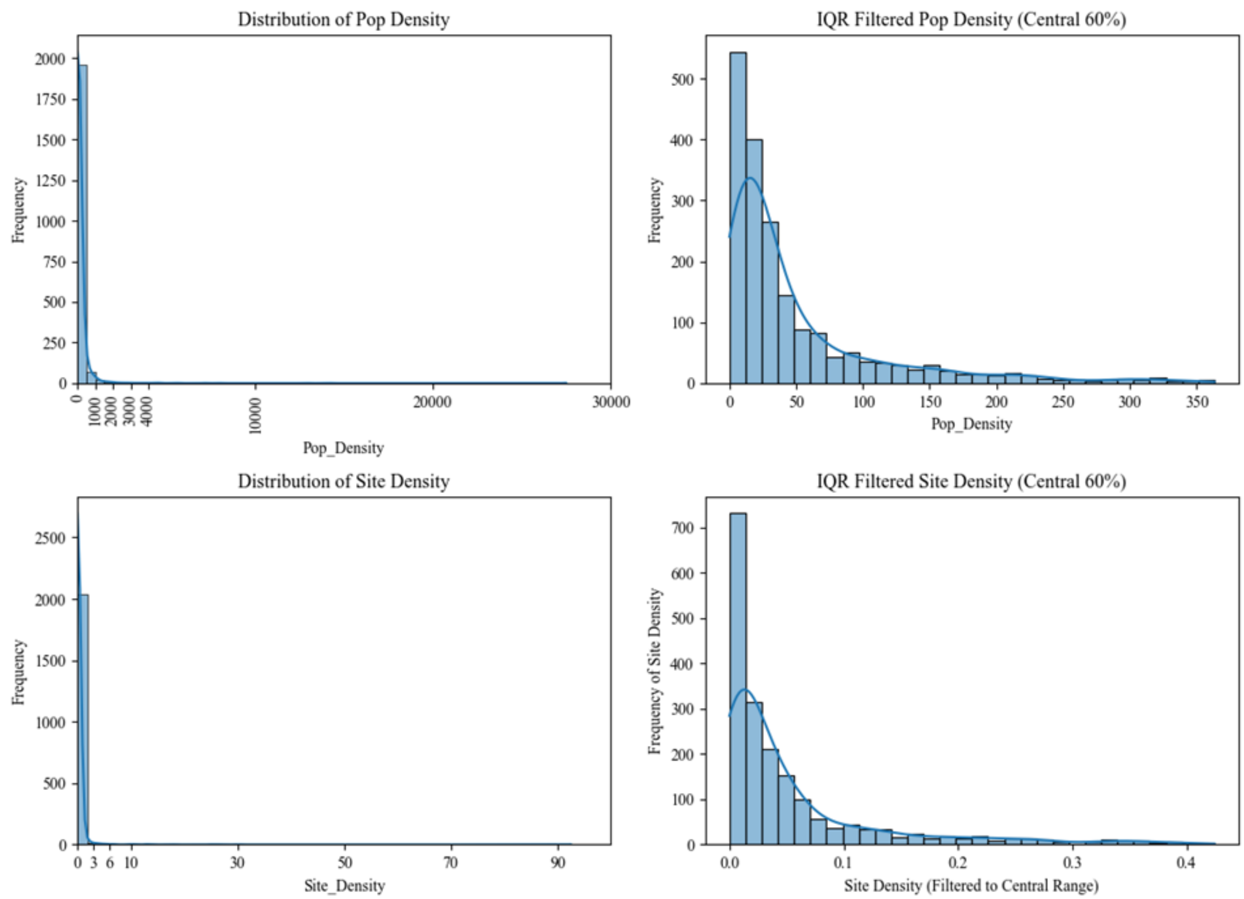

Figure A.1: Distribution of Pop and Site Density Plots.

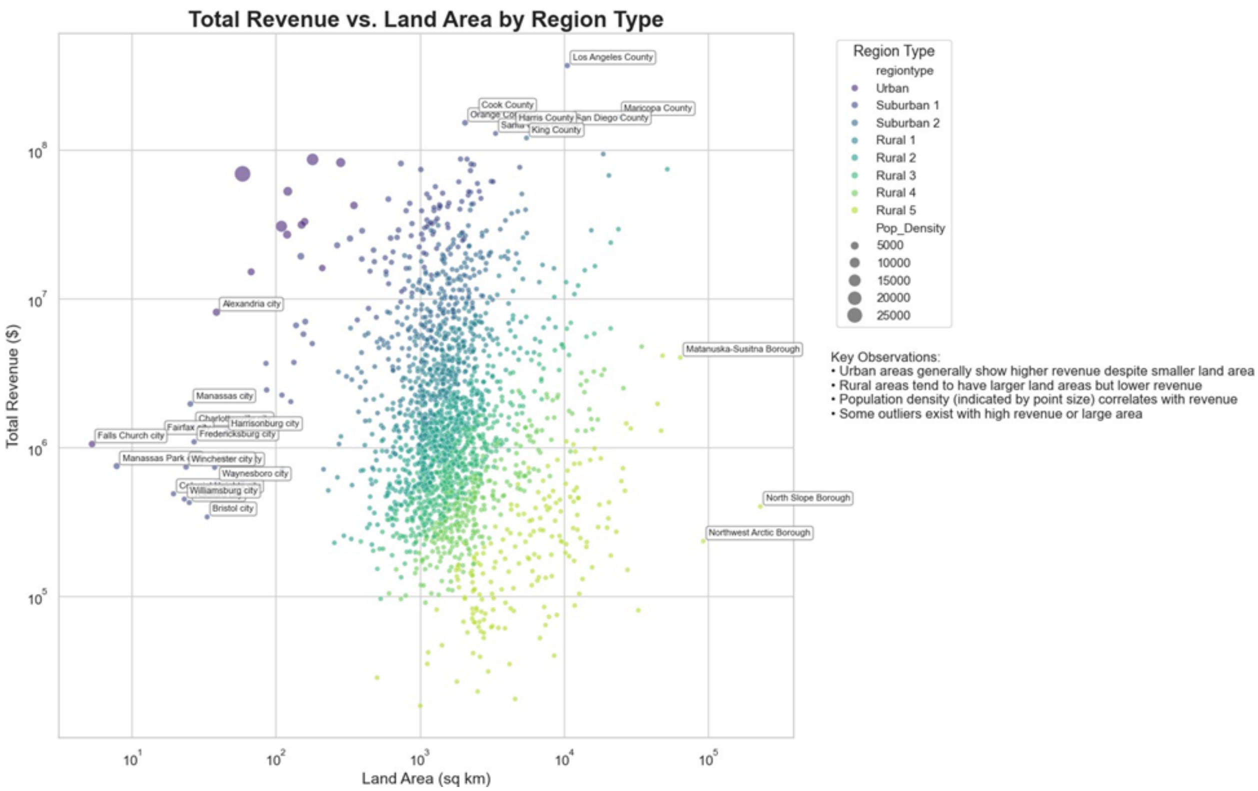

Figure A.2: Total Revenue vs Total Land Area per County.
This scatter plot illustrates the relationship between telecommunications revenue potential and geographic coverage requirements across counties of varying sizes and population densities.

Appendix B

Supplementary Material for Chapter 3

B.1 Formulas

Adjustments for Inflation

To account for economic changes over time, farm income is adjusted using the Consumer Price Index (CPI). The adjustment is computed as

$$\text{Adjusted Income} = \text{Income}_t \times \frac{\text{CPI}_{\text{base year}}}{\text{CPI}_t} \tag{B.1}$$

Equation B.1 is hereby referred to as the *Inflation-Adjusted Farm Income Equation*.

B.2 Figures

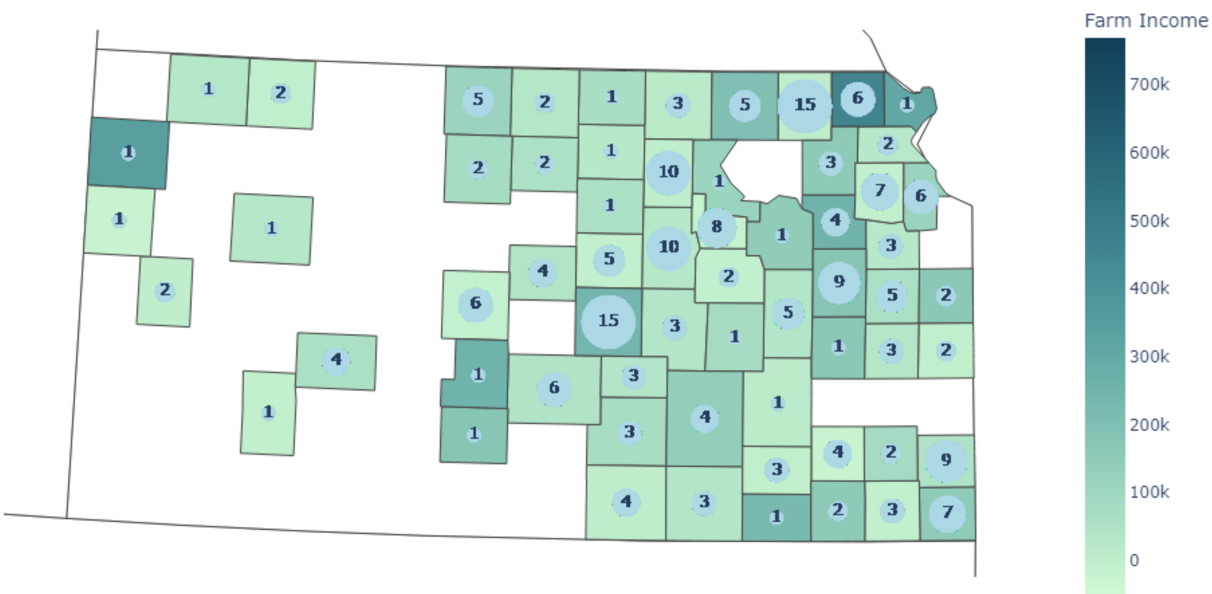

Figure B.1: Average Farm Income and Survey Farm Count by county Kansas,USA

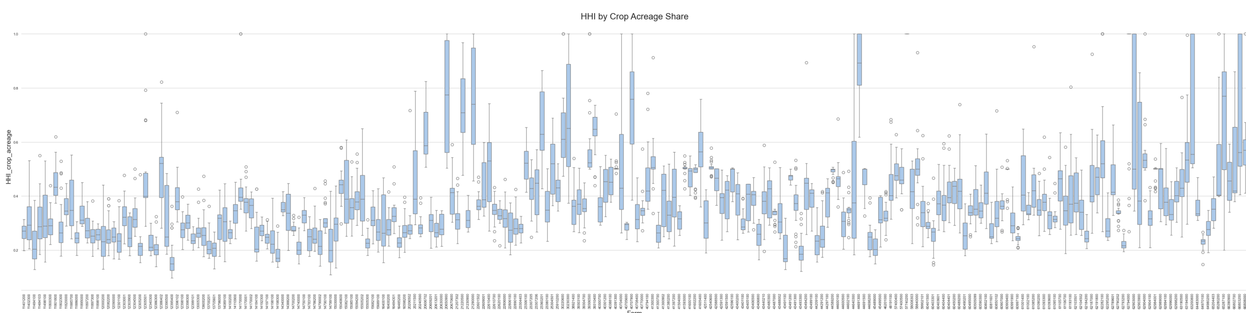

Figure B.2: Farm Level HHI by Crop Acreage Shares

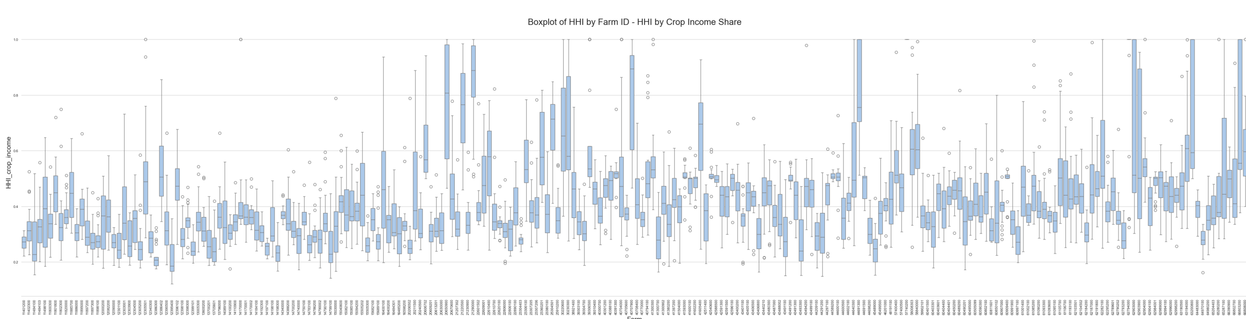

Figure B.3: Farm Level HHI by Crop Income Shares

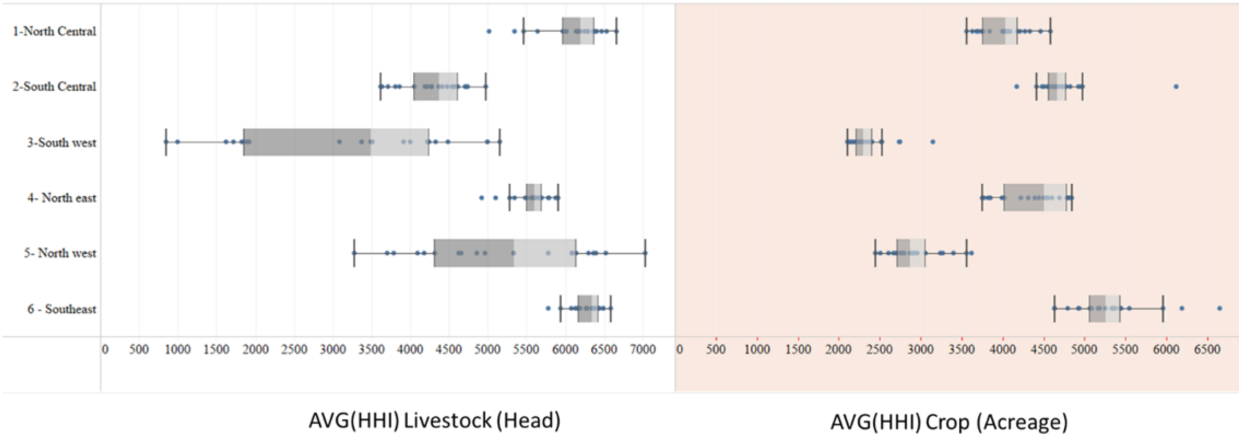

Figure B.4: Comparative Distribution of Average HHI for Livestock and Crop Acreage Across Regions

B.3 Tables

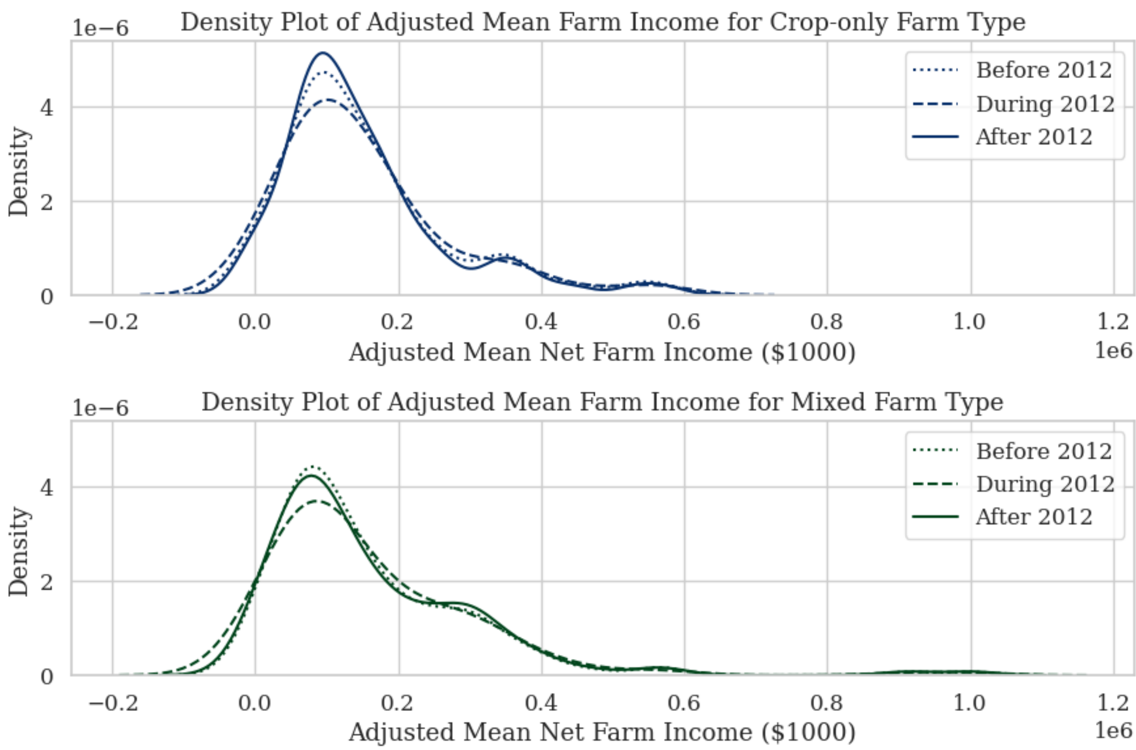

Figure B.5: Density Distribution of Adjusted Net Farm Income Across Crop Count

Table B.1: Comparison of Crop Share Count for Income and Acreage between 2002 (2022).

	(Count by Acreage)							
Count by Income	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**Total**
0	1 (1)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0	1 (1)
1	0	5 (10)	2 (8)	1 (0)	0 (0)	0 (1)	0	8 (19)
2	0	3 (1)	38 (65)	18 (28)	5 (5)	0 (1)	0	64 (100)
3	0	0	22 (8)	57 (63)	17 (13)	2 (3)	0	98 (87)
4	0	0	6 (2)	18 (6)	22 (13)	1 (2)	0	47 (23)
5	0	0	0	4 (1)	5 (0)	3 (1)	0	12 (2)
6	0	0	0	0	1 (0)	0 (0)	1	2 (1)
Total	1 (1)	8 (11)	68 (83)	98 (98)	50 (31)	6 (8)	1	232 (232)

- Majority of farms have two to four crops each accounting for more than 10% of their income and acreage. A very small number of farms reach above 5 level of diversification across both income and acreage.

B.4 Alternate Checks

B.4.1 Crop Income Inequality Analysis Using Theil Index

In addition to farm-level diversification metrics discussed in the main text, we conducted a supplementary analysis of system-level income inequality across different crop types using the Theil T index. The Theil T index belongs to the generalized entropy family of inequality measures and is particularly useful for decomposing inequality into between-group and within-group components. For our analysis of crop income inequality, we define the Theil T index as:

$$T = \sum_{i=1}^{n} \frac{y_i}{\sum_{j=1}^{n} y_j} \ln \left(\frac{y_i / \sum_{j=1}^{n} y_j}{1/n} \right) \tag{B.2}$$

where y_i represents the income from crop type i, and n is the total number of crop types. This can be simplified to:

$$T = \sum_{i=1}^{n} s_i \ln(n \cdot s_i) \tag{B.3}$$

where s_i is the share of total income attributed to crop type i. The Theil index ranges from 0 (perfect equality across crop types) to $\ln(n)$ (maximum inequality, where one crop type receives all income).

Results of Theil Index Analysis

Figure B.6 presents the temporal evolution of the Theil T index for crop income inequality alongside total agricultural income from 2002 to 2022. The Theil index increased from approximately 0.78 in 2002 to 0.88 in 2022, indicating a 12.8% increase in crop income inequality over the 20-year period. Significant fluctuations in the Theil index occurred throughout the period, with pronounced peaks around 2012 and 2016. These peaks coincide with major drought events in Kansas, suggesting that environmental stressors may exacerbate income inequality across crop types. The substantial between-group component suggests that structural factors—including the agricultural policy incentives discussed in Section 1.2 of the main text—play an important role in shaping crop income distribution patterns.

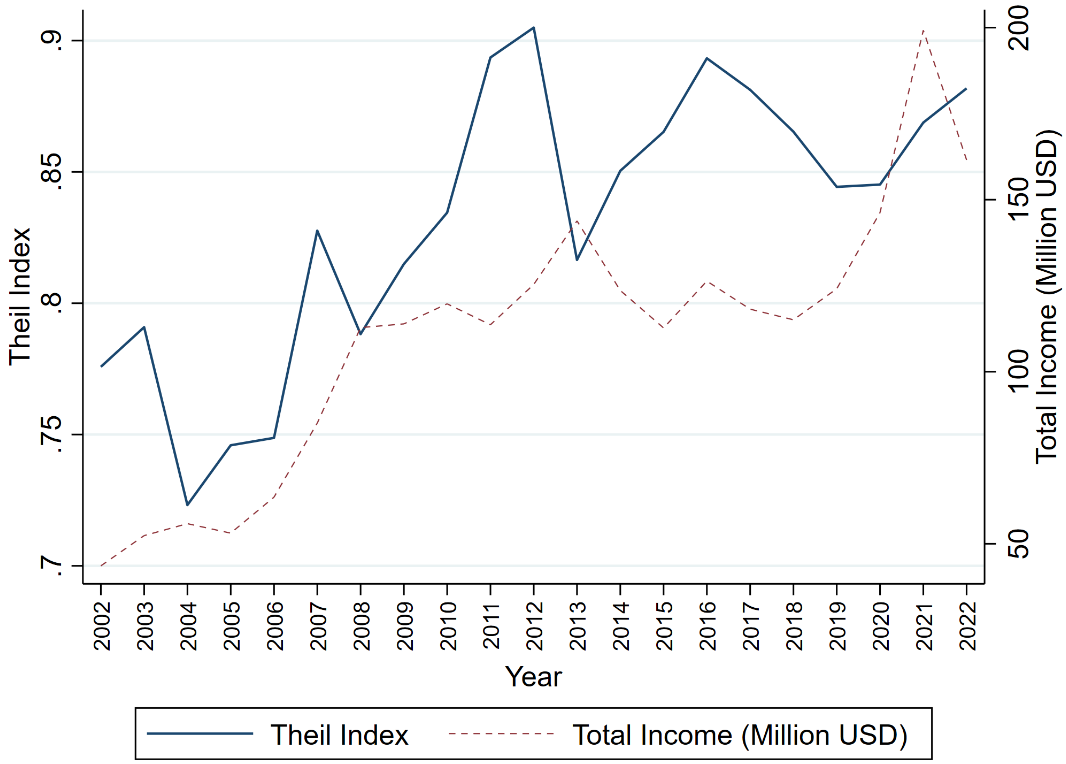

Figure B.6: Temporal Trends in Crop Income Inequality and Total Income (2002-2022). The solid line depicts the Theil T index measuring income inequality across crop types (left y-axis), while the dashed line represents total crop income in million USD (right y-axis). The Theil index quantifies the degree of concentration in income generation among different crop categories, with higher values indicating greater inequality.